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A Comparison of the Effects of Mobile Device Display Size and Orientation, and Text Segmentation on Learning, Cognitive Load, and User Perception in a Higher Education Chemistry Course

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by

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Dedication

It takes a village to complete a doctorate degree and my village runneth over!

For your endless love, support, and encouragement, I dedicate this culmination of six years of work to my mom Ann Daly Karam, my siblings Sara Karam Holtz, Adam Karam, and Samantha Karam Naffah, my aunt Laura Daly, and my dad, the late (and always missed) Solomon J. Karam.

Of special note: On my darkest days, of which this odyssey had many, you were my pillar. Arguably, this degree is as much yours as mine. You are now and forever more my Dr. Mom!

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A Comparison of the Effects of Mobile Device Display Size and Orientation, and Text Segmentation on Learning, Cognitive Load, and User Perception in a Higher Education Chemistry Course

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This study aimed to understand the relationship between mobile device screen display size (laptops and smartphones) and text segmentation (continuous text, medium text segments, and small text segments) on learning outcomes, cognitive load, and user perception. This quantitative study occurred during the spring semester of 2015. Seven hundred and seventy-one chemistry students from a higher education university completed one of nine treatments in this 3x3 research design. Data collection took place over four class periods. The study revealed that learning outcomes were not affected by the mobile screen display size or orientation, nor was working memory. However, user perception was affected by the screen display size of the device, and results indicated that participants in the sample felt laptop screens were more acceptable for accessing the digital chemistry text than smartphone screens by a small margin. The study also found that neither learning outcomes, nor working memory was affected by the text segmentation viewed. Though user perception was generally not affected by text segmentation, the study found that for perceived ease of use, participants felt medium

text segments were easier to learn from than either continuous or small test segments by a small margin. No interaction affects were found between mobile devices and text segmentation. These findings challenge the findings of some earlier studies that laptops may be better for learning than smartphones because of screen size, landscape orientation is better for learning than portrait orientation in small screen mobile devices, and meaningful text segments may be better for learning than non-meaningful, non-segmented, or overly segmented text. The results of this study suggest that customizing the design to the smartphone screen (as opposed to a one-size-fits-all approach) improves learning from smartphones, making them equal to learning from laptops in terms of learning outcomes and cognitive load, and in some cases, user perspective.

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Chapter 1: Introduction

Learning with mobile devices is on the rise. Laptops, tablets, and smartphones now offer a variety of applications and access for learners of all ages. Educators and instructional designers are working to better understand what design principles lead to the best learning experiences. These conversations consider learning gains, screen layout, cognitive load, ideal screen size, user interface (UI) design, content-specific guidelines, and user preferences. Although there are well established instructional design frameworks and principles that have been used with print, video, and computer-based instruction, there are questions related to the applicability of these frameworks to learning within the constraints of the small screen displays of smartphones. However, to date there are few noted instructional design principles for small screen mobile devices, especially for smartphones. Furthermore, research concerning the best practice utilization of specific design elements is sparse, leaving great space for additional research.

In the current consumer landscape, mobile devices are everywhere. Laptop computers, tablets, and smartphones infiltrate communication, economic, political, and social realms. With the speed of technological evolution and the proliferation of mobile devices, industry, government, and education constantly struggle to stay abreast of development. There are many questions yet to be answered. Examples include: How should these devices be incorporated into the business, government, and educational practices which currently operate? Should technology be adapted to older educational models or should older educational models be updated to embrace the technology? How can the affordances, as well as the constraints of the new generation of mobile devices be carefully considered and integrated into the teaching-learning process?

Considering the broadly evolving platforms, operating systems, device sizes, capabilities, and integration of mobile devices, quality software development is a constant challenge. In its most ideal circumstance, software is iterative, adapting as the technology changes. However, such development is extensive and expensive, further adding layers to challenges of integrating these devices into the learning environment.

As mobile device presence surges, expectations for more seamless integration increase (Noel-Levitz, LLC, 2014). A primary mode for both communication and access to information is through mobile devices (mainly smartphones). Given the use of and marketing projections for mobile devices, it seems probable that they are here to stay for the foreseeable future (Ericsson, 2015).

Smartphones especially have risen in numbers sold, both in the United States and around the globe. These small mobile devices rarely leave their owners' sides ("IDC Home," 2015). The ever-evolving affordances and tools accessible through the omnipresent smartphone present unique learning opportunities (Crescente & Lee, 2011). This is especially interesting when one considers that in terms of learning, the relatively small screen is the least effective display for transferring information and knowledge (Kim & Kim, 2012).

Therein lays the conundrum: the mobile device that is most accessed and utilized is seemingly the least advantageous for learning. This study exists within that emerging challenge. On its own, the small screen of a smartphone is less suitable for learning when compared to the larger screens of its mobile cousins, the laptop computer and the tablet

(Kim & Kim, 2012; Luong & McLaughlin, 2009; Molina, Redondo, Lacave, & Ortega, 2014). This study will explore whether specific instructional and user-interface design techniques can be applied to small screens in ways that decrease cognitive load, increase learning, and meet user expectations, thus fostering learning equitability between various-sized mobile devices.

The material presented in chapter one will provide a high-level description of mobile technology, including definitions and statistics. Additionally, it will briefly introduce the body of research for mobile learning theories and the effects of cognitive load on learning (i.e., how human cognitive architecture works to process and store information), and mobile instructional design, which will aid in grounding the literature review, research background, and hypothesis. It will then touch on the significance of this study, both in terms of adding to the current body of research and leading the way for future research, before finally specifying the structure of the following chapters of this dissertation.

MOBILE TECHNOLOGY

Given the constant changing nature of mobile technology, it is necessary provide an overview of the current status of the development, access, and use of mobile technology at the time of this study. Next, statistical evidence demonstrating the proliferation of mobile devices globally and in higher education will help situate this research, which in turn will help identify possible directions for future research.

Mobile technology requires three main components to function: the hardware (physical devices), the software (applications and operating systems, etc.), and connectivity. Hardware refers to all tangible parts required to operate a mobile device. Hardware is the nuts and bolts, from the computer chips and processors to the display screen, casing, and physical buttons. Together these pieces create the variety of devices that exist today.

Software includes all of the coded instructions and applications created to enable visual and informational interactions via the device. Operating systems (OS) are coding language platforms that act as software instructional platforms. OSs vary per device, meaning that the same application written in iOS for an iPhone cannot be used on a device that runs on an Android OS platform. Software is the input and output instructions that allows the device to operate and interact appropriately.

Connectivity is the way in which the device "connects" with other devices and the internet. For mobile devices, connections are mainly wireless, meaning data is transmitted via radio waves and does not require the hard plug and cord connection. It is this wireless capability that has made mobile communication possible. There are several types of wireless connections, including Wi-Fi, Bluetooth, and mobile broadband (3G, 4G, etc.). Each uses different wave lengths and systems to exchange and interpret data between devices.

Mobile devices today take several forms. Mobile personal computers evolved from desk top computers, personal digital assistants (PDAs), and cellular phones into laptops, tablets, and smartphones. There are numerous types of mobile devices ranging from laptops to smartwatches. Of import in this study are laptops, tablets, and smartphones (see Table 1.1). Additionally, two hybrid devices are on the rise and while less directly impacting this study, laplets and phablets (see definition below) are nevertheless worthy of mention given their unique blending of computing capabilities and size, and the increase in units sold.

Laptops have the full computing functionality of a desk top computer with rechargeable battery-operated, portable, slim designs easy for carrying and computing on the go (PC Magazine, 2014a; wikipedia, 2014). Modern “laptops” include diverse categories of devices, such as netbooks, notebooks, and desktop replacements. Laptops feature full keyboards attached to the display, allowing for the clamshell device to flip open and closed. Laptops have fully capable Central Processing Units (CPUs), full-featured OSs, and numerous input/output (I/O) ports. Most laptops are Wi-Fi enabled, but are not mobile broadband enabled. Laptop weights vary per device, while LCD displays range from 11 up to 18 inches.

Tablets are wireless mobile computers accessed via a touchscreen interface. Tablets are smaller in size and computing power than laptops and larger than smartphones. Tablets have digital keyboards and are self-contained, although a few models allow for external keyboard hook up. They offer both Wi-Fi and mobile broadband capability. Tablets include slate tablets, mini tablets, and eReaders. While some larger slate tablets have 10 inch displays, the more popular tablets, like Apple’s iPad, have screens between 7 and 9 inches. Tablets are mostly used for web browsing, light-gaming, and media consumption, though music and design capabilities are expanding (PC Magazine, 2014c). Presently, they do not offer the fully functioning operating systems of laptops.

Smartphones combine cellular telephone technology with some functionalities of a mobile personal computer (PC Magazine, 2014b). Paas, et. al. (2013) define smartphone as mobile phones with mobile operating systems that allow for computing and interactivity. Like tablets, smartphones have limited computing power compared to laptops. Modern smartphone features include phone, SMS/MMS, email, web access, digital cameras, media players, full video and audio capabilities (i.e., you can view, create, share, and even edit your own videos using your smartphone), GPS capabilities, voice-to-text and text-to speech, and numerous tools and applications for measurement, health, language, etc. (Zabel, 2010). Smartphone connectivity includes mobile broadband, Wi-Fi, Bluetooth, and Near Field Communication (NFC). Smartphones range in display size from 3.5 to 5.1 inches. The size and phone capabilities of smartphones make them the most convenient mobile computing device.

A phablet (PHone tABLET) is a hybrid of a smartphone and a tablet. Example phablets include the Samsung Note 4 and the Apple iPhone 6 Plus. Phablets offer better visual experiences than traditional smartphones with larger displays ranging between 5 and 6 inches, but still have the capability of a smartphone in terms of phone capability, connectivity, and personal computing functionalities (PCMagazine, 2014). While most smartphones fit conveniently into clothing pockets, phablets can be bulky.

A laplet (LAPtop tabLET) is a hybrid of a laptop and tablet (also called 2-in-1s and ultramobiles. Example laplets are the Microsoft Surface Pro 3 and the Lenovo Yoga 2. They combine the power and versatility of a traditional laptop with the mobility of a tablet. Like laptops, laplets run on x86-architecture CPU and a full-featured operating system. They include typical laptop I/O ports, such as USB. Some come with detachable keyboards. Like tablets, laplets have touchscreen displays and can convert into a tablet-like device when the keyboard is detached or flipped under.

Table 1.1.

Mobile Devices

Device	Examples	Power/CPU	Connectivity	Display Type	Display Range
Laptop	Apple MacBook, HP Pavillion	Full Range Computing	Wi-Fi	LCD Mouse, LCD Touchscreen	10” – 17”
Laplet	Microsoft Surface Pro 3	Full Range Computing	Wi-Fi, Bluetooth, Mobile Broadband (some models)	LCD Touchscreen	10” – 13”
Tablet	Apple iPad, Samsung Galaxy Tab 10.5 S	Limited Computing	Wi-Fi, Bluetooth, Mobile Broadband	LCD Touchscreen	7” – 10”
Phablet	Samsung Galaxy Note 4, Apple iPhone 6 Plus	Limited Computing	Wi-Fi, Bluetooth, Mobile Broadband	LCD Touchscreen	5.2” – 6”
Smartphone	Samsung Galaxy S5, Apple iPhone 6	Limited Computing	Wi-Fi, Bluetooth, Mobile Broadband	LCD Touchscreen	3.5” – 5.1”

With so many offerings, it is common in the United States for individuals to have more than one mobile device. A 2014 study by Morgan Stanley even found that 91% of Americans keep their mobile devices within reach at all times and the upward trend in mobile device sales is not lagging, having reached 2.4 billion in 2013 with units sold still increasing (Gartner, Inc., 2014). According to Ericsson (2014), mobile subscriptions are predicted to reach 9.3 billion by 2019.

Among the noted mobile computing devices, some are selling substantially more, while others lag behind. Ericsson (2014) predicted that of those 9.3 billion mobile subscriptions, 5.6 billion (well over half) will be for smartphones. Current statistics and marketing projections anticipate the continued proliferation of smartphones and phablets, while laptops and tablet sales decrease (Ericsson, 2015). However, professional use requires the computing power of a laptop, so while experts predict laptop sales to slow, they do not anticipate laptops to fade out of use. Rather, with consumer demand for mobility, some experts speculate that laplets will grow in popularity, replacing laptop sales (Ericsson, 2015).

Due to the continually increasing functionality, convenient size, and expanding connectivity, smartphones are predicted to remain the mobile device of choice for individual use. In fact, the International Data Corporation (IDC) estimates that by 2018, smartphone sales will reach 1.25 billion units, and will make up 51.2% of the total mobile device market (IDC, 2014). Phablet market shares, at 9.8% in 2014 are estimated to increase nearly 15% to 24.4%. These two smart devices are predicted to hold nearly 76% of the global mobile computing device market (Noel-Levitz, LLC, 2014). Note: remember that today's smartphone has the same power as a super computer 20 years ago, so their computing power of smartphones will continue to increase.

Device market share is integral to any conversation that seeks to understand how best to use mobile devices for communication and learning because it provides a snapshot of consumer preferences and expectation of mobile technology, both from a device and a user perspective. Meeting device and use expectations requires utilizing the popular devices, and in expected ways, designing applications that seamlessly incorporate the features and functionality of the device (Seraj & Wong, 2014). Given the cost of mobile software development and maintenance, as well as the rapidity with which newly updated devices are available, government, industry, and educational organizations want to execute technology plans and allocate budgets wisely, while also meeting the expectations of consumers, employees, and students (Potcatilu, 2010; Su, Liu, & Lee, 2011).

On the higher education campus especially, mobile devices blanket the landscape. ICEF Monitor (2014) found that 78% of students have regular access to a mobile device, owning an average of 6.9 mobile devices (2013). While that laptop is presently the most owned mobile device at 85%, smartphone ownership continues to increase as today's high school students become tomorrow's collegiates (Reidel, Chris, 2014). Noelle Levitz (2014) found that nearly 9 out of 10 high school students have access to connected smartphones, while laptop ownership is only at 50% (Noel-Levitz, LLC, 2014). These statistics support the market projections that predict the increasing demand for smartphones as the connected device of choice.

Students tend to use their smartphones for browsing, entertainment, learning, and staying connected (via text, phone, email, and social networking) (ICEF Monitor, 2014). More and more participants in higher education calculate the value of smartphones for learning.

Smartphones offer numerous opportunities for formal and informal learning as they are transforming the way we think about space, community, and discourse (Traxler, 2007). The need to better understand the learning potential and efficacy of mobile devices, and smartphones especially is driven by student and consumer expectation (Seraj & Wong, 2014). Empirical studies on this combination of device and learning are increasing (Churchill, 2011; Kim & Kim, 2012; Reeves, Lang, Kim, & Tatar, 1999; Seraj & Wong, 2014). While the trend in research seems to be moving towards filling notable gaps, the study of mobile learning is still relatively new enough that the gaps remain large despite the increase in research. This body of research has focused on user perception (Al-Zoubi, Alkouz, & Otair, 2008; Demirbilek, 2010; Franklin et al., 2007; Kismihók &

Vas, 2011; Ryu & Parsons, 2012; Terras & Ramsay, 2012), cognitive load (Kim & Kim, 2012; T.-C. Liu, Lin, & Paas, 2013; T.-C. Liu, Lin, Tsai, & Paas, 2012; Molina et al., 2014), learning gains (Cobb et al., 2010; Tarumi et al., 2011), instructional principles (Elias, 2011; Gatsou, Politis, & Zevgolis, 2011; Gu, Gu, & Laffey, 2011), feature and affordance comparisons (Tarumi et al., 2011; Wu, Hwang, Tsai, Chen, & Huang, 2011), specific use applications (Seraj & Wong, 2014), blended use (Shen, Wang, Gao, Novak, & Tang, 2009), and design principles (Gatsou et al., 2011). Some empirical queries have asked questions like how would a mobile device deliver content and how will people perceive using these devices in educational settings (Crescente & Lee, 2011; Su et al., 2011). Others have focused on specific environments to implement this combination of device and learning, like the high school classroom, college campus, or corporate office (T.-C. Liu et al., 2013; Molina et al., 2014; Seraj & Wong, 2014). Still others have investigated mobile learning's use for teaching and learning specific subjects, for example, language learning (Hwang, Shi, & Chu, 2011; Tim de Jong, Specht, & Koper, 2010; Tarumi et al., 2011; Wyatt et al., 2010).

Many studies produced positive results (Demirbilek, 2010; Kismihók & Vas, 2011), while others have found that facets of mobile device use for learning in general and specific areas actually hinder performance (Kim & Kim, 2012; Luong & McLaughlin, 2009), communication (Al-Zoubi et al., 2008; Ryu & Parsons, 2012), recall (Luong & McLaughlin, 2009; Maniar, Bennett, Hand, & Allan, 2008; Sanchez & Goolsbee, 2010), and even entertainment (Heo, 2003; Reeves et al., 1999). Implications and application of those findings are further argued and tested. Growing this body of research is a challenge because the technology continuously evolves and to some degree leaves researchers back at the drawing board with the emergence of new devices and new possibilities. Evidence of this is clearly demonstrated by the fact that many noted studies were completed with now antiquated PDAs, or older model tablets (C. Becker & Dürr, 2004).

Mobile devices, namely laptops, tablets, and smartphones, are now common features both generally and in higher education. Of those devices, smartphones have outpaced laptop and tablet sales and are projected to continue doing so. Consumer, employee, and student expectation for smartphone integration increases, as they rely on their smartphones more and more for integrated tasks that were previously performed on devices with larger displays. On the college campus, smartphone proliferation for learning merits continued research into best practices for combining devices and learning. To further situate this research, the following section will give an overview of mobile learning definitions and research, as well as introduce the variables to be utilized in this study, as they pertain to mobile learning.

MOBILE LEARNING

Mobile learning has been prevalent as a movement in education now for nearly 15 years (Baharum, Ismail, & Idrus, 2010; Crescente & Lee, 2011; Demirbilek, 2010; Mostakhdemin-Hosseini, 2009a; Pimmer, Pachler, & Attwell, 2010). It is occurring because mobile devices are transforming our understandings of space, community, and discourse (Traxler, 2007). Definitions of mobile learning are varied, but range from unique learning experiences owed to handheld mobile devices (Crescente & Lee, 2011; Demirbilek, 2010; Frohberg, Göth, & Schwabe, 2009; Kukulska-Hulme et al., 2011;

Traxler, 2005) to ubiquitous learning (Crescente & Lee, 2011; Laine, Vinni, Sedano, & Joy, 2010; Y. Park, 2011; Pea & Maldonado, 2006; Terras & Ramsay, 2012; Uzunboylu & Ozdamli, 2011) to on-the-go learning (Becking et al., 2004; O'Malley et al., 2005; Yau & Joy, 2010) or just-in-time learning (Y. Park, 2011; Traxler, 2007). Mobile learning can be formal or informal, depending on the learner and the content, environment, and time accessed (Daoudi & Ajhoun, 2008; Traxler, 2010).

Mobile learning offers unique device and learning affordances. Device affordances include the features of the hardware and software. Examples include GPS, camera, NFC, and anywhere connectivity (Zabel, 2010). The learning affordances of mobile learning include portability, expediency, immediacy, accessibility, flexibility, connectivity convenience, cross-context learning, individuality, and interactivity (Baharum, Ismail, & Idrus, 2010; Bhaskar & Govindarajulu, 2009; Crescente & Lee, 2011; Elias, 2011; Klopfer & Squire, 2007; Y. Park, 2011; Terras & Ramsay, 2012; Traxler, 2005; Valk, Rashid, & Elder, 2010). The notions of immediacy and expediency additionally make possible just-in-time, just-in-case, just-for-me, and just-enough learning (Y. Park, 2011; Traxler, 2007). Mobile learning occurs in a range between communication intensive and independent work, with each extreme utilizing different mobile features and levels of productivity. The more independently one works, the greater content-intensive is their learning; while using the mobile device for communication activities relies heavier on learning collaboration (Graham Attwell, 2010; Eliasson, Pargman, Nouri, Spikol, & Ramberg, 2011; M. Wang & Shen, 2012).

User perception and acceptance

At the heart of any technological success in education is the user. Positive user perception and acceptance of mobile learning is crucial for its success (Hwang et al., 2011; Sanchez & Goolsbee, 2010; Seraj & Wong, 2014; Terras & Ramsay, 2012; Traxler, 2005; Valk et al., 2010; Y.-S. Wang, Wu, & Wang, 2009; Yau & Joy, 2010). As such, many studies have focused on these topics (Bhaskar & Govindarajulu, 2009; Crescente & Lee, 2011; Mostakhdemin-Hosseini, 2009b). Results have proven both negative and positive user perception, but generally suggest a positive response to mobile learning (Almaiah & Jalil, 2014; Demirbilek, 2010; Franklin et al., 2007; Kismihók & Vas, 2011; Y.-S. Wang, 2007). This makes sense given the proliferation of hand held devices (namely smartphones) within the bedrock of social, business, and educational culture. As individuals expect to use their devices ubiquitously, there is a growing expectation that use should extend to all facets of life, including into classrooms and offices. One well-tested method for gaging user perception and acceptance is the Technology Acceptance Model (TAM) (Legris, Ingham, & Collerette, 2003; Malhotra & Galletta, 1999; Ma & Liu, 2004; S. Y. Park, 2009; Schepers & Wetzels, 2006; Tsai, Wang, & Lu, 2011; Venkatesh, Morris, Davis, & Davis, 2003). TAM assumes that user perception and perceived ease of use together accurately measure a user's acceptance of a specific technological tool for the task at hand (Davis, 1985, 1989; Davis, Bagozzi, & Warshaw, 1989; Venkatesh, 2000; Venkatesh et al., 2003).

COGNITIVE LOAD THEORY

Cognitive Load Theory is an instructional design theory (Chandler & Sweller, 1991). It operates under the assumption that we each have an infinite long-term memory capacity and a limited working memory (short-term) memory capacity (Ayres & Paas, 2012; Baddeley, 1976; Miller, 1956; Sweller, 1988, 1994, 2002). For information to be learned, it must be moved from the working memory into the long-term memory (F. Paas, Renkl, & Sweller, 2003, 2004; Sweller, Merrienboer, & Paas, 1998). This transition is accomplished through the construction and automation of schema (Chandler & Sweller, 1991; Sweller et al., 1998). A schema is anything learned as a single entity that is stored in the long-term memory (Baddeley, 2001; Hollender, Hofmann, Deneke, & Schmitz, 2010; Sweller, Ayres, & Kalyuga, 2011). Schema reduce working memory load through recall, by combining to make ever-more-complex schema (Chi, Glaser, & Rees, 1982). In this way, working memory is reduced as the complex schema is now treated as only one element in the working memory instead of as the individual bits of information that composes it (Chandler & Sweller, 1991). This continued process leads to schema automation and automatic processing that stems from the long-term memory (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977) and does not take up space in the working memory when accessed (Sweller, 2002). Although the working memory is limited to the number of elements it can process, the size, complexity, and sophistication of each element is unlimited (Hollender et al., 2010; Sweller, 2002, Sweller, 1994).

CLT distinguishes between three types of cognitive load that must be processed for long-term recall to occur. CLT assumes that information is the basic element in learning (Sweller, 1988, 1994). Each element (piece of information) has an intrinsic cognitive load (ICL), meaning what is required to know the element itself (Sweller et al., 1998) or to understand how two elements interact (F. Paas et al., 2004). A single element can have low element interactivity, and therefore a low intrinsic load, or a high element interactivity, and therefore a high intrinsic load (Mayer & Moreno, 2003; Sweller, 1988). Extraneous cognitive load (ECL) occurs when the learning design includes material and activities that are outside of, or 'extra' to what is to be learned, which unnecessarily take up working memory space and may cause cognitive overload and prevent the construction and automation of schema (Chandler & Sweller, 1991; F. Paas et al., 2004; Sweller, 1988). Extraneous cognitive load can be altered via "instructional interventions" (Sweller et al., 1998).

Germane cognitive load (GCL) is also produced by the instructional design of learning (F. G. W. C. Paas & Merriënboer, 1994; F. Paas et al., 2004; Sweller et al., 1998). Germane load fosters active schema construction processes and is beneficial to learning. (Hollender et al., 2010; F. G. W. C. Paas & Merriënboer, 1994). Adaptations on this definition of germane load include Jong's (2010) distinction of intrinsic load as the complexity of the material and germane load as the cognitive process required to process material. Schnotz and Kürschner (2007) espoused that germane load goes beyond simple task performance to the use of meta-cognitive processing.

The expertise level of the learner changes the load values of an activity, and likewise should alter the learning design (Merriënboer & Ayres, 2005). Experts and novices have similar working memory capacity. The difference in experts is simply that they have more schema concerning the topic of their expertise organized and stored in their long-term memory (Sweller, 1988). The total cognitive load of a learning experience is comprised of the summation of ICL + ECL + GCL (Kirschner, 2002), as well as the expertise of the learners (Ton de Jong, 2010; Schnotz & Kürschner, 2007; Sweller et al., 1998). Total load cannot exceed the working memory resources if learning is to occur (F. Paas et al., 2004; F. Paas, Tuovinen, Tabbers, & Van Gerven, 2003; Sweller, 1994).

The underlying goal of Cognitive Load Theory (CLT) is to design learning that increases cognitive recall by decreasing cognitive overload when information is being processed in the working memory (Chandler & Sweller, 1991; Sweller, 1988, 1994, 2002; Sweller et al., 1998), simultaneously taking into account the expertise of the learner (Kalyuga, Chandler, & Sweller, 2000). Accordingly, instructional design should manipulate the types of load in ways that align task requirements with the learner's level of expertise (Schnotz & Kürschner, 2007, p. 490).

Cognitive Theory of Multimedia Learning

Using the limited capacity assumption of Sweller's CLT and the dual channel assumption of Baddelley's (1976) Theory of Working Memory and Pavio's (1986) Dual-Channel Theory, in combination with Mayer's (1999) own theory of Active Learning, Mayer and Moreno (2003) identified the Cognitive Theory of Multimedia Learning. This theory asserts, and follow-up research has seconded, that in specific circumstances, learning occurs more deeply when both the auditory and the visual channels are utilized than with the visual channel alone (Ayres & Sweller, 2005; Mayer, 2003; Mayer & Fiorella, 2014; Mayer & Moreno, 2003). However, some studies have found that there are limitations to the specific effects produced under CTML (Kalyuga, 2000; Schnotz &

Kürschner, 2007; Schüler, Scheiter, & Gerjets, 2013; Schüler, Scheiter, & Schmidt-Weigand, 2011).

CLT and CTML are both essentially instructional design theories based on cognitive psychology (Mayer, 2009; Sweller et al., 1998), and as such, it is commonly the case that when a cognitive overload effect is revealed, its design antidote is also suggested (Mayer & Moreno, 2003; Sweller et al., 2011). As this study is specifically interested in instructional design principles for mobile devices, it follows that avoiding specific cognitive overload effects is beneficial for learning.

Cognitive load effects and text comprehension

Cognitive Load Theory and Cognitive Theory of Multimedia Learning both promote the notion that the primary goal of instructional design is enabling schema construction and the automation of the information in the long-term memory (Sweller et al., 1998). When an instructional designer is designing learning, the goal is to transfer that intrinsic/germane cognitive load to the learner in ways that do not produce cognitive overload (Chandler & Sweller, 1991; Kalyuga et al., 2000; F. Paas, Renkl, et al., 2003). Towards the creation of well-designed instruction, several cognitive overload effects have been discovered. These effects, when observed, have overloaded the working memory and disrupted learning (Ayres & Sweller, 2005; Hollender et al., 2010; F. G. W. C. Paas, Van Merrienboer, & Adam, 1994). They have been observed across learning mediums (Chandler & Sweller, 1996; Mayer, 2003).

Split attention effect occurs when a learner must integrate multiple sources of information in order to understand it, such that the individual pieces of information cannot be understood in isolation (Ayres & Sweller, 2005; Hollender et al., 2010; Kalyuga, Chandler, & Sweller, 1999; Mayer & Fiorella, 2014; Sweller et al., 1998). The process of holding information in working memory, while simultaneously attempting to integrate it with other information is cognitively demanding (Cierniak, Scheiter, & Gerjets, 2009; Kalyuga et al., 1999; Mayer & Moreno, 1998), especially for low prior knowledge learners (Ayres & Sweller, 2005; Chandler & Sweller, 1991; Florax & Ploetzner, 2010). Split attention effect can be caused by the learning design (T.-C. Liu et al., 2013; F. Paas et al., 2004), or be caused by intrinsic or germane load when the material surpasses the learner's zone of proximal development, thus over-whelming the working memory (Ginns, 2006; Kalyuga et al., 1999; Sweller, 2002; Sweller et al., 1998). Several studies about small screen mobile devices have reproduced split attention effect, mainly because the small display breaches the spatial and temporal contiguity of the learning content (Austin, 2009; Keefe et al., 2012; Kim & Kim, 2012; T.-C. Liu et al., 2013, 2012; Luong & McLaughlin, 2009; Maniar et al., 2008; Molina et al., 2014).

A second cognitive load effect, segmentation effect occurs when something is divided into meaningful pieces such that it does not over-whelm the working memory as does continuous learning material (Ayres & Paas, 2012; Mayer, 2003; Mayer & Chandler, 2001; Mayer & Moreno, 2002; F. Paas, Renkl, et al., 2003; Spanjers, Gog, & Merriënboer, 2010; Spanjers, van Gog, & van Merriënboer, 2012; Wong, Leahy, Marcus, & Sweller, 2012). Segmentation assists with learning because it both creates pauses between segments, breaking up transience of dynamically presented material (Ayres & Paas, 2012; Florax & Ploetzner, 2010; Mayer & Chandler, 2001; Mayer & Fiorella, 2014; Mayer & Moreno, 2003; Moreno, 2007; Spanjers et al., 2010, 2012; Wong et al., 2012), and because it helps break the content down into meaningful pieces improving text comprehension (Ayres & Paas, 2012; Catrambone, 1995, 1998; Florax & Ploetzner, 2010; Hassanabadi, Robatjazi, & Savoji, 2011; Kurby & Zacks, 2008; Spanjers et al., 2012, 2012; & Sung & Mayer, 2013). In all studies on segmentation, learner control of pre-segmented material appeared to better facilitate learning than system control by preventing transience and minimizing extraneous load (Ginns, 2005; Hassanabadi et al., 2011; T.-C. Liu et al., 2013; Mayer, 2003, 2009; Mayer & Chandler, 2001; Moreno, 2007; Spanjers et al., 2010, 2012; Tabbers, 2002).

Another observed cognitive load effect is modality effect, which states that the addition of visualizations and the use of spoken, rather than written text, reduce the amount of cognitive effort required (Eitel, Scheiter, Schüler, Nyström, & Holmqvist, 2013; Hollender et al., 2010; Kalyuga et al., 2000; Mayer, 1999, 2005; Mayer & Moreno, 2002, 2003; Schüler et al., 2013). The modality effect also occurs when multiple sources of information are required for understanding. The extraneous load of the visual modality can be reduced by transforming written text into narration, thus using the auditory processor (dual-channel) in working memory (Ayres & Paas, 2012; Brunken, Plass, & Leutner, 2003; Chandler & Sweller, 1991; Hollender et al., 2010; Kalyuga et al., 2000). Studies have shown that when high element interactivity material was presented in audio/visual formats, performance was substantially higher as compared to presentations in visual/visual formats (Mayer, 2005; Mayer & Moreno, 2002, 2003; Savoji, Hassanabadi, & Fasihipour, 2011; Schmidt-Weigand, Kohnert, & Glowalla, 2010). These findings were extended to smartphone learning, when positive learning gains resulted from audio/visual presentations (T.-C. Liu et al., 2013).

The modality effect has some boundary conditions, under which the disappearance or reversal of the modality effect was witnessed. The reverse modality effect occurs when material has too low in intrinsic load (Mayer & Anderson, 1991; Mayer & Moreno, 1998, 2003), when students are high prior-knowledge learners (Kalyuga et al., 1999, 2000), when short phrases or single words accompany spoken text (Sombatteera & Kalyuga, 2012), when the lesson was learner-paced and transience was decreased (Huib K Tabbers, 2004; Scheiter, Schüler, Gerjets, Huk, & Hesse, 2014; Schmidt-Weigand et al., 2010; Schüler et al., 2013), and finally when the content was too long or too complex (Crooks, Cheon, Inan, Ari, & Flores, 2012; Schüler et al., 2013; Schüler, Scheiter, Rummer, & Gerjets, 2012; Schüler et al., 2011; Wong et al., 2012). In these cases, the advantage of the audio/visual duo decrease, disappear, or completely reverse (as noted when time is abundant and text is complex and long).

The supremacy of written text when passages are longer, more complex, or expository is supported by numerous text comprehension studies (A. Furnham, Gunter, & Green, 1990; A. Furnham, Proctor, & Gunter, 1988; Kintsch, 1994; Mannes & Kintsch, 1987; McNamara, Kintsch, Songer, & Kintsch, 1996; Schmidt-Weigand et al., 2010; Schüler et al., 2013, 2011). These studies explain this supremacy by the ability of readers under these conditions to utilize text comprehension strategies that are unavailable in system-controlled learning scenarios that offer only spoken text narration. Such strategies include learner control of the reading pace (Byrne & Curtis, 2000; Frazier & Rayner, 1982; A. Furnham et al., 1990; Hyönä & Nurminen, 2006; Just & Carpenter, 1987; Kozma, 1991; Schüler et al., 2011), rereading as needed for understanding (A. Furnham et al., 1988; Hyönä & Nurminen, 2006; Schmidt-Weigand et al., 2010; Schüler et al., 2013), and self-selecting to skip extraneous or overly difficult passages (A. Furnham et al., 1990; Schmidt-Weigand et al., 2010; Schüler et al., 2013). Under these conditions, the reversal of the modality effect is expected, as well as a superiority of written text.

MOBILE LEARNING DEVELOPMENT AND INSTRUCTIONAL DESIGN

Instructional design does not occur in a vacuum if it is to deliver learning in the most appropriate, efficient, and successful ways. It seems appropriate, then to first present mobile development and its challenges, before engaging in a conversation about instructional design principles for mobile devices (mainly small screen handhelds, a.k.a. smartphones). There are several ways to use mobile devices for learning, including using the features of the device to supplement learning, accessing already published content and wrapping learning around it, accessing specifically tailored web content via a mobile device through mobile web, and finally, developing a dedicated mobile application or system to meet learning and educational needs. Mobile web pages for education content delivery are easier and cheaper to build and maintain, but do not have access to many of a mobile devices features (GPS, camera, etc.). Additionally, information accessed via the web has even less screen real estate given it must be viewed within a web browser. Dedicated mobile applications offer all of the capacity of computer software (including speed, device feature use, interactions specific to learning engagement, and full control over content). Dedicated mobile applications are, however, expensive to build and complicated to maintain. They also require thoughtful UX/UI design, various platforms development, and specific implementation (Potcatilu, 2010).

Mobile learning is not without its technological challenges. These include network connectivity, device limitations, platform inconsistency, and high development costs. Small screen display also present challenges for learning and cause user frustration. Some of these challenges are owing to the hardware, some the design of the content, and some to the ill-matched combination of the two. Several studies have used dedicated mobile applications to examine the possibilities of creating original content and software systems for mobile learning. Regardless of these issues, mobile devices are ingratiated into our cultural fabric in ways that are infiltrating homes, classrooms, and offices.

Mobile learning and small screen devices

Evidence suggests that small screen displays especially are not always ideal for learning. Researchers have both singularly examined the design and feature affordance of the devices for learning, as well as have compared small screen display devices with larger screen displays.

DESIGN PRINCIPLES FOR MOBILE LEARNING

While literature on mobile learning is growing, there are remarkably few studies that look specifically at instructional design (Al-Zoubi et al., 2008; Crescente & Lee, 2011; Molina et al., 2014; Mostakhdemin-Hosseini, 2009a; Terras & Ramsay, 2012). Even fewer recommend instructional design principles, particularly in terms of smartphones and other small mobile devices. A few studies have approached the question of instructional design for small screen displays (Churchill, 2011; T.-C. Liu et al., 2013; Luong & McLaughlin, 2009; Seraj & Wong, 2014).

There are, however, numerous studies on minimizing cognitive overload that have implemented and recommended noted instructional design principles (Chandler & Sweller, 1991; Mayer, 2009; Sung & Mayer, 2013; Sweller et al., 2011). In terms of reducing cognitive overload, eliminating design created extraneous content is among the first recommendations (Ayres & Paas, 2012; Brunken et al., 2003; Chandler & Sweller, 1991; Mayer, 2009; Mayer & Fiorella, 2014; Sweller et al., 2011). This is in line with the coherence principle (Mayer, Bove, Bryman, Mars, & Tapangco, 1996; Mayer & Chandler, 2001), namely that all visual and auditory material is pertinent to the topic of learning.

In terms of reducing split attention, the spatial and temporal contiguity principles (Mayer, 1999, 2003; Mayer & Moreno, 2002, 2003) state that integrating content by combining two sources of information into one will alleviate split attention (Ayres & Sweller, 2005; Cierniak et al., 2009; Florax & Ploetzner, 2010; Kalyuga et al., 1999; Mayer, 2003). Several studies found cueing or signaling decrease split attention and assist with segmentation (Florax & Ploetzner, 2010; Kurby & Zacks, 2008; T.-C. Liu et al., 2013, 2012; Spanjers et al., 2012; Sung & Mayer, 2013). For mobile devices, it is recommended that whenever possible, using mobile devices as the focus of learning is less over-whelming to the working memory than using it as a supplemental tool with real objects (T.-C. Liu et al., 2013, 2012). Finally, whenever possible, giving the learner control over the learning pace (specifically) has shown numerous times to decrease cognitive load (Hassanabadi et al., 2011; Mayer & Chandler, 2001; Schmidt-Weigand et al., 2010; Schüler et al., 2013; Spanjers et al., 2012; Sung & Mayer, 2013; Tabbers, 2002).

Specific to small screen display mobile devices (namely smartphones), the design guidelines can be divided into two categories. First, in terms of screen real estate, maximizing space by utilizing the full screen is recommended (Churchill, 2011; Churchill & Hedberg, 2008; Seraj & Wong, 2014). With few exceptions (Jin, 2013; Leavitt & Shneiderman, 2006), scrolling has proven to lower reading comprehension. Zooming can increase cognitive load (Luong & McLaughlin, 2009). Finally, designing for landscape orientation was found to improve overall learning and user experience (Churchill, 2011; Churchill & Hedberg, 2008; Sanchez & Branaghan, 2011; Sanchez & Goolsbee, 2010).

Recommendations for text formatting and small screen display make up the second category. Using a single (Churchill, 2011), smaller font (Sanchez & Goolsbee, 2010) that is spaced enough for line distinction without unnecessarily causing the need to scroll (C.-H. Chen & Chien, 2005) seemed to produce the best learning outcomes. Limiting the amount of text on screen, through elimination or segmentation is emphasized (Churchill & Hedberg, 2008; Seraj & Wong, 2014; M. Wang & Shen, 2012). Finally, when possible, text should be replaced with images, audio, and narration (Bradley, Haynes, & Boyle, 2006; Churchill & Hedberg, 2008; Sung & Mayer, 2013).

LITERATURE GAPS

While the literature covers a great many topics of mobile learning, cognitive load, and instructional design, there are several critical research gaps that require empirical attention. A majority of the studies did not design full capability mobile applications and mobile devices under study were simulated (Kim & Kim, 2012; Luong & McLaughlin, 2009), or learning was delivered via web browser, which limits control of space and screen (Molina et al., 2014). In most cases, the design process was not revealed (Heo, 2003; Keefe et al., 2012; T.-C. Liu et al., 2013, 2012; Reeves et al., 1999; Sung & Mayer, 2013). Though some studies examined the effectiveness of specific dedicated mobile applications (T.-C. Liu et al., 2013; Seraj & Wong, 2014), they offered little in the way of generalizable and actionable design principles. Furthermore, when principles were recommended, the reasoning behind the recommendation was unclear. This is true of the recommendation to design smartphone learning in landscape orientation (Churchill, 2011; Sanchez & Branaghan, 2011). Additionally, it appeared that many of the studies comparing large and small screen displays retrofitted the learning design of the large screen for the small one (Churchill & Hedberg, 2008; Molina et al., 2014), which takes into account neither user perception and use of smartphones, nor the device affordances that are dissimilar to those of a laptop.

In terms of the cognitive load effects specific to small screen mobile devices, there is a clear need for device specific design guidelines (T.-C. Liu et al., 2012). While the cognitive load design principles are applicable across devices (Sung & Mayer, 2013), the research does not advise on how to design efficient single-mode presentations (Reimann, 2003). Split attention effect is more easily mitigated because it is easier to identify and the design recommendations for avoiding it are somewhat straightforward, even for text only, small screen mobile displays. Recommended design for modality effect, (Ginns, 2005; Hassanabadi et al., 2011; Kalyuga et al., 2000; Reimann, 2003; Savoji et al., 2011; Schmidt-Weigand et al., 2010) is a dual-modal approach. In cases where the learning material is long or complex text, text comprehension research suggests learners will implement reading comprehension strategies (Fournier, 2013;

Kalyuga, 2000; Kintsch, 1994; Mannes & Kintsch, 1987; Schüler et al., 2013, 2012). There is however, little information on how to craft such presentations in ways that minimize cognitive overload and promote schema construction and automation, much less in terms of constructing this type of learning scenario for a small screen mobile display. Studies on segmentation effect have shown the learning benefits of segmenting material, but offer little in the way of how to segment content (Eitel et al., 2013; Hassanabadi et al., 2011; Mayer et al., 1996; Mayer & Chandler, 2001; Molina et al., 2014; Schüler et al., 2013). Especially in terms of smartphone learning, segmenting material into meaningful chunks of content may prove beneficial and design guidelines for how to segment for small screen displays could be exceptionally helpful.

Summary

In summary, the critical gaps in the literature on mobile learning design include: offering actionable design principles for small screen displays to assist in increased learning outcomes and positive user perspective, empirically examining the effects of designing authentic and dedicated smartphone applications, explaining the reasoning behind landscape orientation design recommendations for small screen mobile displays, and comparing large and small screen displays when design is customized to the device, versus a retrofitted, one-size-fits-all design.

The pertinent gaps in the literature on cognitive load and text comprehension include: investigating media configurations for smartphone devices and environments, detailing device specific design principles for avoiding split attention effect, maximizing design for segmentation effect, applying modality effect (especially when the material does not lend itself to images, and/or is more complex than can be communicated through audio/visual presentation), crafting single-modal presentations of materials that minimize cognitive overload and promote schema construction and automation, and explaining how to design and segment appropriate text-only passages for a small screen mobile display.

RESEARCH PURPOSE

This study concerns instructional design for mobile learning, smartphones specifically. The greater goal of this study was to reveal design principles related to segmenting text specific to mobile devices displays in ways that promote user satisfaction, reduce cognitive overload, and maximize learning gains. This study compared large and small screen mobile displays for learning, namely laptops and smartphones. What this study adds to the body of research is an in-depth look at design approach that begins with designing a dedicated application for smartphones, and then migrates and customizes that design to the laptop screen. The results demonstrate the importance of design in both learning from and empirically studying varied mobile screen display sizes for learning.

Additionally, in terms of mobile devices, this study compared landscape and portrait orientation for learning from smartphones. The results give a clearer view of current user preferences and learning results of designing for various screen orientations. Finally, this study analyzed what length of text segment is most beneficial for reading comprehension when low prior-knowledge learners access high intrinsic text via laptop and smartphone. The results begin to uncover how to optimally design and prepare text for communicating and learning from these devices.

Learning outcomes, cognitive load, and user perception were measured to assist in these comparisons. Learning outcomes measured whether or not participants could recall the content following each treatment. However, learning recall offered only one point of reference for determining if a particular treatment was successfully designed and/or was advantageously delivered given the display size and orientation (Churchill & Hedberg, 2008; Kim & Kim, 2012; Molina et al., 2014). Measuring for cognitive load added perspective on participant experiences with each treatment by demonstrating whether students were cognitively overloaded, under loaded, or remained successfully in the ZPD (Schnotz & Bannert, 2003; Schnotz & Kürschner, 2007). Positive user perception has been demonstrated by the literature as a viable piece of total mobile learning success (Hwang, Shi, & Chu, 2011; Valk, et al., 2010; Yau & Joy, 2011; Traxler, 2005; Sanchez & Goolsbee, 2010; Seraj & Wong, 2014; Wang et al., 2009; Terras & Ramsey, 2012). It is thus important that the treatments not only produced positive learning outcomes and minimized cognitive load, but also were viewed positively by the participants. Therefore, the research questions of this study are detailed below.

Research questions

To address the gap in literature concerning mobile device comparison when design is tailored specifically to the device, as well as to answer additional questions about smartphone screen display and orientation, this study conducted research around the following question group:

When specific formatting variables are held constant:

RQ1 (*mobile device comparison*): Do display size and orientation affect

A: learning outcomes of a digitally delivered chemistry text lesson?

B: cognitive load of a digitally delivered chemistry text lesson?

C: user perception of a digitally delivered chemistry text lesson?

To address the gap in literature regarding text segmentation characteristics for various screen displays, this study conducted research around the following question group:

When specific formatting variables are held constant:

RQ2 (*text segmentation comparison*): Do digitally continuous text, medium text segments, and short text segments compare in terms of

A: learning outcomes of a digitally delivered chemistry text lesson?

B: minimizing cognitive load for a digitally delivered chemistry text lesson?

C: influencing user perception of a digitally delivered chemistry text lesson?

Finally, to determine if any interactions exist between the two groups, this study conducted research around the following question group:

When specific formatting variables are held constant:

RQ3 (*mobile device and segmentation interaction*): Do text segmentation and screen display size and orientation affect

A: learning outcomes of a digitally delivered chemistry text lesson?

B: cognitive load of a digitally delivered chemistry text lesson?

C: user perception of a digitally delivered chemistry text lesson?

LIMITATIONS OF THIS STUDY

This research had several known technology, design, and measurement limitations. From a technology perspective, this study though it used both dedicated mobile applications and a web version of the application (for the laptops), assessment of this difference on the findings was not planned. The reason for this was two-fold. First, making this comparison in a balanced way would have required both web and dedicated treatment versions be created for all devices. Second, adding this to this research study would have extended the workload beyond the boundaries of practicality considering time and budget. The comparison between web and dedicated applications is an important one that should be examined in the future.

A second limitation (both a technology and design condition) of this study was that navigation of the learning module will differ between the laptops, which use both mouse/click and touchscreen navigation, and smartphones, which have touchscreen navigation. Touchscreen technology offers a unique experience to the user. There are numerous studies on touchscreen technology (Brasel & Gips, 2014; Fong-Gong Wu, 2011a, 2011b; Shamus P. Smith, 2012; Sunghyuk Kwon, 2010). While this is an interesting facet of mobile technology to research, the touchscreen interaction was not a focus here. To mitigate this limitation, the applications were designed with minimal navigation. For the laptop version, movement from screen to screen occurred via clicking on a left/right arrow. For the smartphone, swiping left and right moved participants from one screen to the next.

Another limitation concerned how learning gains will be measured. The study only measured immediate recall given the parameters of the data collection environment and limited access to the participants in that setting. However, measuring for transfer would reveal the long-term learning potential of the text and device treatments. This is an area where future research that continues exploring the topic, could unveil more specific design guidelines for mobile learning designers. After all, how to best design instruction for smartphones is at the heart of interest in this study, so any future work that continues in that vein would be beneficial.

DISSERTATION STRUCTURE

There are four remaining chapters of this dissertation. Chapter 2 reviews current literature applicable to this study. The literature review will be grouped by topic and summarily combined to describe how this research will meet at the intersection of these individual topics. Chapter 3 provides a thorough description of the research methodology, from the study design and data collection procedures through the data analysis techniques. It additionally includes explanation of the reasoning and design choices behind the learning module developed for this study. Chapter 4 presents the results of the research and summarizes the important findings from the data analysis. Finally, Chapter 5 provides discussion of and conclusions drawn from the data collected, as well as identifies topics for future research in this arena.

Chapter 2: Literature Review

MOBILE LEARNING

Mobile learning, as a concept, has numerous definitions, with none dominant at present (Crescente & Lee, 2011; Pimmer et al., 2010). Crescente and Lee (2011) link the absence of a standard definition back to the debate of where mobile learning belongs. The various camps argue that mobile learning is a "subset of e-learning," or "an independent discipline," or a "lateral move in the distance learning universe" (Crescente & Lee, 2011; Mostakhdemin-Hosseini, 2009a). While understanding mobile learning as a concept is still in nascent stages, its utilization is quickly catching the attention of K-12, higher education, and business and government institutions, as it provides numerous affordances that alter traditional concepts of learning (Lee, 2011). Mobile devices have altered the way we approach and consume information, and as a result, the way we learn (Baharum, Ismail, & Idrus, 2010; Baloch, Rahman, & Ihad, 2012). Traxler (2010) suggested that within the education system, mobile learning can be characterized as a specific project that some propose may upset the sustainability of the current education system. Agreement with this proposition may depend on the subscribed to definition of mobile learning.

For example, initially many defined mobile learning as education, or learning opportunities through content delivery that use handheld and mobile devices as the sole or dominant technology (Baharum, Ismail, & Idrus, 2010; Crescente & Lee, 2011; Demirbilek, 2010; Frohberg et al., 2009; Kukulska-Hulme et al., 2011; Pimmer et al., 2010; Traxler, 2005). As the concept evolved more attention was paid to the ubiquitous affordances of mobile devices (Crescente & Lee, 2011; Laine et al., 2010; Y. Park, 2011). Uzunboylu and Ozdamli (2011) described mobile learning as "a kind of learning model allowing learners to obtain learning materials anywhere and anytime using mobile technologies and the Internet" (p. 544). Terras & Ramsey (2012) noted that the 24/7 access provided by mobile technology allows users to engage in anytime learning and social networking. Park (2011) and Pea and Maldonado (2006) added the mobile technology enables learners to work at unique activities in ways that were previously impossible. Crescente and Lee (2011) further asserted that mobile learning is ubiquitous in terms of the now widespread availability and versatility of mobile devices, describing the concept of anyplace.

Others have defined mobile learning as learning on the go, or "learning that happens when the learner is not at a fixed, predetermined location" regardless of the tool used to access the learning (Becking et al., 2004; O'Malley et al., 2005; Yau & Joy, 2010). Mobile learning then is not necessarily an outcome of mobile technology. This concept shifts the definition of mobile learning from the device and environment to the user's individual or collaborative learning journey from place to place.

Atwell (2003) identified mobile learning opportunities as newly offering contextualized learning access for those with limited access to traditional educational. Mobile learning overcomes traditional space and time constraints, while often enhancing the context and situation of both formal and informal learning (Daoudi & Ajhoun, 2008; Traxler, 2010). Mobile learning can help improve teaching and learning effectiveness through wireless technology, through flexibility and access (Baharum, Ismail, & Mohamed Idrus, 2010). Mobile learners can augment knowledge building with situated and contextualized practice. In this way “mobile learning is considered as ‘the processes of coming to know through conversations across multiple contexts among people and personal interactive technologies’” (Pimmer et al., 2010; Sharples, Arnedillo-Sánchez, Milrad, & Vavoula, 2009, p. 238). Pimmer et al. noted the shift from a technical perception of meaning-making through technology to an educational one. They asserted that the conversation is moving towards examining mobile learning through social, cultural, and psychological lenses.

Arguably, wherever one may fall in the debate, mobile learning exists at the intersection of several key components (Figure 2.1) (Koole, 2009; Y. Park, 2011; Traxler, 2010).

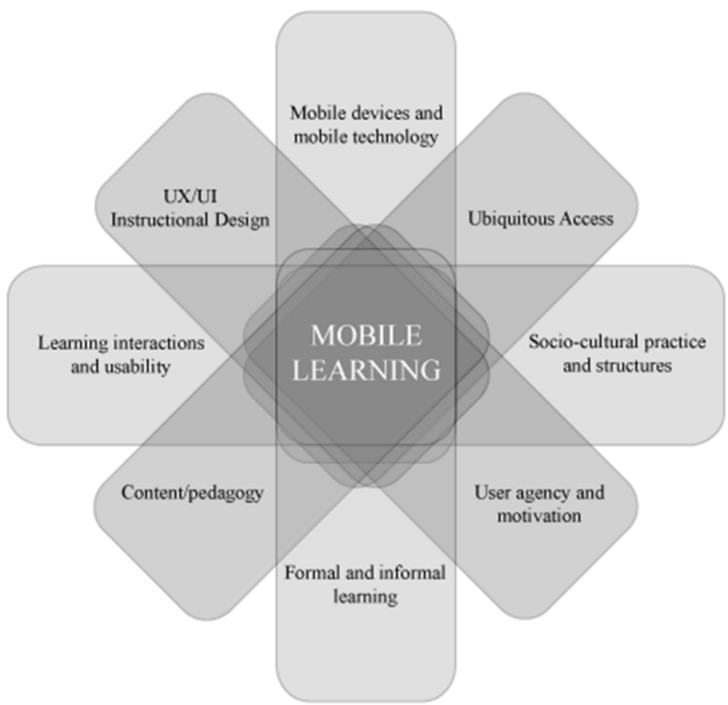


Figure 2.1. Key components of mobile learning.

According to Traxler (2007), mobile learning is occurring because mobile devices are transforming our understandings of space, community, and discourse. It allows learners to engage in personalized, collaborative, and interactive learning and has enabled teachers to instruct and communicate in innovative ways through the unique characteristics of the devices (Demirbilek, 2010). Two types of mobile learning affordances, device affordances and learning affordances, describe the characteristics of the action of learning and the features that make it impossible and engaging.

The ever-evolving technology itself provides numerous device affordances through the features and applications, which now come standard with purchase or are easily downloadable. Such features and applications include SMS, MMS, email, web access (Zabel, 2010), video, audio, and GPS to name a few. Better memory, larger storage capacity, and longer battery life all provide mobile-enabled learners advantages of which "facilitate a constructivist approach for maximum professional relevance like never before" (Zabel, 2010, p. 10).

Some studies noted that certain features, like small screen size and limited web access, can present challenges for certain users (Crescente & Lee, 2011; Y. Park, 2011; Pea & Maldonado, 2006). Despite these constraints, Crescente and Lee asserted that mobile learning "may become a mode of choice with learners since current and future generations will not know life without elaborate electronic technology" (p. 112).

Mobility permits greater control over learning experiences (Zabel, 2010), thereby allowing learners to take advantage of intervals of downtime (Traxler, 2005; Valk et al., 2010). Mobile learning also provides alternate modes of delivery and optimal privacy for learners (Crescente & Lee, 2011). Unlike traditional models of education that operate by transferring knowledge from teachers to students, mobile learning empowers learners to participate in the learning process and actively construct their own learning (Valk et al., 2010). Therefore, the learning affordances of mobile learning include portability, expediency, immediacy, accessibility, flexibility (Baharum, Ismail, & Idrus, 2010; Crescente & Lee, 2011; Terras & Ramsay, 2012), connectivity convenience, cross-context learning, individuality, and interactivity (Bhaskar & Govindarajulu, 2009; Eliasson et al., 2011; Klopfer & Squire, 2007; Y. Park, 2011). The notions of immediacy and expediency additionally make possible just-in-time, just-in-case, just-for-me, and just-enough learning (Y. Park, 2011; Traxler, 2007). Mobile learning also facilitates peer-to-peer and collaborative learning both in person and virtually, allowing individuals and groups to create and share learning artifacts free of time and space (Graham Attwell, 2010; Eliasson et al., 2011; M. Wang & Shen, 2012).

Valk et al. note that as a facilitator of new learning, mobile learning goes beyond information possession to emphasize learner agency in locating, manipulating, and evaluating information. In professional settings, mobile technologies alter the nature of (knowledge) work as well as the balance between training and performance support (Pimmer et al., 2010; Traxler, 2007), in addition to further increasing the importance of human capital. Knowledge is the product of the interaction between people and the environment and is viewed more and more as a viable commodity inside organizations (Smits & Moor, 2004; M. Wang & Shen, 2012). Human capital is the knowledge of humans, that which they cannot be separated from, also called tacit knowledge (G. Becker, 2008; Smits & Moor, 2004; Wenger & Snyder, 1999). Businesses seek to leverage that knowledge through a collection of processes that manage the creation and dissemination of knowledge (Smits & Moor, 2004). The use of mobile devices to support situated work-based learning is based on the idea that appropriation of both technologies and processes will lead to the formation of developmental competences based on intrinsic motivation (Graham Attwell, 2010; Nyhan, Cressey, Tomassini, Kelleher, & Poell, 2003). This is especially true in small and medium businesses, in which there exists a growing need for on-the-job, just-in-time learning.

Additionally, mobile learning affordances simplify the training process in school and work settings, thereby decreasing training costs and increasing productivity and the return on investment (roi) (Crescente & Lee, 2011). Mobile devices are supporting corporate training for mobile workers (Gayeski, 2002; Lundin & Magnusson, 2003; Pasanen, 2003) and are enhancing medical education (Smørdal & Gregory, 2003), teacher training (Seppälä & Alamäki, 2003), music composition (Polishook, 2005), nurse training (Kneebone, 2005), science learning (Hwang, Yang, Tsai, & Yang, 2009; Wyatt et al., 2010), language learning (Tim de Jong et al., 2010), social sciences learning (Tarumi et al., 2011), learning in general higher education settings (N.-S. Chen, Teng, Lee, & Kinshuk, 2011; Wu et al., 2011), vocational learning in areas with a broad occupational application (Akkerman & Filius, 2011; G. Attwell et al., 2003; Graham Attwell & Costa, 2009; Uzunboylu & Ozdamli, 2011), and numerous other disciplines (Traxler, 2007, p. 3).

Mobile devices allow for a variety of learning behaviors and interactions that take place in a wider social context (Kukulska-Hulme & Traxler, 2005). According to Park (2011), mobile learning occurs in a range between communication intensive and independent work, with each range utilizing different mobile features and levels of productivity. The more independently one works, the greater content-intensive is their learning; while using the mobile device for communication activities relies heavier on learning collaboration. "This shows that students can consume and create information both collectively and individually" (Koole, 2009, p. 26). The wide range of learning activities allows for numerous types of learning including memorizing (Schwabe & Göth, 2005), scaffold learning (Crescente & Lee, 2011; Naismith, Lonsdale, Vavoula, & Sharples, 2004), situated learning (M. Wang & Shen, 2012), supplemental learning (T.-C. Liu et al., 2013), collaborative learning, informal and lifelong learning (M. Wang & Shen, 2012), and support coordination (Crescente & Lee, 2011; Naismith et al., 2004).

In terms of learning gains, some studies have found evidence through quantitative methods with pre and post-test assessment that indicates mobile learning produces significant learning gains (Başoğlu & Akdemir, 2010; Cavus & Ibrahim, 2009; Chandran, 2010; G. D. Chen, Chang, & Wang, 2008; I.-J. Chen & Chang, 2011; Che, Lin, Jang, Lien, & Tsai, 2009; Delgado-Almonte, Andreu, & Pedraja-Rejas, 2010; Hwang et al., 2011; M. Liu, Geurtz, Karam, Navarrete, & Scordino, 2013; Wu et al., 2011). Among these, Chen et al. (2008) found introductory compute science students test results were improved when scaffold learning was supported by a ubiquitous learning website. In another example, Cavus and Ibrahim (2009) found that mobile learners scored better than conventional learners in using short message system for learning vocabulary items. Positive learning gains were not universally reported. In fact, some studies, like Cobb et al. (2010) and Coens, Reynvoet, and Clarebout (2011) showed no significant learning gains when mobile learning was compared with more traditional forms of learning.

User perception and acceptance of mobile learning

Terras and Ramsey (2012) stated, “It has long been recognized that an understanding of human behavior is essential to the design and development of effective and usable technology” (p. 822). If learning is about the learner, then mobile learning is more so personalized, learner-centered, situated, collaborative, ubiquitous, and lifelong (Hwang et al., 2011; Sharples et al., 2009; Valk et al., 2010), and design of mobile learning should be user-focused. Learners will approach mobile learning with their own learning styles or attitudes and behaviors that determine a preferred way of learning (Yau & Joy, 2010). This is amplified by the increase in mobile device features’ potential use to deliver learning and drives competition even more (Traxler, 2005). Crescente and Lee (2011) asserted that mobile learning “may become a mode of choice with learners since current and future generations will not know life without elaborate electronic technology” (p. 112). Sanchez and Goolsbee (2010) noted that “advances in the power and availability of mobile technology, coupled with the ‘on-the-go’ lifestyle of many individuals, have made small screen devices nearly ubiquitous in everyday life. Professionals and non-professionals alike often carry at least one small device that is used regularly for many daily activities” (p.1056). User perspective on both the use of mobile devices for learning and the engagement and enjoyment of the learning applications are paramount for determining the success of mobile learning (Seraj & Wong, 2014).

In their study on user perspectives of mobile learning, Wang et al. (2009) indicated the following factors as important determinants of users’ intentions to adopt mobile learning: “learning at a self-managed pace, perceived usefulness, social influence, performance expectancy, and effort expectancy” (p. 149-150). If learning agrees with the learner, it will positively influence their success with mobile learning. Iqbal & Qureshi (2012) called this perceived usefulness. Mostakhdemin-Hosseini (2009) further added that there is need for mobile learning that will accommodate different learner perspectives. Although the application of technology is appealing, it is important to remember that the most successful applications tend to be those perceived by the users as useful (Bhaskar & Govindarajulu, 2009; Mostakhdemin-Hosseini, 2009b; Terras & Ramsay, 2012). Good user experience relies on proper utilization of the mobile device components and features. Wang et al. (2009) further elaborated that mobile learning systems designers who "focus on the development of valuable functions and content of m-learning systems on potential users" can increase the perceived usefulness and usage of mobile learning (p. 109).

Rogers, Connelly, Hazlewood, and Tedesco (2009) explained that the versatility and mobility of mobile devices meant that people can use them in diverse settings. Several studies noted that mobile learners prefer to be aware of how they learn in general and how that changes when engaging in mobile learning (Platzer & Petrovic, 2011; Terras & Ramsay, 2012). In fact, "design relevance is enhanced by providing information concerning basic motivations for usage of mobile applications and linking them to best practice examples" (Platzer & Petrovic, 2011, p. 44).

Numerous studies found users' general perceptions of mobile learning positive (Almaiah & Jalil, 2014; Demirbilek, 2010; Franklin et al., 2007; Kismihók & Vas, 2011; Y.-S. Wang, 2007), and surmised that positive responses possibly stemmed from the notion that communication is a key feature in education and using mobile devices can enhance access and communication (Demirbilek, 2010). In a study by Corlett, Sharples, Bull, and Chan (2005), students were supplied with PDAs to use for their studies and found the device highly useful in terms of organization. Additionally, some studies reported that well-designed mobile learning accelerated learning in ways that learners appreciated. Su et al. (2011) noted that self-learning of air traffic controllers increased when they enjoyed the curriculum design.

While it was generally determined that users need an overall positive outlook when using mobile devices for learning, not all studies reported positive user feelings. In fact, several studies specifically identified several mobile learning challenges that left negative impressions on learners (Kismihók & Vas, 2011). Corlett et al. (2005), for example, found that there were significant issues with implementation, including hardware problems such as poor battery life, and external factors, such as the inability to view Web pages on the mobile device when required. Such occurrences frustrated learners, creating negative perspectives (Franklin et al., 2007). In their study on the usefulness of a dedicated application which aided in measuring the change of trees over time, Rogers et al. (2009) found that participates felt using the mobile device as a learning supplement in a science class actually slowed learning down when interacting with the device and application became too tedious.

Technology Acceptance Model

User perception and acceptance of both learning tools and content delivery systems are important for the success of mobile learning. The Technology Acceptance Model (TAM) (Davis, 1985, 1989; Davis et al., 1989; Venkatesh, 2000; Venkatesh et al., 2003) is one of the most widely accepted theories among information-system researchers for studying the system acceptance behavior of users (Legris et al., 2003; Ma & Liu, 2004; Schepers & Wetzels, 2006) and many studies have used it to gauge subjective user perception of mobile learning (Molina et al., 2014). The Technology Acceptance Model (TAM) is an information systems theory which was adapted from the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975). TAM was the first model to mention psychological factors affecting computer acceptance, and the "model assumes that both perceived usefulness and perceived ease of use of a new technological resource are central in influencing the individual's attitude towards using that resource. An individual's attitude is hypothesized to influence the behavioral intention to use a certain technology, finally relating to actual use" (Molina et al., 2014, p. 447).

The model is concerned with the determinants of consciously intended behaviors (Malhotra & Galletta, 1999; S. Y. Park, 2009). The basic theory of TAM is that perceived usefulness and perceived ease of use determine an individual's intention to use a system with intention to use serving as a mediator of actual system use (Gardner & Amoroso, 2004). Perceived usefulness is also seen as being directly impacted by perceived ease of use (Davis, 1985, 1989; Davis et al., 1989; Venkatesh, 2000; Venkatesh et al., 2003). According to the TAM theory (Venkatesh et al., 2003), the two also directly influence one another. For example, an individual may find a colorful, interactive, and fun learning module to be useful even if the content and scaffolding for learning are lacking. Likewise, a very well-designed learning module may prove unsuccessful if the learners' perception of it is negative. In their 2003 article, Lu et al. used TAM to understand user perceptions of accessing wireless internet via mobile devices.

Summary

In summary, mobile learning has been prevalent as a movement in education now for nearly 15 years. It is occurring because mobile devices are transforming our understandings of space, community, and discourse. Definitions of mobile learning are varied, but range from unique learning experiences owed to handheld mobile devices to ubiquitous learning to on-the-go learning or just-in-time learning. Mobile learning can be formal or informal, depending on the learner and the content, environment, and time accessed.

To describe the action of mobile learning and the characteristics that make it impossible and engaging, there are device affordances and learning affordances. Device affordances include the features of the hardware and software. Examples include GPS, camera, NFC, and anywhere connectivity. The learning affordances of mobile learning include portability, expediency, immediacy, accessibility, flexibility, connectivity convenience, cross-context learning, individuality, and interactivity. The notions of immediacy and expediency additionally make possible just-in-time, just-in-case, just-for-me, and just-enough. Mobile learning occurs in a range between communication intensive and independent work, with each range utilizing different mobile features and levels of productivity. The more independently one works, the greater content-intensive is their learning; while using the mobile device for communication activities relies heavier on learning collaboration.

At the heart of any technological success in education is the user. Positive user perception and acceptance of mobile learning is crucial for its success. As such, many studies have focused on these topics. Results have proven both negative and positive user perception, but generally suggest a positive response to mobile learning. This makes sense given the proliferation of hand held devices (namely smartphones) within the bedrock of social, business, and educational culture. As individuals expect to use their devices ubiquitously, there is a growing expectation that use should extend to all facets of life, including into classrooms and offices. One well-tested method for gaging user perception and acceptance is the Technology Acceptance Model (TAM). TAM assumes that user perception and perceived ease of use together accurately measure a user's acceptance of a specific technological tool for the task at hand.

In the following section, I will present Cognitive Load Theory, beginning with its definition and evolution and then explaining the pertinent cognitive load effects that have developed as a way to determine cognitive overload. Finally, I will look at the research on text segmentation as it compares to the findings of cognitive load theory.

COGNITIVE LOAD THEORY

Human cognitive architecture, or the manner in which cognitive structures are organized, is composed of a limited capacity short term or working memory and an unlimited long-term memory (Miller, 1956; Sweller, 1988). The underlying goal of Cognitive Load Theory (CLT) is to design learning that increases cognitive recall by decreasing cognitive overload when information is being processed in the working memory (Sweller, 1988, 1994; Sweller & Chandler, 1994; Sweller et al., 1998). The term "working memory" was first proposed in the book *Plans and the Structure of Behavior* by Miller, Galanter, and Pribram (1960, 2013). The term has been adopted in Cognitive Psychology to describe the "system or systems involved in the temporary maintenance and manipulation of information" (Baddeley, 2001, p. 852). CLT finds its roots in George A Miller's (1956) *The magical number seven, plus or minus two: some limits on our capacity for processing information*, which describes the limitations of the working memory as incapable of holding more than seven items (plus or minus two depending on the person) in working memory. Of those only two or three can be actively processed simultaneously (Baddeley, 1976; Chandler & Sweller, 1996; Miller, 1956). Humans can monitor only what is in their working memory. Other cognitive functionality is hidden from view unless and until it is brought into the working memory (Sweller et al., 1998).

While some like Atkinson and Shiffrin (1968) see the working memory as a unitary short-term store, others such as Baddeley and Hitch (1974), proposed instead that it is a system comprising three main components, namely the visuospatial sketchpad, the central executive, and the phonological loop (this concept is explored further in the modality effect section of this literature review). Both approaches to understanding working memory agree to its limited capacity (Sweller et al., 1998). In fact, several studies have found that anything beyond the simplest cognition activities appear to overwhelm working memory, such that meaning-making is impossible (Chandler & Sweller, 1991; Miller, 1956; Sweller et al., 1998). Meanwhile, the long-term memory capacity has been found to be vast. CLT assumes that the seat of human intellectual prowess comes from knowledge stored in the long-term memory (Chandler & Sweller, 1991). For information to be learned, i.e. become knowledge (Hollender et al., 2010), it must be moved from the short-term memory into the long-term memory (Baddeley, 1976, 2001; Chandler & Sweller, 1991; Sweller et al., 1998). This is accomplished through the construction and automation of schema (F. Paas et al., 2004; Sweller et al., 1998).

Derived from schema theory (Chi et al., 1982), which asserts that knowledge is stored in the long-term memory as mental schemata, this major learning mechanism categorizes elements of information according to how they will be used. Empirical research on schemas goes as far back as Piaget (1928) and Bartlett (1932), but de Groot (1966) and Chase and Simon (1973) demonstrated the importance of schemas in general problem-solving. Chi et al. (1982) further showed the critical role of schemas and expert problem-solving. Schema theory assumes that it is only with the creation of specific schema that expertise is achievable (Sweller, 2002).

A schema is anything learned as a single entity that is stored in the long-term memory. Schema reduce working memory load through recall. Schema formation is an active, constructive process (Sweller, 2002; Sweller et al., 1998). As information grows, schema can be combined to make ever-more-complex schema (Chi et al., 1982). In this way, working memory is reduced as the complex schema is now treated as only one element in the working memory instead of as the individual bits of information that composes it (Chandler & Sweller, 1991). Although the working memory is limited to the number of elements it can process, the size, complexity, and sophistication of each element is unlimited (Sweller, 1994). With sufficient practice and exposure over time, application of complex information or procedures can be carried out with minimal effort, requiring few to no spots in the working memory (Shiffrin & Schneider, 1977). This continued process leads to schema automation.

Schneider and Shiffrin (1977) and Shriffin and Schneider (1977) deduced that all information can be processed either consciously or automatically, with conscious processing taking place in the working memory and automatic processing stemming from the long-term memory, without need of the working memory (Sweller, 2002). With practice and automaticity, procedures can be executed with minimal conscious effort, thereby leaving space in the working memory for new information to be processed and stored (Figure 2.2) (Hollender et al., 2010; Sweller, 2002).

Until automated, a schema will act as one of the seven items taking up working memory space. However, long-term memory storage appears infinite and new information elements are constantly understood by recalling old information (Chandler & Sweller, 1991). Subsequently schema are created, enhanced, and stored, creating knowledge and expertise (Chi et al., 1982). In this regard, the difference between a novice and an expert is simply that the expert has numerous stored and automated schema to reference, where the novice has only what is presently before him or her (Chase & Simon, 1973; Groot, 1966). Both the novice and the expert are subject to the cognitive limitations of the working memory and are susceptible to cognitive overload when the process is inundated (Chandler & Sweller, 1996; Sweller, 1994).

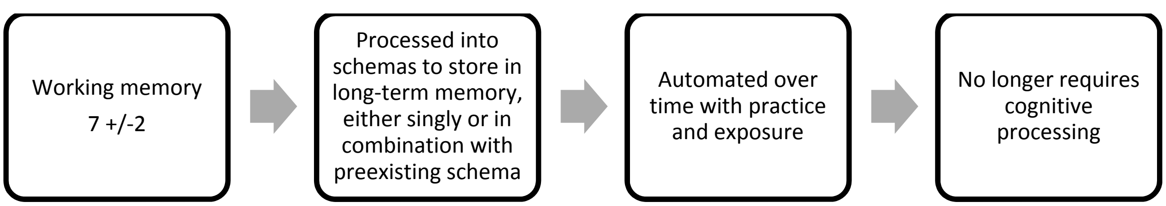


Figure 2.2. The process of schema automation.

Types of cognitive load

Cognitive load theory is concerned with techniques for managing working memory load in order to facilitate the changes in long term memory associated with schema construction and automation (F. Paas et al., 2004). CLT distinguishes between three types of cognitive load that must be processed for long-term recall to occur: intrinsic cognitive load, extraneous cognitive load, and germane cognitive load. The first is intrinsic to the thing to be learned. The last two are imposed by the design and organization of the learning material. Added together, these three make up the total cognitive load, which cannot exceed the working memory resources if learning is to occur (F. Paas et al., 2004; Sweller, 1994).

Intrinsic cognitive load

CLT assumes that information is the basic element in learning (Sweller, 1988, 1994). Each element (piece of information) has an intrinsic cognitive load (ICL), meaning what is required to know the element itself (Sweller et al., 1998) or to understand how two elements interact (F. Paas et al., 2004). Intrinsic load cannot be altered (Sweller et al., 1998). There are two element intrinsic cognitive load measurements (Chandler & Sweller, 1991). Low element interactivity means an element is easy to learn, or has a low intrinsic load. Vocabulary words are an example of elements with low intrinsic load because each word can be learned independently (Hollender et al., 2010). Elements which are harder to learn, in that they require numerous elements be held simultaneously in the working memory, have high element interactivity, or a high intrinsic load (Mayer & Moreno, 2003; Sweller, 1988). Using the same example, learning how to construct a sentence is a high intrinsic load activity because the learner must know the individual meanings of each word, understand how they fit together to make meaning, and use proper grammar to make the sentence correctly (Hollender et al., 2010; F. Paas et al., 2004).

Extraneous cognitive load

When a learning experience includes learning material or activities that are extra to knowing the thing itself, this extra material creates extraneous cognitive load (ECL) (Mayer, Heiser, & Lonn, 2001; Sweller, 1988). Extraneous cognitive load can be altered via "instructional interventions" (Sweller et al., 1998) because it is determined by the instructional design. This "extraneous material" takes up scarce space in the working memory, making a learner reach cognitive overload more quickly (Chandler & Sweller, 1991). In this case, the extraneous material does not contribute to the construction and automation of schema (F. Paas et al., 2004). Additionally, managing unnecessary information in the working memory can confuse the learner, forcing them to integrate the extra information into the process meaning making, again creating cognitive overload (Ayres & Sweller, 2005; Hollender et al., 2010).

Germane cognitive load

Germane cognitive load (GCL) is also produced by the instructional design of learning (F. G. W. C. Paas & Merriënboer, 1994; F. Paas et al., 2004; Sweller et al., 1998). That is, if the extra load is imposed by relevant learning activities, it will have a positive effect on learning (F. G. W. C. Paas & Merriënboer, 1994). Where extraneous load disrupts schema construction and automation, germane cognitive load contributes to or fosters active schema construction processes and is thus beneficial for learning (Hollender et al., 2010). Germane load was first introduced by Paas and Van Merriënboer

(1994) who found that more complex variations of worked examples increased cognitive load, but still beneficially led to learning. In their study, they showed that learners profited from the germane load imposed by a high variability of practice problems when they studied previously worked examples. These findings were verified by Sweller, et al. (1998). These studies changed the focus of CLT from only minimizing extraneous load, to also optimizing germane load.

The distinction of GCL is debated among theorists (Kalyuga, 2011; F. Paas, Tuovinen, et al., 2003; Sweller, 1988). Kalyuga (2011) argues that germane load is actually part of intrinsic load and is unnecessary to evaluate separately. He continues that distinguishing between intrinsic and germane load “clouds the applications of the theory for instructional design practitioners” (Kalyuga, 2011, p. 17). De Jong (2009) describes intrinsic load as the complexity of the material, while germane load refers to the cognitive process required to process material. Schnotz and Kürschner (2007) further elaborate that germane load goes beyond simple task performance. Rather, germane load is fostered by meta-cognitive processes such as application activities, pattern exploration, restructuring, and restructuring (Hollender et al., 2010; Schnotz & Kürschner, 2007). In this way, “learning can occur without germane load, but germane load can further enhance learning” (Schnotz & Kürschner, 2007, p. 497).

Balancing cognitive load through instructional design

Added together, these three (ICL + ECL + GCL) make up the total cognitive load (Kirschner, 2002), which cannot exceed the working memory resources if learning is to occur (F. Paas et al., 2004; F. Paas, Tuovinen, et al., 2003; Sweller, 1994). Early concepts of the theory espoused that simply by reducing ECL, i.e. cognitive overload, learners have more working memory to process ICL and GCL for schema processing of relevant material (F. G. W. C. Paas & Merriënboer, 1993; Sweller, 1988, 1994; Sweller et al., 1998). Avoiding cognitive overload can also be accomplished by reducing the amount of ICL by limiting the interacting elements in each segment of instruction (F. Paas et al., 2004). Van Merriënboer, Kirschner, and Kester (2003) have argued that applying a simple-to-complex, scaffolded learning sequence can reduce intrinsic load while simultaneously allowing for full understanding (*see also* F. Paas et al., 2004).

However, the nature of the intrinsic load can also influence overall learning (Hollender et al., 2010). In fact, it is now generally accepted that performance and learning decrease when learning scenarios have either extremely high or extremely low intrinsic load (F. Paas et al., 2004). Minimizing ECL such that learning is always at minimum load is not always beneficial to learning because extremely low load will not engage the learner (Hollender et al., 2010; Kirschner, 2002). Likewise, maximizing the ICL can overload the learner, preventing schema creation (F. Paas et al., 2004; Sweller, 2002). In other words, learning ceases with both cognitive overload and cognitive under load and it is the goal of an instructional designer to balance the overall load by understanding the intrinsic and germane load of the content and the learning design, as well as knowing the learners (whether they novices or experts).

The expertise level of the learner changes the load values of an activity, and likewise should alter the learning design. Experts and novices have similar working memory capacity. The difference in experts is simply that they have more schema concerning the topic of their expertise organized and stored in their long-term memory

(Sweller, 1988). De Groot (1966) compared the abilities of grand chess players with novice chess players. He found that grand masters did not process more at any given time than novice players. Rather, they had stored in their long-term memories more game board configurations than novice players. These configurations allowed the experts to anticipate several more moves than the novice players who did not have the configurations memorized.

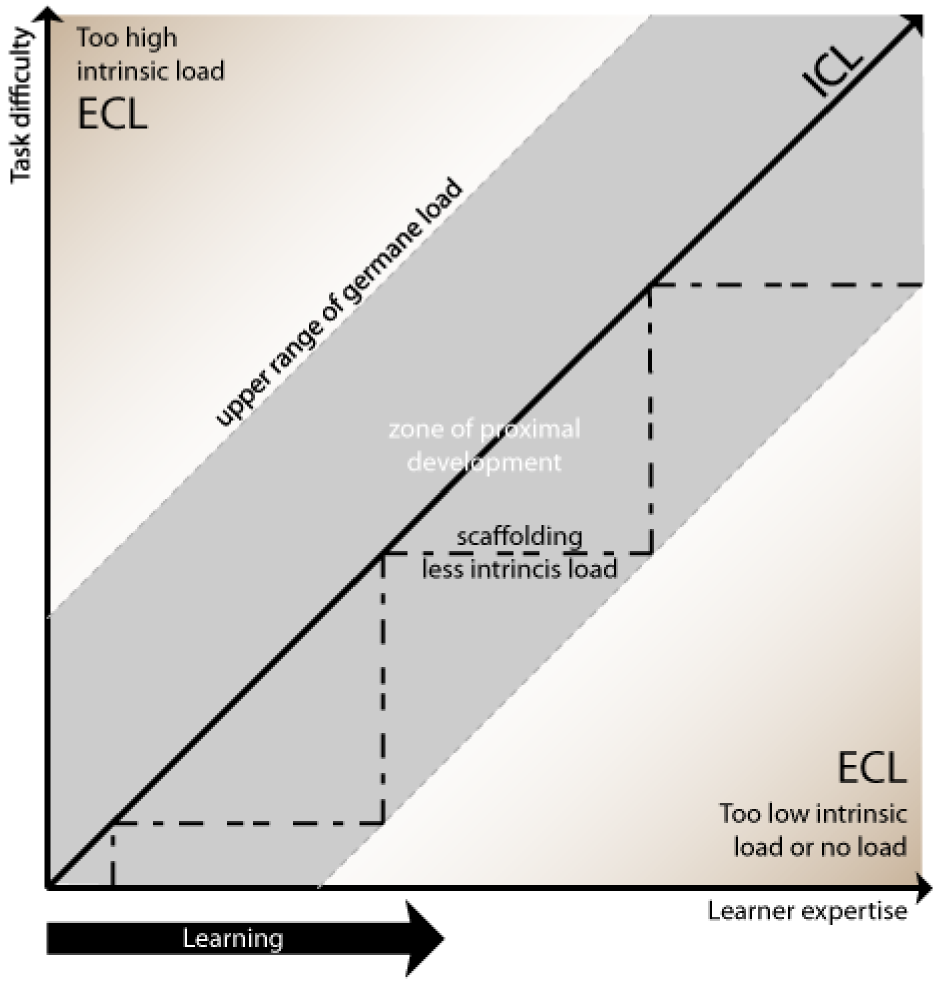


Figure 2.3. Cognitive Load Theory. Aggregated findings. No learning occurs the closer a learner gets to the top left and bottom right corners, where intrinsic load is either too high or too low.

It was thus found that the learning process is more complex than the simple addition of ICL, ECL, and GCL (Ton de Jong, 2010; Schnotz & Kürschner, 2007), and in fact, learning changed depending on the expertise of a learner (Figure2.3) (Sweller et al., 1998). In this way, an expert may still learn in scenarios that contain high ECL, where novices in similar scenarios will be overloaded (Hollender et al., 2010). To the expert, the element of learning has a low intrinsic load. To the novice, the element of learning has a high intrinsic load. Schnotz and Kürschner (2007) further argued that learning designs with too high ICL can hinder learning from GCL and this balance depends on the expertise level of the learner. Learning optimized to the level of the learner allows for germane load to enhance learning (Hollender et al., 2010). Schnotz and Kürschner (2007) use Vygotsky's (1963) zone of proximal development (ZPD) to further explain this balance between the types of cognitive load. If the task difficulty and resulting cognitive schema construction are higher than the learner's ZPD, the learner will face cognitive overload. Likewise, if the task difficulty and resulting cognitive processing is lower than the learner's ZPD, the learner will face cognitive under load (Hollender et al., 2010; F. Paas et al., 2004; Schnotz & Kürschner, 2007). It is, therefore, the goal of the instructional designer according to CLT to design learning experiences that are tailored to the experience of the learner and offer balanced loads for optimized learning without cognitive overload or under load.

Summary

Cognitive Load Theory is an instructional design theory, which operates under the assumption that human cognition has both a long-term and short-term, working memory. For learning to occur, it must be moved from the working memory into the long-term memory. This transition is accomplished through the construction and automation of schema. Schemas combine to make ever-more-complex schema, reducing working memory as the complex schema is now treated as a single element in the working memory. This continued process leads to automation. Automatic processing that stems from the lone-term memory does not take up space in the working memory when accessed.

CLT distinguishes between three types of cognitive load that must be processed for long-term recall to occur. Every learning element (piece of information) has an intrinsic cognitive load (ICL). A single element can have low element interactivity and therefore a low intrinsic load, or high element interactivity, and therefore a high intrinsic load. Extraneous cognitive load (ECL) occurs when the learning design includes material and activities are outside of, or 'extra' to what is to be learned, which unnecessarily take up working memory space and may cause cognitive overload. Germane cognitive load (GCL), load also produced by the instructional design of learning, fosters active schema construction processes and is beneficial to learning. Adaptations on types of cognitive load include De Jong's (2009) distinction of intrinsic load as the complexity of the material and germane load as the cognitive process required to process material and Schnotz and Kürschner's (2007) espousal that germane load occurs during of meta-cognitive processing.

The expertise of the learner changes the load values of an activity, and likewise should alter the learning design. The total cognitive load of a learning experience is comprised of the summation of ICL + ECL + GCL, as well as the expertise of the learners. Total load cannot exceed the working memory resources if learning is to occur. The underlying goal of Cognitive Load Theory (CLT) is to design learning that increases cognitive recall by decreasing cognitive overload when information is being processed in the working memory, simultaneously taking into account the expertise of the learner. Accordingly, instructional design should manipulate the types of load in ways that align task requirements with the learner's level of expertise. In the following section, I will explain the Cognitive Theory of Multimedia Learning and explain its importance in this specific study.

COGNITIVE THEORY AND MULTIMEDIA LEARNING

Mayer and Moreno's (2003) Cognitive Theory of Multimedia Learning (CTML) extends CLT theory by adding its main assumption to those of Baddely's (1976) Theory of Working Memory and Pavio's (1986) Dual-Channel Theory, and well as to Mayer's (1999) Theory of Active Learning. CTML operates under three main assumptions: the dual channel assumption, the limited capacity assumption, and the active processing assumption. Mayer (2003) defines a multimedia instructional message as a presentation consisting of words and pictures that is designed to foster meaningful learning.

A basic notion of CLT is that human cognition has a limited working memory capacity and an unlimited long-term memory (the limited capacity assumption) (Chandler & Sweller, 1991; Hollender et al., 2010; Miller, 1956). The human capacity to learn is fed via multiple sensory channels, which act as independent processors within the limited working memory (Baddeley, 1976, 2001; Mayer & Moreno, 2003). Of import in this case are the auditory and visual sensory channels. Baddeley's (1976) Theory of Working Memory assumed auditory information occurred in a ''phonological loop" and visual information occurred via a "visuo-spatial sketchpad."

Pavio's (1986) dual-channel theory further adds credence to the notion that auditory and visual channels together can enhance learning. He assumes that human information processing has an auditory/verbal channel and visual/pictorial channel (the dual-channel assumption). The working memory receives information through audio and visual, however these systems are separately processed. Separately, each channel has a limited capacity at any given moment (Baddeley, 1976; Chandler & Sweller, 1991; Mayer & Moreno, 2003). However, By including and specifically manipulating both sensory channels, as opposed to only one, the working memory capacity can be increased (Hollender et al., 2010). Information is more easily learned when both channels are represented (T.-C. Liu et al., 2013; Mayer & Moreno, 2003; Paivio, 1990). For example, something heard is processed in the auditory channel, while something viewed is processed in the visual channel.

If something is both seen and heard (like a video or animation), both channels simultaneously process the information. However, for meaningful learning to occur, the learner must actively participate in the learning (the active processing assumption) (Mayer, 2003; Mayer & Moreno, 2003). CTML assumes that "meaningful learning occurs when learners engage in active cognitive processing including paying attention to relevant incoming words and pictures, mentally organizing them into coherent verbal and pictorial representations, and mentally integrating verbal and pictorial representations with each other and with prior knowledge. This process of active learning results in a meaningful learning outcome that can support problem-solving transfer" (Mayer, 2003, p. 129).

According to CTML, learning occurs when words and pictures are selected and organized in the working memory, after which they can be integrated into the long-term memory (Figure 2.4) (Ayres & Sweller, 2005; Mayer & Moreno, 2003).

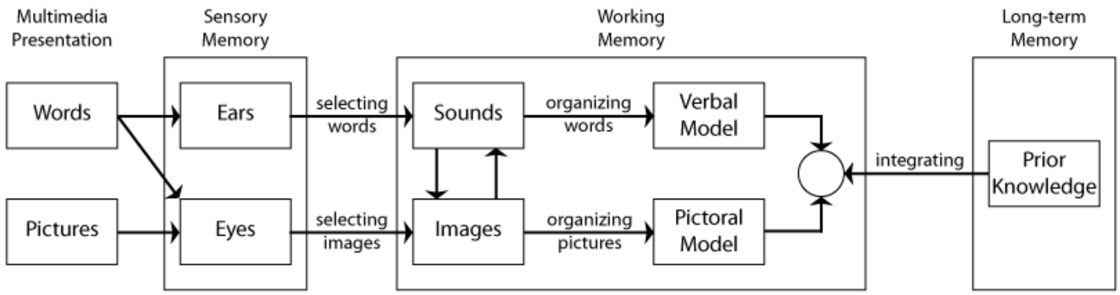


Figure 2.4. Cognitive Theory of Multimedia Learning (Mayer & Moreno, 2003, p. 44)

Mayer and Moreno's (2003) noted three types of cognitive processing in CTML: essential processing, incidental processing, and representational holding. Essential processing is aimed at making sense of presented material, i.e., to select, organize, and integrate (words and images). Essential processing is required to make sense of the presented material. Incidental processing occurs when non-essential aspects of presented material are processed. This type of processing is created by the learning design. Representational holding occurs when verbal or visual representations must be held in working memory in order for essential processing to occur. The total of all three processes are considered the total cognitive load. If the total is greater than the limited working capacity can hold, then cognitive overload will occur (Ayres & Sweller, 2005; Mayer, 2003; Mayer & Moreno, 2003).

CTML asserts that meaningful learning will only occur if all three processes are occurring for the visual and verbal representations (Mayer, 2005, 2009). Therefore, instructional methods should be designed to enable and promote these processes. Mayer (2003) asserts that single medium presentations will be less effective than dual-medium presentations. He calls this the multimedia effect (Mayer, 1999; Mayer & Anderson, 1991; Mayer et al., 1996; Mayer & Chandler, 2001). According to this effect, learning will occur more deeply when material is presented in words and pictures than from words alone (Ayres & Sweller, 2005; Mayer, 2003, 2009). Many studies have found that this assertion is true under specific circumstances (Austin, 2009; Ayres & Paas, 2012; Brunken et al., 2003; Eitel et al., 2013). Others have discovered that there are limitations to the multimedia effect and the CTML (Kalyuga, 2000; Leutner, Leopold, & Sumfleth, 2009; Reimann, 2003; Scheiter et al., 2014; Schüler et al., 2013; Tabbers, 2002).

Summary

Using the limited capacity assumption of Sweller's CLT and the dual channel assumption of Baddelley's Theory of Working Memory and Pavio's Dual-Channel Theory, in combination with his own theory of Active Learning, Mayer and Moreno describe the Cognitive Theory of Multimedia Learning. This theory asserts, and follow-up research has seconded, that in specific circumstances, learning occurs more deeply when both the auditory and the visual channels are utilized than with the visual channel alone. However, some studies have found that there are limitations to the specific effects produced under CTML.

CLT and CTML are both essentially instructional design theories based on cognitive psychology, and as such it is commonly the case that when a cognitive overload effect is revealed, its design antidote is also suggested. As this study is specifically interested in design principles, I will first define the pertinent cognitive overload effects and detail findings from various studies that support and negate these learning conditions. I will follow that section with a detailed description of suggested instructional design principles as they relate to each effect, and as they have been more generally related to mobile learning.

THE EFFECTS OF COGNITIVE OVERLOAD

Cognitive Load Theory and Cognitive Theory of Multimedia Learning both promote the notion that the primary goal on instructional design is enabling schema construction and the automation of the information in the long-term memory (Sweller et al., 1998). With practice (Chandler & Sweller, 1991; Merriënboer & Ayres, 2005) and through active learning (Mayer, 2003; Mayer & Moreno, 2003), schema will be processed with decreasing conscious effort (Schnotz & Kürschner, 2007). Understanding occurs when high element interactivity material can be held simultaneously in working memory (Ayres & Sweller, 2005; Chandler & Sweller, 1996; Sweller et al., 1998). Mayer (2003) asserts that learning through auditory and visual sensory channels assists with this. Learning occurs when high element interactivity material can be easily recalled and applied towards various new understandings and complex activities (F. G. W. C. Paas & Merriënboer, 1994). However as Sweller et al. (1998) point out, "The implications of working memory limitations on instructional design can hardly be overestimated…and instructional design that flouts or merely ignores working memory limitations inevitably is deficient" (p. 252).

When an instructional designer is designing learning, the goal is to transfer that intrinsic/germane cognitive load to the learner in ways that do not produce cognitive overload (Chandler & Sweller, 1991; Kalyuga et al., 2000; F. Paas, Renkl, et al., 2003). Intrinsic load cannot be altered, it is therefore essential to minimize extraneous load, and when possible, to limit the elements to be learned (Sweller et al., 1998). In multimedia especially, it is a challenge to avoid adding extraneous cognitive load (Chandler & Sweller, 1991; Mayer, 2003, 2009). Towards the creation of well-designed instruction, several cognitive overload effects have been discovered. These effects, when observed, have either improved learning or overloaded the working memory and disrupted learning (Ayres & Sweller, 2005; Hollender et al., 2010; F. G. W. C. Paas et al., 1994). They have been observed across learning mediums (Chandler & Sweller, 1996; Mayer, 2003).While there are numerous cognitive overload effects aimed at manipulating the three types of cognitive load (Hollender et al., 2010; Merriënboer & Ayres, 2005; Schnotz & Kürschner, 2007), there are only a few that directly relate to the study at hand.

Split attention

One cognitive load effect discovered early on in the theory's history and recreated numerous times with various media and content is split attention effect (see also spatial and temporal contiguity) (Chandler & Sweller, 1991; Mayer & Fiorella, 2014; Mayer & Moreno, 1998). Split attention occurs when a learner must integrate multiple sources of information in order to understand it, such that the individual pieces of information cannot be understood in isolation (Ayres & Sweller, 2005; Hollender et al., 2010; Kalyuga et al., 1999; Mayer & Fiorella, 2014; Sweller et al., 1998). The process of holding information in working memory, while simultaneously attempting to integrate it with other information is cognitively demanding (Cierniak et al., 2009; Kalyuga et al., 1999; Mayer & Moreno, 1998). This is especially true for low prior knowledge learners or novices who are viewing high intrinsic load material (Ayres & Sweller, 2005;

Chandler & Sweller, 1991; Florax & Ploetzner, 2010). The split attention effect can be a form of extraneous cognitive load, when it is caused by the design and presentation of instruction (T.-C. Liu et al., 2013; F. Paas et al., 2004), or be caused by intrinsic or germane load when the material surpasses the learner's zone of proximal development, thus over-whelming the working memory. According to Sweller, et al., split attention is a common design flaw (Kalyuga et al., 1999; Sweller, 2002; Sweller et al., 1998). Mayer (2001, 2003) also argues in his Cognitive Theory of Multimedia Learning that disparate words and images or animations and audio cause learners to search for and integrate information across the screen(s). This causes split attention effect, or special and temporal discontiguity because learners are forced to hold multiple pieces of information in their working memory to make whole meaning of them (Ginns, 2006).

The split attention effect has been found in numerous empirical studies (Florax & Ploetzner, 2010; Ginns, 2006). For example, in a series of six experiments in which novice learners studied learning materials about electronic circuits or the human heart, Chandler and Sweller (1991) found that studying previously worked examples caused split attention instructions were not integrated with the diagrams. Additionally, they found that participants who were required to integrate text descriptions with separate illustrations performed less successfully than students who did not need to integrate the two. Chandler and Sweller (1996) found using secondary task analysis that when high element interactivity was involved accessing instructions on a computer, separate from the product itself created a split attention effect, whereas integrating the instructions with the product did not. Mayer and Moreno (1998) found that students who had to split attention between text and images performed lower than students who viewed the image while listening to the same text. This resulting split-attention effect was consistent with a dual-processing model of working memory consisting of separate visual and auditory channels. Cierniak, Scheiter, and Gerjets, (2009) investigate split-source formatting and found that learners with the split-source formatting achieved lower learning outcomes than students with integrated formatting. By using secondary task performance as one form of measurement, they were also able to demonstrate that both extraneous and germane load contributed to split-attention effect.

In terms of mobile devices specifically, several empirical studies have reproduced split-attention effect. Findlater and McGrenere (2008) noted that the limited display size of small screen mobiles forces designers to split content onto multiple screens. That small screen displays require the breach of the spatial and temporal contiguity of learning content is supported by numerous researchers (Austin, 2009; Keefe et al., 2012; Kim & Kim, 2012; T.-C. Liu et al., 2013, 2012; Luong & McLaughlin, 2009; Maniar et al., 2008; Molina et al., 2014).

Keefe et al. (2012) found that split attention occurs when mobile devices were used as supplemental tools in informational visual design studies. This finding was replicated by Liu et al. (2012) and Liu et al. (2013), who both found that mobile devices used by science students to supplement a real-object botany lesson caused split-attention effect, when compared to the same lessons done entirely via the mobile device.

Mainar et al. (2008) found that zooming on a mobile device to increase the size of the content created a split-attention when compared to viewing the same material on a larger screen. Luong and McLaughlin (2009) reproduced this effect in their study on viewing bar graphs on both large and small devices.

Segmentation effect

One cognitive load effect that has been found in numerous studies is the segmentation effect (Spanjers et al., 2012). Segmentation effect is simply that when something is divided into meaningful pieces, it does not over-whelm the working memory as does continuous learning material (Ayres & Paas, 2012; Mayer, 2003; Mayer & Chandler, 2001; Mayer & Moreno, 2002; F. Paas, Renkl, et al., 2003; Spanjers et al., 2012; Wong et al., 2012). Segmentation has been proposed as a way to improve the effectiveness of learning material (Mayer & Moreno, 2003). The effect was noted by Mayer and Chandler (2001), who found that students who had seen segmented animations were better able to solve transfer problems than those who viewed the continuous animation. This seems especially the case for low prior knowledge learners (Mayer, 2009).

The research has given two main explanations for why segmentation assists in learning. First, segmentation creates pauses between segments, which breaks up the transience of dynamically presented information (Mayer & Chandler, 2001; Spanjers et al., 2010, 2012). In other words, system-controlled presentations will show the learning material for too brief a time before it disappears from screen. Under these conditions, learners are unable to process the elements in their working memory (Mayer & Moreno, 2003; Moreno, 2007). The body of empirical research around this notion is growing (see Ayers & Paas, 2012; Leahy & Sweller, 2011; Wong, Leahy, Marcus, & Sweller, 2012). With pauses between segments, the learner has a chance to "catch up" to the content and appropriately process the information to combine it with prior knowledge (Mayer, 2003; Spanjers et al., 2012). This is especially true when the learning material has a high intrinsic load. If not segmented, information is lost before it can be fitted into schema (Florax & Ploetzner, 2010; Mayer & Fiorella, 2014).

Catrambone (1995) found that visually isolating tasks in worked examples fostered learning (i.e. segmenting). In their 2001 experiments, Mayer and Chandler found that giving the learner a button to click from one screen to the next, that pause placed less cognitive load on the learners, who outperformed the non-segmented group in transfer tests. Moreno (2007) showed participants shown segmented content outperformed participants who were shown continuous content on transfer tests. Hassanabadi, Robatjazi, and Savoji (2011) found that learner controlled pauses were beneficial for learning. Sung and Mayer (2013) found that learner-controlled pauses allowed for better learning performance than whole/continue learning pieces.

The second explanation for why segmentation helps minimize cognitive load is that it helps break down the content into meaningful pieces, influencing the way learners organize and store information (Kurby & Zacks, 2008; Spanjers et al., 2012). When content is pre-segmented, these pieces provide cues or signals to learners about boundaries of meaning (Moreno, 2007). This reduces cognitive load by removing that task from the working memory process, thereby helping learners integrate information from the recent past to improve predictions about the near future (Kurby & Zacks, 2008), leading to an increase in what can be learned (Spanjers et al., 2010, 2012). Catrambone (1998) demonstrated this in his study of subgoal learning. Florax and Ploetzner (2010) found a significant effect on learning outcomes when text and images and text alone were segmented. Sung and Mayer (2013) found that participants presented segmented content outperformed those presented whole content. Studies also showed that when students were asked to actively segment or make the segments themselves, this increased cognitive load because the extra information processing taxed the working memory and became extraneous load (Spanjers et al., 2012). Accordingly, performance was observed to be best when the content segments were pre-determined (Hassanabadi et al., 2011; Spanjers et al., 2010).

Segmentation of text specifically was found to improve text comprehension (Ayres & Paas, 2012; Florax & Ploetzner, 2010), as segments inform learners how to create meaning units of the material (Florax & Ploetzner, 2010). In their 2010 study on split attention effect and text segmentation, Florax and Ploetzner demonstrated that split attention does not always occur when images and text are separated, rather they found that it is the segmentation of text that fosters learning and merging images and text (a recommendation for negating split attention) necessitated segmenting the text. In their study on single medium learning material and segmentation, Singh, Marcus, and Ayres (2012) found that segmented written text produced higher learning outcomes that segmented spoken text, but segmented spoken text outperformed continuous spoken text (see also Ayers & Paas, 2012).

In all studies on segmentation, learner control of pre-segmented material appeared to better facilitate learning than system control (Ginns, 2005; Mayer, 2003, 2009; Mayer & Chandler, 2001; Moreno, 2007; Spanjers et al., 2010, 2012), especially when comparing text only with bi-modal presentations (Hassanabadi et al., 2011). Allowing the learner to control the pace of learning, prevents transience, thus minimizing extraneous load and enhancing the capabilities of the working memory to process information (T.-C. Liu et al., 2012; Mayer, 2003; Spanjers et al., 2012; Tabbers, 2002).

Modality effect

Derived mainly from the dual channel assumption of the Cognitive Theory of Multimedia, and extending the multimedia effect, the modality effect is a much studied cognitive load effect (Hollender et al., 2010; Kalyuga et al., 2000; Mayer, 1999, 2005; Mayer & Moreno, 2002; Schüler et al., 2013). In CTML, the multimedia effect states that multimedia messages are more effective when they are presented simultaneously in text and images, rather than through one medium alone (Eitel et al., 2013; Mayer, 2003; Mayer & Moreno, 2002). This has been demonstrated through measuring perceived difficulty and learning gains (Mayer & Moreno, 2003; Schüler et al., 2013). Rather than text alone, the addition of visualizations reduces the amount of cognitive effort required.

The modality effect also occurs when multiple sources of information are required for understanding. The extraneous load of the visual modality can be reduced by transforming written text into narration, thus using the auditory processor (dual-channel) in working memory (Hollender et al., 2010; Kalyuga et al., 2000). The modality effect further defines multimedia effect by adding that narration or spoken text (Brunken et al., 2003; Kalyuga, 2000), when presented with images, provides even better learning moments because the visual and auditory senses are utilized, minimizing the workload to be processed in the working memory (Ayres & Paas, 2012; Kalyuga et al., 1999; Sweller & Chandler, 1994). Additionally, it continues that replacing written text with spoken text is different than adding spoken text to written text. This combination of both written and spoken text creates the redundancy effect, i.e., the working memory is over-whelmed by having to process both forms of redundant text (Chandler & Sweller, 1991; Mayer, 2003; Schüler et al., 2013). Adding audio to images also seemed to help reduce split attention as the working memory was freed to only visually observe the images instead of having to integrate the meaning of the text with the meaning of the images (Kalyuga et al., 1999).

Mayer and Moreno (1999, 2003) demonstrated that when high element interactivity material was presented in audio/visual formats, performance was substantially higher as compared to presentations in visual/visual formats. In a study by Kalyuga (2000), participants were tested on computer-based instruction using a visual diagram with visual text, visual diagram with audio text, or visual diagram with both audio and visual text. Results showed that presenting both audio and visual created a redundancy effect, while the visual diagram with audio text was rated the least difficult demonstrating the modality effect. An experiment with 80 8th-grade students, showed that less time and mental effort was spent by the group whose presentation was audio and visuals, versus the group who were presented with written text and visuals (Savoji et al., 2011). Schmidt-Weigand, Kohnert, and Glowalla (2010) showed that when text was spoken instead of written, participants spent more time studying the images than when text was written, in which case, participants spent more time reading the text.

In terms of technology specifically, Wong, Leahy, Marcus, and Sweller (2012) found that technology results in the transformation of permanent material into transient information (especially in cases of animation and narration) creating additional cognitive load. They found that when learning material is longer, static images and text are better for learning than animation and narration. Liu et al. (2013) conducted a study on modality effect using smartphones and showed positive learning gains when for groups with audio and images.

Reverse modality effect

While the modality effect has been widely studied, there have been found numerous boundary conditions, under which, the modality effect is diminished, attributed to another factor, or completely reversed. For example, in two studies the modality effect was not found with material low in intrinsic load (Mayer & Anderson, 1991; Mayer & Moreno, 1998, 2003). In their 2000 study how learner experience alters the modality effect, Kalyuga et al., found that for high prior-knowledge learners, diagrams alone were preferred to diagrams with explanatory text demonstrating the importance of understanding expertise when designing instruction (Kalyuga et al., 2000).

In their 2012 study how specifically placed key words and phrases affected learning from visuals and narrated text, Sombatteera and Kalyuga found that the redundancy effect was not repeated under these specific conditions, thus highlighting a boundary condition of the modality effect. Schüler, Scheiter, Rummer, and Gerjets (2012) examined whether the modality effect was a result of a lack of temporal contiguity or high visuo-spatial load. A hundred and forty-seven participants looked at scientific images either with audio or written text. Additionally, the text was provided either before the images, simultaneously with the images, or after the images. The results indicated no modality effect for verbal recall, but showed a modality effect for pictorial recall when text was simultaneously presented. In terms of the written text, participants in the simultaneous treatment tended to focus more on the text than the images. In their 2012 study, a reverse modality effect was found as participants who studied the materials with written text outperformed those who studied the audio materials on free recall, matching comprehension, and spatial recall tests (Crooks et al., 2012). The latter group however, expended less effort than the former group.

Explanations for reverse modality effect are varied. Kalyuga (2011) espouses that the transiency produced by many animations may demonstrate why studies on animations do not always find the modality and redundancy effects. Transiency can over-whelm the working memory processes. Tabbers (2004) found in his study of 111 participants in a classroom setting that the modality effect was reversed when study was learner-paced. Schmidt-Weigand, Kohnert, and Glowalla (2010) made similar findings in their study, failing to find a modality effect in learner-paced learning scenarios. This was supported by Schüler et al. (2013), who also noted a reverse modality effect under learner-paced circumstances. Scheiter, Schüler, Gerjets, Huk, and Hesse (2014) found that the modality effect was reversed as well when learners had high prior-knowledge.

Wong, Leahy, Marcus, and Sweller (2012) demonstrated that the modality effect disappears when content is longer. This lends evidence to a third possibility for the reversal of the modality effect. The auditory recency effect (Schüler et al., 2013) predicts the disappearance of the superiority of spoken text when the text is longer. Stemming from Penney (1989) and Baddelley (2001), this is due to the acoustic sensory code, which states that acoustic sensory is less susceptible to decay when the audio is short (Baddeley, 2001; Penney, 1989; Rummer & Engelkamp, 2003; Rummer & Schweppe, 2005). This has been proved in studies where recall of single words or phrases is high, demonstrating the superiority of spoken text. However, when text is longer, the advantage disappears as one sentence is quickly replaced with the next (Schüler et al., 2011). In these circumstances, written text is superior to spoken text because the advantage of audio is no longer there (Rummer, Schweppe, Fürstenberg, Scheiter, & Zindler, 2011; Schüler et al., 2013). This effect appears independent of whether or not images partnered the text (Schüler et al., 2013). This supposition is supported by text comprehension research, which has found a superiority of written text when longer texts are presented with sufficient enough time for applying text comprehension strategies (discussed in the following section). Schüler et al. did observe a reverse modality effect in their 2013 study when longer text was presented, however, they did not find that this was based on the superiority of written text, but rather on the auditory recency effect.

Text comprehension research

Text comprehension research, as it pertains to the topic of this study, assumes that written texts are superior to spoken text when the text is long, complex, and/or expository (Schüler et al., 2013). This assumption is based on findings that suggests written text attracts attention, as compared to images and spoken text (Schmidt-Weigand et al., 2010). It is also argued that greater mental activity is involved in reading, which will result in better retention (A. Furnham et al., 1988). Several studies have noted a higher recall performance by participant groups who view written text materials as opposed to spoken text materials or audio visual materials (Byrne & Curtis, 2000; A. Furnham, 2001; A. F. Furnham & Gunter, 1985; A. Furnham & Gunter, 1989; A. Furnham et al., 1990, 1988; Gunter & Furnham, 1986; Hron, Kurbjuhn, Mandl, & Schnotz, 1985; Müsseler, Rickheit, & Strohner, 1985; Sanders, 1973).

Mannes and Kintsch (1987) examined the effect of learning from text-only advanced organizers. They found that organized advanced organizers produced better recall, while inconsistent organizers enhanced problem solving capabilities. In their 1990 study comparing audiovisual, audio, and text only printed stimulus material, Furnham, Gunter, and Green found that the group who read the paper script remembered the most cued and free recalled details. In a second experiment, they repeated their measures with a complex science extract. Again the study revealed a supremacy of the printed text materials. Rasch and Schnotz (2009) found that adding pictures to text was neither beneficial nor harmful for learning. They also found that learning from text only was more successful in terms of learning efficiency that learning from text and images. In their study with 100 eleventh graders, Leutner, Leopold, and Sumfleth (2009) found that making mental images after reading expository science text lead to higher reading comprehension than actually drawing images of the same text. They concluded that constructing mental images reduces cognitive load, thus increasing comprehension and learning because the mental visualization processes are not disturbed by externally drawing pictures on paper.

Kintsch (1994) looked at text comprehension differences for high and low knowledge learners. He found that novice learners benefit more from well-written texts while high knowledge learners benefit from less thoroughly written text. (McNamara et al., 1996) supported this finding by arguing that “poorly written text forces the knowledgeable readers to engage in compensatory processing to infer unstated relations in the text” (p. 1). Additionally, knowledge seems to facilitate different types of comprehension (Voss, Fincher-Kiefer, Greene, & Post, 1986).

These findings are in direct conflict with the multimedia and modality effects which suggest that reading text, as opposed to viewing images and hearing spoken text, will produce higher cognitive load and prevent recall (Mayer, 1999; Schüler et al., 2011). Along those lines, text comprehension research consistently has found that when written and spoken texts are compared without images, a disappearance (and sometimes reversal) of the multimedia and modality effect occurs (A. Furnham et al., 1988). The disappearance/reversal is cause by the ability of the reader to implement three reading comprehension strategies.

First, where spoken text is transient, written text is permanently available (Schüler et al., 2011). This permanence allows readers to slow down and take time reading the text (Furnham, Gunter, & Green, 1990; Byrne & Curtis, 2000; Kozma,1991) and to make as many regressions over the text as needed. This has been shown to lead to better understanding of the material (Craik & Tulving, 1975; A. Furnham et al., 1988), and is an especially useful strategy when text is complex and learners are lower-prior knowledge learners (Frazier & Rayner, 1982; Hyönä & Nurminen, 2006; Just & Carpenter, 1987; Schüler et al., 2011).

Second, a reader of written text, given the time, is able to make several passes of the material (A. Furnham et al., 1988; Schüler et al., 2011), which aids in understanding complex or ambiguous passages (A. Furnham et al., 1990). Hyönä and Nurminen (2006) showed that learning recall is better the more passes that are made. Empirical evidence collected from eye-tracking studies support this finding (Schmidt-Weigand et al., 2010).

Finally, when text is written, a reader can skip extraneous passages that are either not relevant or are too difficult to understand and concentrate on the more important parts of the text (Schüler et al., 2013, 2011). With the implementation of these three strategies, and under the specific conditions (time and complex material), reading comprehension improves (A. Furnham et al., 1990; Schmidt-Weigand et al., 2010; Schüler et al., 2013).

Under these conditions, the reversal of the modality effect is expected, as well as a superiority of written text. In their experiments on the topic, Schüler et al. (2013) did find a disappearance of the modality effect, but they were unable to show a superiority of written text unlike their colleagues. In terms of spoken verses written text under these specific conditions, one condition did not prove better than the other for comprehension despite the numerous studies before this one have found evidence of the superiority of written text. Nevertheless, Schüler et al. noted that the implications of the general text comprehension findings "have important theoretical but also practical implications: Due to the fact that written texts are normally cheaper to produce and easier to implement into computer based learning environments, instructional designers may decide to present longer text segments in written instead of spoken format" (p. 1598-99). They concluded that these findings in the least identify some boundary conditions for the multimedia and modality effects.

Summary

Towards the creation of well-designed instruction, several cognitive overload effects have been observed. Split attention effect occurs when a learner must integrate multiple sources of information in order to understand it, such that the individual pieces of information cannot be understood in isolation. The process of holding information in working memory, while simultaneously attempting to integrate it with other information, is cognitively demanding, especially for low prior knowledge learners. Split attention effect can be caused by the learning design, or be caused by intrinsic or germane load when the material surpasses the learner's zone of proximal development, thus over-whelming the working memory. Several studies about small screen mobile devices have reproduced split attention effect, mainly because the small display breaches the spatial and temporal contiguity of the learning content.

A second cognitive load effect, segmentation effect occurs when something is divided into meaningful pieces such that it does not over-whelm the working memory as does continuous learning material. Segmentation assists with learning because it both creates pauses between segments, breaking up transience of dynamically presented material, and because it helps break the content down into meaningful pieces improving text comprehension. In all studies on segmentation, learner control of pre-segmented material appeared to better facilitate learning than system control by preventing transience and minimizing extraneous load.

Another observed cognitive load effect is modality effect, which states that the addition of visualizations, in combination with the use of spoken, rather than written text reduces the amount of cognitive effort required. The modality effect also occurs when multiple sources of information are required for understanding. The extraneous load of the visual modality can be reduced by transforming written text into narration, thus using the auditory processor (dual-channel) in working memory. Studies have shown that when high element interactivity material was presented in audio/visual formats, performance was substantially higher as compared to presentations in visual/visual formats. These findings were extended to smartphone learning, when positive learning gains resulted from audio/visual presentations (T.-C. Liu et al., 2013).

The modality effect has some boundary conditions, under which the disappearance or reversal of the modality effect was witnessed. The reverse modality effect occurs when material has too low and intrinsic load, when students are high prior-knowledge learners, when short phrases or single words accompany spoken text, when the lesson was learner-paced and transience was decreased, and finally when the content was too long or too complex. In these cases, the advantage of the audio/visual duo, decrease, disappear, or completely reverse (as noted when time is abundant and text is complex and long).

The supremacy of written text when passages are longer, more complex, or expository is supported by numerous text comprehension studies. These studies explain this supremacy by the ability of readers under these conditions to utilize text comprehension strategies that are unavailable in system-controlled learning scenarios that offer only spoken text narration. Such strategies include learn control of the reading pace, rereading as needed for understanding, and self-selecting to skip extraneous or overly difficult passages. Under these conditions, the reversal of the modality effect is expected, as well as a superiority of written text.

In the following section, I will review mobile learning literature from a learning and describe the recommended development process for mobile applications. This will include a detailed comparison of the differences between mobile web and dedicated mobile applications and an examination of some technical constraints. Finally, I will survey the literature on small screen displays and learning.

Mobile learning: Application development and instructional design

Early studies on mobile learning focused on theory (G. Attwell et al., 2003; Graham Attwell, 2010; Nyhan et al., 2003), on using mobile devices and existing content in a supplementary fashion (Kim & Kim, 2012), and on user acceptance (Al-Zoubi et al., 2008; Demirbilek, 2010; Franklin et al., 2007; Kismihók & Vas, 2011; Y.-S. Wang, 2007), however fewer studies looked at dedicated mobile application development. Especially in a formal learning setting, dedicated learning applications are especially useful (T.-C. Liu et al., 2013). Of those that examined the process and outcomes of this type of development, some designed individual applications (Du, Hao, Kwok, & Wagner, 2010; Motiwalla, 2007; Taylor et al., 2010), while others built entire mobile educational systems (Hwang et al., 2009; Osawa et al., 2007; S.-L. Wang & Wu, 2011; Wu et al., 2011). Generally, these studies focused on networked communication, dedicated learning material (Du et al., 2010), and content management systems (S.-L. Wang & Wu, 2011). In these cases, the mobile devices were used in lieu of traditional tools. The most common focus of the evaluation of these tools was usability, practicality, overall design, and learning outcomes of participants (M. Liu et al., 2013).

There were a few studies which featured the unique affordances of mobile devices for learning. In these studies, such as the study by Hwang et al. (2011) which used smartphone digital cameras and quick response (QR) code readers to access database information, the unique attributes of mobile devices were applied in ways that created new learning experiences. Osawa et al. (2007) used the built in GPS capabilities of smartphones to complete outdoor science lessons. Taurie et al. (2011), created smartphone history lessons using GPS and augmented reality. They found that using the mobile devices at the location in question provided students with a rich lesson that connected the past and the present.

Interestingly, most of these studies spent little time reporting on the design and development of the mobile applications, instead evaluating feasibility, usability, and learning gains. Son, Park, & Kim (2011) used learner perspective surveys to measure the success of the software. Similarly, Chen and Huang (2010) used a technology acceptance model (TAM) approach with elementary education major students to determine the mobile learning capacity of a mobile knowledge management learning system and found that ease of use may improve learning. Other studies (e.g. Chen & Hsu, 2008; Foley & Luo, 2012; Huang et al., 2011; Motiwalla, 2007) used qualitative methods, such as in-depth interviews, observations, and focus groups along with quantifiable survey ratings in order to rate the quality of the system implemented. Participants tended to respond positively, pointing to the importance of user buy-in. However, while these studies did develop some type of dedicated mobile software, they did not make elaborate reports on the development process.

Mobile application development for learning

Given the unique affordances of mobile devices for learning, full integration will require dedicated application development (M. Wang & Shen, 2012), as opposed to using mobile devices as a supplemental tool or using retroactively integrating existing content. The benefits of mobile devices from a design point of view are numerous and the studies mentioned that the emergence of embedded intelligence, flexible and interactive features, and the ability to create instruction in multiple modalities have given educators a method to engage learners in ways that are interesting and relevant to them (Laine et al., 2010; Ogata & Yano, 2004; Y.-S. Wang et al., 2009). Mobile consumers expect interactive, flexible, and seamless applications for their devices. Zabel (2010) acknowledged that mobile users are in an excellent position to choose their learning opportunities from a variety of applications. In response, developers must increase the complexity of mobile applications (Young, 2010). The disciple and research of mobile learning must begin to move from nascent research stages into more complex reviews, with the intention to identify replicable learning design principles. As there are multiple types and styles of learners, there are also multiple types and styles of mobile learning. Incorporating these factors into learning application development is essential (Crescente & Lee, 2011).

The development of mobile education applications requires more than simply graphical treatment. Mobile devices allow for the manipulation of an infinite virtual space that a user can move around by clicking and dragging interactions with the device (Y.-S. Wang et al., 2009). A single mobile learning moment is the culmination of a massive body of design, development, and planning. Thoughtful design, development, and implementation of mobile learning in educational settings can be thought of as a total system (Seraj & Wong, 2014). Pocatili (2010) asserts that a mobile learning system has three main components: the device hardware, the device software, and the learning content. This definition pertains to both large, complex systems, and smaller dedicated applications.

The mobile development process has several main components, including user experience (UX or UE) architecture, user interface (UI) design, programming (coding), beta-testing, and quality assurance (QA). Of these steps, instructional designers are most concerned with UX and UI. Together these create the interactive communication between the users and application. UX architects anticipate the overall user feeling, both emotional and practical and attempt to design an application that delivers the intended experience. UI designers arrange all textual, graphical, and interactive elements keeping in mind the flow of the interaction and the ease-of-use. If the flow is clunky and the application is tedious or difficult to move within, users will dislike it, even if the computational power and functionality it exhibits are powerful (Faghih, Azadehfar, & Katebi, 2014).

If the learning content must be developed (verses using what already exists and is accessible), perhaps the first consideration for mobile learning design, is identifying the best type of delivery. The software required for any mobile process comes in the form of simple mobile Web browser or a dedicated mobile application (Lee, 2011; Platzer & Petrovic, 2011). There are major differences between the two, which directly impact design, delivery, and success of learning.

Mobile web vs mobile application

Mobile web applications are accessed via the World Wide Web through the use of a browser-based Internet service. Essentially, a mobile web application is similar to a website. It is accessed through browsing and it is static and limited to the features of the site itself (as opposed to the features of the mobile phone – like GPS and camera). Additionally, it requires that a mobile device have a wireless or broadband connection. Access and navigation to a mobile web application will occur as quickly as the connection service allows. Mobile web applications are freely accessed, unless a specific site is password protected or requires a membership fee to access. More recently, programming for mobile web applications is optimized, meaning they are often designed specifically for mobile devices, verses accessing a regular-sized website. The appeal of mobile web design is that it is comparatively inexpensive to build, it requires no approval from the device makers and vendors, and it has a still relatively fast operating speed, so long is the device is connected by a strong signal (3G, 4G, or wireless).

Mobile application (mobile app or app) is a type of dedicated application software designed to be downloaded to and run on a mobile device. Akin to downloading software to a desktop PC, mobile applications are installed and housed on your mobile device hard drive. From the users' perspective, mobile applications are different from mobile web applications in two ways. First, the mobile applications do not necessarily need a connection to run once installed on a device. Second, the mobile applications can access and interact with the unique features of the mobile device, like camera, GPS, SMS, and NFC. Mobile applications are relatively small, individual software units with limited function. They have interactive user interfaces, and generally perform faster than the mobile web. They can be purchased from app vendors, like the Apple App Store or the Google Play store, or are restricted and accessed only via secure networks. Mobile applications sometimes require approval of the device makers and/or the vendors and can be very expensive to develop.

Sometimes, mobile applications are built as hybrid applications. This means that the application is installed on device and operates without a connection. However, the app also, when connected, interacts via broadband or the web to deliver updated content information or to exchange information and resources with other users through the Internet.

The distinction between mobile web and mobile apps is an important one to make in conversations about mobile learning development. Consumers want "innovative end-to-end service offerings and are increasingly aware that they need to measure the effectiveness of the services holistically" as the various parts of the industry work towards meeting consumer needs (Knight, 2011). From the development perspective, this requires constant changes to any application as operating systems are updated, new devices are created, and existing device displays and capabilities change. Constant updates and redesigns are expensive (G. Becker, 2008). Much of the empirical dialog about the topic includes discussion about the unique affordances and features of the devices (Seraj & Wong, 2014; Sung & Mayer, 2013; M. Wang & Shen, 2012). A mobile web application cannot utilize many of those features, but at the same time, is much cheaper and easier to produce. Whereas, the richly developed mobile learning platforms will be dedicated mobile applications, which take a long time to build, require the expertise of many people, must sometimes be approved by a completely separate entities, and for more complex apps, can run upwards of $100,000 to produce.

Technical and design challenges of mobile learning.

While mobile learning does present unique and engaging opportunities for learners (Elias, 2011), the genre is also fraught with challenges (Al-Zoubi et al., 2008; M. Wang & Shen, 2012). Studies discovered issues like poor network connectivity (Al-Zoubi et al., 2008; Crescente & Lee, 2011; Y. Park, 2011; Pea & Maldonado, 2006), high development costs (M. Wang & Shen, 2012), and mobile device feature incongruity (Mostakhdemin-Hosseini, 2009a). Sanchez & Goolsbee (2010) reported cognitive overload due to poor design, while Crowe & VanHooft (2006) found the lack of a standard platform across devices impeded successful integration of mobile device for learning. One of the most prevalently reported issues with mobile learning pertained specifically to the small screen displays of handheld devices, namely smartphones, PDAs, and iPod-type devices (T.-C. Liu et al., 2013, 2012; Luong & McLaughlin, 2009; Maniar et al., 2008).

Mobile learning and small screen displays

Sanchez & Goolsbee (2010) noted the prevalence of smartphones among both professionals and students, raising expectations for smartphone integration into school, work, and life. If fact, Sung and Mayer (2013) compared desktops with tablets and found that while recall and transfer tests were not better, students enjoyed using the tablet for the learning activity more than the desktop, increasing their motivation to learn. There is nevertheless some debate as to whether or not small screen displays are good for learning given the size constraints (Ng & Nicholas, 2009), especially as compared to the handheld's larger display mobile cousins, i.e., laptops and tablets (Molina et al., 2014). Wang & Shen (2012) assert that learning from small screen mobile devices is not useful for full content, backing their statement with their finding that many scholars believe small screens do not provide a "comfortable learning environment" (p 568). This skepticism is supported by numerous studies, which found the small size of handheld devices problematic.

These reports can be split into three categories: user frustrations with small displays, physical limitations of small displays, and poor content and UI design issues of small displays (including interaction with onscreen content). Small screen displays were found to impede user reception of mobile learning (Crescente & Lee, 2011). Churchill & Hedberg (2008) found that small screen displays negatively impact both acceptance and educational integration, while Jones, Buchanan, & Thimbley (2003) reported that small screen displays reduce learning performance, resulting in user dissatisfaction. The general consensus of these studies is that frustrated learners make user perception of the learning experience negative, which in turn hinders user acceptance of the delivery method (Pea & Maldonado, 2006), thus impeding its success in education (Y. Park, 2011).

In physical terms, viewing and interacting with a small screen device has limitations. In his study on small touchscreen displays, Cockburn et al. (2012), found that the error rate of finger input was high due to large finger size and small screen touch targets. This issue is often referred to as the "fat finger" problem. Maniar, Bennett, Hand & Allen (2008) refer to the limits of human visual perception, which limits the level of small details seen on small screens, affecting attention span. This finding was supported by Seraj and Wong (2014) who stated, "small screen displays trigger a more difficult reading process that directly impacts the normal pattern of eye movements and indirectly influences human interactions" (p. 24). Swan, et al. (2005) found that even using a stylus, accurate tap targeting was challenging.

In terms of UI and content design, smartphones and the like have limited capacity to present information (Kim & Kim, 2012). Small screen display research has included a variety of content topics and genres, presented in numerous ways, including but not limited to talking head, text, animation, full-features vs. segments, comedy, and action-adventure (Bracken, Pettey, Guha, & Rubenking, 2010; Heo, 2003; Kim & Kim, 2012; Luong & McLaughlin, 2009; Reeves et al., 1999). Vogt, Schaffner, Ribar, & Chavez, (2010) found that small screen text diminished learning gains. Ng & Nicholas (2009) noted concerns that small screens caused overload by cutting off information found via a mobile we browser, forcing participants to scroll and navigate through ill-defined chunks of content. Churchill & Hedberg (2008) similarly found in their study that small screens adversely affected clarity and understanding of the learning material, given the small amount of content visible on the screen at one time. In this way, accessing longer resources via small displays is generally discouraged (Corlett, Sharples, Bull, & Chan, 2005; Crowe & van't Hooft, 2006), especially if the content is in text format verses enhanced with audio, video, and/or animation. Kim & Albers (2001) asserted that a lack of specific small screen design principles for text formatting, compression and scrolling resulted in poor learning design.

Several studies specifically compared large and small mobile screens for learning and found the latter lacking. Kim & Kim (2012) found that small screens impeded vocabulary learning outcomes when compared to large and medium screens. Heo found in a 2003 study with 75 participants that large screen displays out performed small screen displays in terms of attention, arousal, and memory. Luong & McLaughlin's 2009 findings agreed that large screen displays are better for learning than small screen displays. Sanchez & Goolsbee (2010) examined the effects of text size and scrolling on both small and large screen mobile learning content. They found that scrolling negatively impacted learning on small screens especially. The small screen content in their study was simulated and scrolling occurred via vertical scrollbar on the right side of the screen (Sanchez & Goolsbee, 2010). These results are consistent with those of Sanchez & Branaghan (2011), who found that the limited screen real estate of small displays created a need for scrolling when reading longer texts. This need to scroll negatively impacted recall.

Small screens have also been found to limit spatial presence and social realism, as well as with content interaction when compared to 32 inch flat screens (Bracken et al., 2010). In their comparison of PCs, tablets, and smartphones which tracked eye movement in addition to learning gains, cognitive load, and user acceptance, Molina et al. (2014) found that students learned best from PCs before tablets, and both PCs and tablets, before smartphones, given the same content. The content was retrofitted to the various screens and delivered via mobile web, and the researchers found that special end temporal contiguity was diminished in the smartphone treatment. Reeves et al. (2000) found that regardless of content, large screen displays increase attention and arousal for media messages. One reason they attributed this finding to was that large displays allow for more picture to be viewed in the perimeter of vision, and peripheral vision has been shown to respond to novelty and motion more than faux real vision (Livingstone & Hubel, 1988; Reeves et al., 1999).

Summary

In summary, there are several ways to use mobile devices for learning, including using the features of the device to supplement learning, accessing already published content and wrapping learning around it, accessing specifically tailored web content via a mobile device through mobile web, and finally, developing a dedicated mobile application or system to meet learning and educational needs. Mobile web pages for education content delivery are easier and cheaper to build and maintain, but do not have access to many of a mobile devices features (GPS, camera, etc.). Additionally, information accessed via the web has even less screen real estate given it must be viewed within a web browser. Dedicated mobile applications offer all of the capacity of computer software (including speed, device feature use, interactions specific to learning engagement, and full control over content). Dedicated mobile applications are, however, expensive to build and complicated to maintain. They also require thoughtful UX/UI design, various platform development, and specific implementation (Potcatilu, 2010).

Mobile learning is not without its technological challenges. These include network connectivity, device limitations, platform inconsistency, and high development costs. Small screen display also present challenges for learning and cause user frustration. Some of these challenges are owing to the hardware, some the design of the content, and some to the ill-matched combination of the two. Several studies have used dedicated mobile applications to examine the possibilities of creating original content and software systems for mobile learning.

Regardless of these issues, mobile devices are ingratiated into our cultural fabric in ways that are infiltrating homes, classrooms, and offices. The use of smartphones and tablets are significantly changing human-computer interaction and the way humans communicate and learn (Ahmadi & Kong, 2012; Molina et al., 2014; Sanchez & Branaghan, 2011). While evidence does suggest that small screen displays are not always ideal for exemplar learning experiences, the devices will nevertheless remain a tool of choice for the foreseeable future. Given that we know of these challenges, perhaps there is a new research direction to consider is: design recommendations for smartphone learning that enhance the learning experience, minimize cognitive load, and ensure better content recall/transfer in ways that are comparable to larger screen devices.

In the following section, I will outline the design principles suggested in the research. I have subdivided these into two groups. The first includes design principles recommended to minimize cognitive overload. The second examines the suggestions for small screen display instructional design.

DESIGN PRINCIPLES FOR SMALL SCREEN DISPLAYS

Several studies noted that theoretical, practical, and design guidelines are needed to enable to the design and development of successful mobile learning (Al-Zoubi et al., 2008; Crescente & Lee, 2011; Molina et al., 2014; Mostakhdemin-Hosseini, 2009b; Terras & Ramsay, 2012). Al-Zoubi1 et al. (2008) explained that such guidelines are needed to construct better mobile environments for learning and to create a more education mobile society in the future. Design is also becoming more complicated, as instructional designers must now consider applying a variety of design principles in the design and evaluation of instructional media (M. Wang & Shen, 2012), while simultaneously considering user-perception, communication, learning, and systems architecture (UX/UI). Crescente and Lee (2011) noted that guidelines are needed to address not only the pedagogical learning styles aptitudes, and strategies, but also the andragogical ones (p. 114). Wang and Shen continued, “M-learning must overcome some core challenges in order to have a signification impact on the global educational environment" (p. 566).

Some studies have approached the question of design when it comes to learning from small screen displays (Churchill, 2011; T.-C. Liu et al., 2013; Luong & McLaughlin, 2009; Seraj & Wong, 2014). But design has numerous elements, any combination of which may provide a different outcome. Adding to this formula, the complexity and nature of the content to be learned can also alter the learning experience (Tarumi et al., 2011). For this reason, it seems necessary to look at individual design elements and the success of application of those design elements on learning from small screens.

Design principles for minimizing cognitive load

To begin, there are several design principles recommended to minimize the effect of cognitive overload (Chandler & Sweller, 1991; Mayer, 2009; Sung & Mayer, 2013; Sweller et al., 2011). First and foremost, eliminating extraneous content is necessary for preventing cognitive overload. In terms of mobile learning, this includes excluding background music (Brunken et al., 2003) and random animations or screen decorations (Mayer & Fiorella, 2014), which have been shown to be extraneous to learning material. This is in line with the coherence principle (Mayer et al., 1996; Mayer & Chandler, 2001), namely that all visual and auditory material is pertinent to the topic of learning. Wherever possible, avoid repeating information by adding audio to written text. This will prevent the redundancy effect (Mayer, 2003; Sweller et al., 2011).

In terms of split attention, integrating content whenever possible is ideal (Ayres & Sweller, 2005; Mayer & Moreno, 2002). By combining two information sources into one, split attention should be alleviated (Cierniak et al., 2009; Florax & Ploetzner, 2010; Kalyuga et al., 1999). This is Mayer's temporal contiguity principle (Mayer, 2003). Mayer further adds that where possible, aligning words with images will prevent split attention. This follows the spatial contiguity principle (Mayer, 1999; Mayer & Moreno, 2002).

For mobile devices, it is recommended that whenever possible, using mobile devices as the focus of learning is less over-whelming to the working memory than using it as a supplemental tool with real objects. The latter has proven in several studies to create split attention effect when learners must move from the mobile display to the real object and back again (T.-C. Liu et al., 2013, 2012).

Cueing also a beneficial technique for decreasing split attention. Also called signaling, cueing alerts the learner to essential elements or to make connections. Liu et al. (2012, 2013) found that arrow line cueing significantly improved learning in mobile science lessons. They found that cuing guides learners to essential information and emphasized the organization of instruction (T.-C. Liu et al., 2013).

Cueing through segmentation is also recommended to alleviate cognitive overload (Florax & Ploetzner, 2010). In this case, segmentation of longer content into meaningful pieces signals learners how to organization the information, reducing cognitive load (Kurby & Zacks, 2008; Spanjers et al., 2012; Sung & Mayer, 2013). It is also recommended to add strategic pauses to learning modules, so that students are not overloaded by the transience of continuous material (Hassanabadi et al., 2011; Moreno, 2007; Spanjers et al., 2010). Mayer and Chandler (2001) achieved this simply by adding arrow buttons at the end of each segment that learners clicked to move forward.

Finally, whenever possible, giving the learner control over the learning pace (specifically) has shown numerous times to decrease cognitive load (Hassanabadi et al., 2011; Mayer & Chandler, 2001; Schmidt-Weigand et al., 2010; Schüler et al., 2013; Spanjers et al., 2012; Sung & Mayer, 2013; Tabbers, 2002).

Design recommendations for small screen displays

Specific to small screen display mobile devices (namely smartphones), there is less research in terms of specific design principles. Additionally, many conflicting reports have been made in terms of specific recommendations, suggesting that some design questions can only be answered within context of the learning to be completed. The research included here has been divided into two larger groups: small screen display real estate design recommendations and small screen display text formatting recommendations. The findings mainly address navigation and manipulation of the device and the content, though some make content recommendations, which may or may not be possible given the topic at hand.

Small display screen real estate design recommendations

Maximizing space. The total display represents the total screen real estate. In terms of design for small screens, the more ratio of the screen utilized, the more space will be available for content (Churchill, 2011). For this reason, it is recommend to design for full screen and avoid web browsers, the header and footer ribbons of which take up valuable space(Churchill, 2011; Churchill & Hedberg, 2008). Seraj and Wong (2014) advise that the application should not be taller or wider than the display, which would force users to slide the screen up/down and left/right to view the whole.

Scrolling. Scrolling has been found to cause split attention effect (Luong & McLaughlin, 2009) and is generally recommended to avoid (Churchill, 2011; Churchill & Hedberg, 2008). Sanchez and Wiley (2009) found that scrolling while reading text reduces text comprehension because information had to continually be located and relocated as it was moved up and down the screen. Sanchez and Goolsbee (2010) confirmed this finding. In addition to limiting or eliminating scrolling, limiting the number of taps and/or swipes is also recommended for maximum learning gains (Seraj & Wong, 2014).

In contrast, Leavitt & Shneiderman (2006) asserted that in cases of long text and reading for comprehension, scrolling was preferred to pagination. Jin (2013) followed that scrolling is better for expository text. However, these studies were done using larger screens, and it is unclear whether or not this extends to small screens.

Zooming. Zooming has been shown to increase cognitive load, especially when the zoom is learner-controlled (Maniar et al., 2008). In their study that compared three zoom functionalities on small screens to determine cognitive load, Luong & McLaughlin (2009) found that zooming created higher cognitive load than no zooming. Additionally, they found that controlled zoom created less cognitive load than learner-controlled zoom. In contrast, Churchill (2011) recommends adding zoom functionality to content in small mobile device settings.

Screen orientation. Several studies recommended using landscape orientation when designing instruction for small screen displays, thus turning the device so it is wider than high. Most smartphones allow users to manipulate the view between portrait and landscape. In a 2011 study by Sanchez and Branaghan which sought to evaluate learner recall and complex reasoning when learning from smartphones, results indicated that turning the device to landscape mode eliminated decreased performance as compared to portrait orientation of the same device. This seemed especially true for lower working memory capacity learners. The benefits of user controlled adaptive design were also, recommended so that learners could adjust for their individual comfort (Sanchez & Branaghan, 2011). In contrast, it was also noted that multi-touch manipulation of text (including landscape view) still place demand on user to constantly manipulate screen (Sanchez & Goolsbee, 2010) creating extraneous load.

Small screen display text formatting recommendations

Text size. In a study that compared character size on small and larger screen displays, Sanchez and Goolsbee (2010) found that smaller font produced better overall retention than larger font on small screens, in part because it limited the need to scroll. Though earlier findings suggest that inter-character and inter-line spacing increases recall (C.-H. Chen & Chien, 2005), adding these buffers would increase the length of text on a small screen device and require either more scrolling or more pages to navigate through. Churchill (2011) recommends designing mobile learning with a single font, though varied shades, sizes and styles are okay.

Text length and segmentation. Given the constraints of smartphone displays, the recommendation to limit the amount of written text content is repeatedly emphasized (Churchill & Hedberg, 2008; Seraj & Wong, 2014; M. Wang & Shen, 2012). When possible, text should be replaced with images, audio, and narration (Bradley et al., 2006; Churchill & Hedberg, 2008; Sung & Mayer, 2013). When that is not possible, designing for short, task-centered interactions is appropriate (Churchill, 2011). Additionally, formatting text in ways that provide meta-knowledge (Churchill & Hedberg, 2008), segment text into smaller, manageable chunks (Seraj & Wong, 2014), and/or provide key point summaries (M. Wang & Shen, 2012) will assist with minimizing cognitive overload[1].

Summary

While literature on mobile learning is growing, there are remarkably few studies that look specifically at instructional design. Even fewer recommend instructional design principles, particularly in terms of smartphones and other small mobile devices. A few studies have approached the question of instructional design for small screen displays.

There are, however, numerous studies on minimizing cognitive overload that have implemented and recommended noted instructional design principles. In terms of reducing cognitive overload, eliminating design created extraneous content is among the first recommendations. This is in line with the coherence principle, namely that all visual and auditory material is pertinent to the topic of learning.

[1] As a side note, some researchers have developed programs to automatically segment content based on advanced algorithms that measure content, subject, preferred user views, and display availability (Ahmadi & Kong, 2012; Beeferman, Berger, & Lafferty, 1999; Fournier, 2013). Though not of use in this study, automatic text segmentation is interesting to consider for future mobile learning content.

In terms of reducing split attention, the spatial and temporal contiguity principles state that integrating content by combining two sources of information into one will alleviate split attention. Several studies found that cueing (signaling) decreases split attention and assist with segmentation. For mobile devices, it is recommended that whenever possible, using mobile devices as the focus of learning is less over-whelming to the working memory than using it as a supplemental tool with real objects. Finally, whenever possible, giving the learner control over the learning pace (specifically) has shown numerous times to decrease cognitive load.

Specific to small screen display mobile devices (namely smartphones), the design guidelines can be divided into two categories. First, in terms on screen real estate, maximizing space, by utilizing the full screen is recommended. With few exceptions, scrolling has proven to lower reading comprehension. Zooming can increase cognitive load. Finally, designing for landscape orientation was found to improve overall learning and user experience.

Recommendations for text formatting and small screen display make up the second category. Using a single, smaller font, that is spaced enough for line distinction without unnecessarily causing the need to scroll seemed to produce the best learning outcomes. Limiting the amount of text on screen, through elimination or segmentation is emphasized. Finally, when possible, text should be replaced with images, audio, and narration.

LITERATURE GAPS

While the literature covers a great many topics of mobile learning, cognitive load, and instructional design, there are several critical research gaps that require empirical attention. Mobile learning is a challenging field in part because the technology is constantly enhanced. Generally, by the time a study is published, the particular devices considered are antiquated. Every year, new smartphones are released with enhanced screens (dimensionally and higher definition clarity), features, connectivity, and capability. It is questionable how exactly the findings from studies completed with old style PDAs apply to the sleek handhelds today. From a user perspective alone, the immersion of smartphones into the social and cultural fabric paints a much different picture than it did ten, even five years ago (Ericsson, 2015). In this regard, the literature is clear that positive user acceptance and perspective of any mobile learning platform is crucial for its success (Bhaskar & Govindarajulu, 2009; Mostakhdemin-Hosseini, 2009a; Terras & Ramsay, 2012).

A majority of the studies did not maximize the smartphone design used for testing. Maximizing in this case means designing dedicated smartphone applications that allow for maximum design control over screen real estate and content interactions. Perhaps limited by capacity, budget, or time, several studies used simulated small screen displays instead of real mobile devices (Kim & Kim, 2012; Luong & McLaughlin, 2009). While still valuable in terms of findings, such studies lack an authentic mobile/smartphone experience, which could potentially influence the results. Some studies did use mobile devices, but offered few details as to the thought process behind the design (Heo, 2003; Keefe et al., 2012; T.-C. Liu et al., 2013, 2012; Reeves et al., 1999; Sung & Mayer, 2013). Others created mobile web applications (Molina et al., 2014) (as opposed to dedicated mobile applications), in which the screen display was decreased and manipulation of the content was limited by the web browsers (Churchill, 2011). Though some studies examined the effectiveness of specific dedicated mobile applications (T.-C. Liu et al., 2013; Seraj & Wong, 2014), they offered little in the way of generalizable and actionable design principles.

In terms of screen real estate specifically, some researchers advised designing for landscape orientation to promote learning transfer, as opposed to portrait orientation (Churchill, 2011; Sanchez & Branaghan, 2011). Sanchez and Branaghan (2011) attributed this landscape orientation benefit to limiting scrolling. However, this explanation was supposition and the topic needs further exploration, especially given the proliferation of eReaders and larger smartphones.

Additionally, it appeared that many of the studies comparing large and small screen displays retrofitted the design of the large screen for the small one (Churchill & Hedberg, 2008; Molina et al., 2014). Some even recommended that this process was ideal for smartphone learning, i.e., design for eLearning, then fit for mobile (Ahmadi & Kong, 2012; Churchill, 2011; M. Wang & Shen, 2012). This does not take into account, however, the differences in touchscreen, size, interaction capabilities, and user expectations. Smartphones offer a completely different ergonomic experience than a desktop PC or laptop (Maniar et al., 2008; Seraj & Wong, 2014). There are differences even in the way human eyes are capable of viewing the screens (Seraj & Wong, 2014). With these differences in mind, it seems appropriate to consider different instructional design approaches. As such, it is fair to question if the results of these comparisons would vary if the instruction was first designed for a smartphone and then retrofitted for a larger screen, or if the designs used were custom designed for the screen and device. Otherwise, we are not comparing apples to apples.

In terms of the cognitive load effects specific to small screen mobile devices, Liu et al. (2012) note the need to investigate the media configurations specific to the mobile learning device and environment. They asserted that doing so may add further clarity to design principles for mitigating cognitive overload in small screen instructional design, especially since extraneous load exists in part just by interacting with the device (T.-C. Liu et al., 2013). Sung and Mayer (2013) suggest that cognitive design principles work across devices and this has been supported by other recent studies (Ayres & Paas, 2012; Sweller et al., 2011; Wong et al., 2012). However, these principles are generally applied to the design as a whole. They do not advise on how to design efficient individual elements. In the case of single modal instruction (i.e. pictures only, text only), there are limits to applying them (Reimann, 2003). Split attention effect is more easily mitigated because it is easier to identify and the design recommendations for avoiding are somewhat straightforward, even for text only, small screen mobile displays.

Modality effect, though seemingly simple, adds a layer of design complexity. Several studies (Ginns, 2005; Hassanabadi et al., 2011; Kalyuga et al., 2000; Reimann, 2003; Savoji et al., 2011; Schmidt-Weigand et al., 2010) mention the relationship between prior-knowledge and the occurrence or disappearance of cognitive load effects given this range of novice to expert. In cases where the material has high intrinsic load and the learners are novices, Mayer (2003, 2005, 2009) recommends a dual-modal approach. In some cases, however, the material does not lend itself to images, and/or is more complex than can be communicated through audio/visual presentation. Text comprehension research suggests in these cases that text is superior to audio/visual and/or audio (Fournier, 2013; Kalyuga, 2000; Kintsch, 1994; Mannes & Kintsch, 1987; Schüler et al., 2013, 2012), because given time and the permanence of written text, learners can implement reading comprehension strategies (Schüler et al., 2012, 2011). Though studies on the reverse modality effect questioned the superiority of dual-modal presentation for learning, there remains a question about how to craft a single-mode presentation of materials through the lens of CLT and CTML, in other words, how to craft such presentations in ways that minimize cognitive overload and promote schema construction and automation. Kintsch (1994) and McNamara et al. (1996) distinguished that well-written passages work best for novices, while poorly written passages work better for experts. Outside of this recommendation, there is little offered in the way of how to design appropriate text-only passages, much less in terms of constructing this type of learning scenario for a small screen mobile display.

Specific to the segmentation effect, the literature talks about segmenting material, but offers little in the way of how to segment content (Eitel et al., 2013; Hassanabadi et al., 2011; Mayer et al., 1996; Mayer & Chandler, 2001; Molina et al., 2014; Schüler et al., 2013). For example, Eitle et al. (2013) admitted that their study did not aim to find the "optimal way to present text and pictures with regard to learning success" (p. 60). Hassanabadi et al. (2011) noted that future research should examine the critical role of segmentation length, pointing out that length of segments is different than how much is on screen. Segmentation is an important design implication for mobile learning (smartphones specifically) because the limitations of the screen displays may require different or extra criteria for proper segmentation. Segments are meaningful chucks of content (Mayer & Moreno, 2003), but "meaningful chunks" can be small, medium, or large. The literature excluded this comparison.

Summary

In summary, the literature is clear that positive user perspective of a mobile learning platform is crucial for its success. However, few generalizable and actionable design principles for small screen displays to assist in increased learning outcomes and positive user perspective are defined. Of the studies that did examine instructional design for mobile learning, most did not design dedicated smartphone applications, which prevents a rich, authentic mobile/smartphone experience. In terms of screen orientation, some researchers advise designing for landscape orientation to promote learning transfer, but do not thoroughly explain this claim.

Of the studies that compared large and small screen displays, few take into account the influence of device differences, i.e. touchscreen, display size, device ergonomics (like holding in the hand versus using a mouse), interaction capabilities, and user expectations. Furthermore, there is little discussion about how the empirical results of these comparisons may vary if customized smartphone UX/UI instructional design is implemented (versus a retrofitted, one-size-fits-all design).

In terms of cognitive load effects, it is recommended (T.-C. Liu et al., 2013) that future research investigate media configurations specific to mobile learning device and environment to add clarity to design principles for mitigating cognitive overload in small screen instructional design. Since cognitive load principles are generally applicable, there is little advice currently offered for device specific design for avoiding split attention effect, implementing segmentation effect, and applying modality effect (especially when the material does not lend itself to images, and/or is more complex than can be communicated through audio/visual presentation). Studies on the reverse modality effect question the superiority of dual-modal presentation for learning in all cases. However, there remains a question about how to craft a single-mode presentation of materials through the lens of CLT and CTML; in other words, how to craft such presentations in ways that minimize cognitive overload and promote schema construction and automation. Towards this end, the literature on segmentation effect and text comprehension offer little in the way of how to design and segment appropriate text-only passages, much less in terms of constructing this type of learning scenario for a small screen mobile display.

RESEARCH QUESTIONS

There are three main comparisons under examination in this study that attempt to fill in noted gaps in the literature. First, this study compared large and small screen mobile displays for learning when the design is specific to the device (as opposed to retrofitted or minimized). This comparison included a sub comparison of small screen display landscape versus portrait orientation for learning to determine if the findings from earlier studies apply to today's mobile devices and why. Second, this study compared three text segmentation length variations for learning from the mobile devices under examination. Finally, this study identified if there exists any interactions between all treatments. The research questions which addressed these comparisons are following.

To address the gap in literature concerning mobile device comparison when design is tailored specifically to the device, as well as to answer additional questions about smartphone screen display and orientation, this study conducted research around the following question group:

When specific formatting variables are held constant:

RQ1 (*mobile device comparison*): Do display size and orientation affect

A: learning outcomes of a digitally delivered chemistry text lesson?

B: cognitive load of a digitally delivered chemistry text lesson?

C: user perception of a digitally delivered chemistry text lesson?

To address the gap in literature regarding text segmentation characteristics for various screen displays, this study conducted research around the following question group:

When specific formatting variables are held constant:

RQ2 (*text segmentation comparison*): Do digitally continuous text, medium text segments, and short text segments compare in terms of

A: learning outcomes of a digitally delivered chemistry text lesson?

B: minimizing cognitive load for a digitally delivered chemistry text lesson?

C: influencing user perception of a digitally delivered chemistry text lesson?

Finally, to determine if any interactions exist between the two groups, this study conducted research around the following question group:

When specific formatting variables are held constant:

RQ3 (*mobile device and segmentation interaction*): Do text segmentation and screen display size and orientation affect

A: learning outcomes of a digitally delivered chemistry text lesson?

B: cognitive load of a digitally delivered chemistry text lesson?

C: user perception of a digitally delivered chemistry text lesson?

IMPLICATIONS OF RESEARCH

As outlined in the previous section, there are several literature gaps which require research. To begin, this study compared large and small screen mobile displays for learning, namely laptops and smartphones. What this study adds to the body of research is an in-depth look at design approach that begins with designing a dedicated application for smartphones, and then migrates and customizes that design to the laptop screen. While building the dedicated mobile applications (for iOS and Android phones) was an important piece of the study, it was not the main focus in terms of learning outcomes. Rather, it was appropriate to provide complete design control, in terms of utilizing the full screen real estate and having maximum control over screen orientation, user interaction, and element/asset formatting. Given the low occurrence of dedicated mobile application development for the empirical study of mobile learning, future research will need to begin analyzing how such specifically designed applications influence learning and learner motivation. The results demonstrate the importance of design in both learning from and empirically studying varied mobile screen display sizes for learning.

The benefits of screen orientation for mobile learning are surmised in the literature, but further analysis specific to smartphones is required. Therefore, this study also compared landscape and portrait orientation for learning from smartphones. The results further explain earlier findings, giving a clearer view of current user preferences and learning results of designing for various screen orientations.

Finally, this study focused on answering single mode, text segmentation questions yet addressed by the literature. It analyzed what length of text segment is most beneficial for reading comprehension when low prior-knowledge learners access high intrinsic text via laptop and smartphone. The results begin to uncover how to optimally design and prepare text for communicating and learning from these devices.

Learning outcomes, cognitive load, and user perception were used to assist in measuring these comparisons. Learning outcomes measured whether or not participants can recall the content following each treatment. However, learning recall offered only one point of reference for determining if a particular treatment was successfully designed and/or was advantageously delivered given the display size and orientation (Churchill & Hedberg, 2008; Kim & Kim, 2012; Molina et al., 2014). Measuring for cognitive load added perspective on participant experiences and learning with each treatment by demonstrating whether students were cognitively overloaded, under loaded, or remained successfully in the ZPD (Schnotz & Bannert, 2003; Schnotz & Kürschner, 2007). Positive user perception has been demonstrated by the literature as a viable piece of total mobile learning success (Hwang et al., 2011; Sanchez & Goolsbee, 2010; Seraj & Wong, 2014; Terras & Ramsay, 2012; Traxler, 2005; Valk et al., 2010; Y.-S. Wang et al., 2009; Yau & Joy, 2010). It is thus important that the treatments not only produced positive learning outcomes and minimize cognitive load, but also were viewed positively by the participants. The methodology for this study is discussed in Chapter Three.

Chapter 3: Research Methods

The following sections present the research questions and describe the proposed approach to address them including the research design, the participants, the materials, the measurements and before-treatment surveys, the research design rationale, the planned statistical analysis, and the general timeline of the study.

There were three main comparisons under examination in this study that attempted to fill in noted gaps in the literature. First, this study compared large and small screen mobile displays for learning when the design is specific to the device (as opposed to retrofitted or minimized). This comparison included a sub comparison of small screen display landscape versus portrait orientation for learning to determine if the findings from earlier studies apply to today's mobile devices and why. Second, this study compared three text segmentation length variations for learning from the mobile devices under examination. Finally, this study identified if there exists any interactions between all treatments. Therefore, this study hoped to find answers to the following research questions:

RESEARCH QUESTIONS

To address the gap in literature concerning mobile device comparison when design is tailored specifically to the device, as well as to answer additional questions about smartphone screen display and orientation, this study conducted research around the following question group:

When specific formatting variables are held constant (variables explained in materials section below):

RQ1 (*mobile device comparison*): Do display size and orientation affect

A: learning outcomes of a digitally delivered chemistry text lesson?

B: cognitive load of a digitally delivered chemistry text lesson?

C: user perception of a digitally delivered chemistry text lesson?

To address the gap in literature regarding text segmentation characteristics for various screen displays, this study conducted research around the following question group:

When specific formatting variables are held constant:

RQ2 (*text segmentation comparison*): Do digitally continuous text, medium text segments, and short text segments compare in terms of

A: learning outcomes of a digitally delivered chemistry text lesson?

B: minimizing cognitive load for a digitally delivered chemistry text lesson?

C: influencing user perception of a digitally delivered chemistry text lesson?

Finally, to determine if any interactions exist between the two groups, this study conducted research around the following question group:

When specific formatting variables are held constant:

RQ3 (*mobile device and segmentation interaction*): Do text segmentation and screen display size and orientation affect

A: learning outcomes of a digitally delivered chemistry text lesson?

B: cognitive load of a digitally delivered chemistry text lesson?

C: user perception of a digitally delivered chemistry text lesson?

QUANTITATIVE RESEARCH DESIGN

These questions were answered using a 3x3 quantitative research design (Table 3.1). The independent variable groups were mobile devices and text segmentation. Within the mobile device variable group wer three devices: laptops (LPT), smartphones landscape (SML), and smartphone portrait (SMP). The devices ranged in make and model and came from the participants of the study. Given that screen dimensions vary per device, the learning module was designed to cover as many screens as possible. Within the text segmentation group were three text segmentation types: long, continuous text (TS1), medium text segmentation (TS2), and short text segmentation (TS3). (Each text segmentation treatment is detailed in the materials section below.)

The dependent variables to measure the outcomes were learning outcomes (material recall) (LO), cognitive load measurement (CLM), and user perception survey of the experience (UPS). The learning outcomes instrument was a twenty question multiple choice test. The cognitive load measurement was a ten-question, self-reporting survey. The user perception survey consisted of 12 survey questions that reported on perceived ease of use (PEU), perceived use (PU), use intentions (UI), and perceived satisfaction (PS). (These instruments are detailed in the measurements sections below.)

Table 3.1.

Research Questions and Design

Text Segmentation Treatments

Device Treatments	TS1	TS2	TS3	
LPT	T1a	T2d	T3g	**RQ1a**
SML	T1b	T2e	T3h	**RQ1b**
SMP	T1c	T2f	T3j	**RQ1c**
	RQ2a, RQ2b, RQ2c			**RQ3a RQ3b RQ3c**

Research design:
9 treatment groups (3x3 design): T1a-T3j

Independent variables:
Device treatments: laptop (LT), smartphone landscape (SML), smartphone portrait (SMP)
Text segmentation treatments: continuous text (TS1), medium segmented text (TS2), small segmented text (TS3)

Research questions:

- RQ1 (mobile device comparison): Do display size and orientation affect (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception of a digitally delivered chemistry text lesson?
- RQ2 (text segmentation comparison): Do digitally continuous text, medium text segments, and short text segments compare in terms of (a) learning outcomes of a digitally delivered chemistry text lesson, (b) minimizing cognitive load for a digitally delivered chemistry text lesson, and (c) influencing user perception of a digitally delivered chemistry text lesson?
- RQ3 (mobile device and segmentation interaction): Do text segmentation and screen display size/orientation affect (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception digitally delivered chemistry text lesson?

Participants

A total of 771 participants took part in this study. All participants were undergraduate chemistry students in a higher education university. The participants were required to take a prerequisite Chemistry course to register for this Chemistry course, but the topic under examination here had not been covered prior to this study.

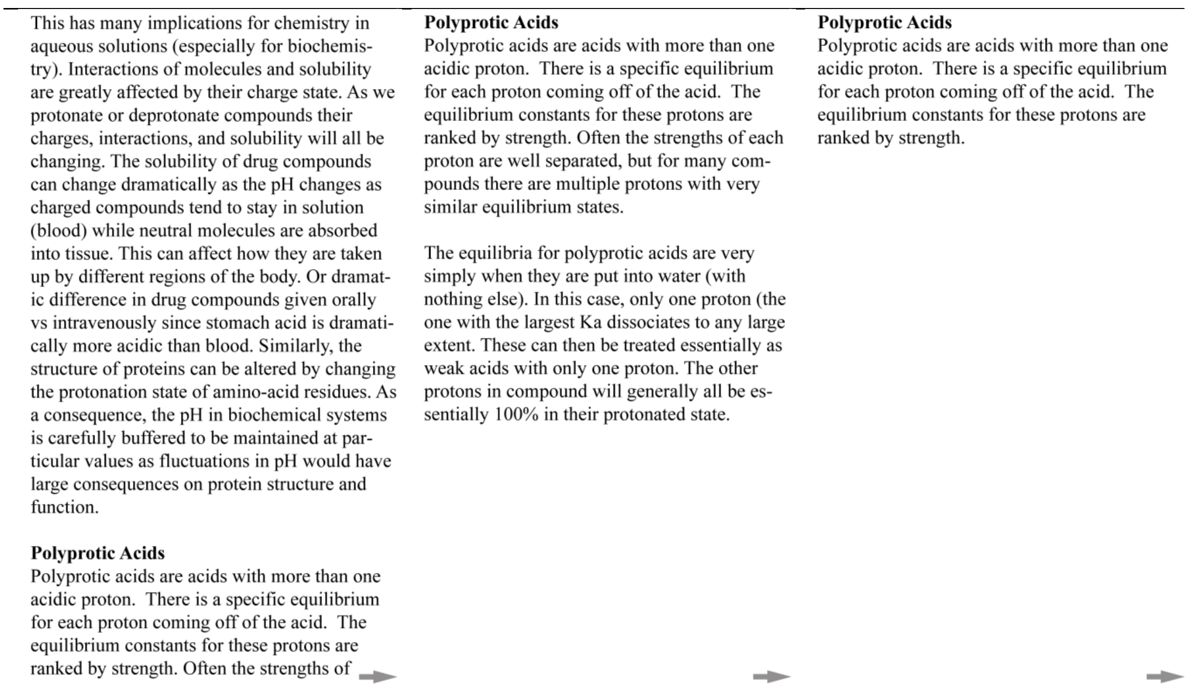
Materials

Content selection

Based on the cognitive load literature, to ensure learners are not cognitively overloaded or under loaded, the material under examination must have a somewhat high intrinsic cognitive load, while the participants are low prior-knowledge learners (Kalyuga et al., 2000). However, the material should not be so hard that it pushes them out of their ZPD (Schnotz & Kürschner, 2007). For this reason, the content selected for this study was the chemistry topic: protonation state. Protonation state is a key idea to consider with any acid/base conjugate pair at a given pH. If the molecule in a solution at a particular pH has the proton "on" the molecule, it is protonated, or if the proton is "off" the molecule, it is deprotonated (Vanden Bout & LeBrake, 2015). This topic was scheduled in the syllabus falls in the middle of the spring semester. While the students had not yet covered this material, they had built the foundational concepts needed to understand the material in earlier classes, a notion that was supported by the Chemistry faculty. In this way, it met the parameters of CLT as good material to conduct research. The content was provided by the Chemistry Department at the university. It made up one chapter of the Aqueous Equilibria Unit, material for an undergraduate Chemistry course, which is offered every spring semester. The material was assembled and approved by the Chemistry faculty and is used every spring for the course.

Content segmentation

Mayer and Moreno (2003) describe a segment as a piece of text or image with a meaningful beginning and end. The content for protonation state already existed as a single chapter with three main sections (Vanden Bout & LeBrake, 2015). One goal of this study was to determine what length of segmented text, within a multi-page learning module is better for reading comprehension on the devices in question. Therefore, I made three copies of the material (see Figure 3.1). The first copy (TS1) was the continuous flow treatment (Kintsch, 1994; Mannes & Kintsch, 1987; McNamara et al., 1996). The continuous flow treatment appeared like an eBook, in that as much content as could fit on the display was viewable. It cut off where a sentence ran out of room and continued on the following screen until the text was completed. This treatment had fewer pages (4 to 9 screens depending on the device), but the material on each screen did not necessarily begin and end a meaningful thought. The second copy (TS2) was the medium-sized segmentation treatment (Churchill, 2011). In this treatment, I segmented the content down into medium-sized, meaningful segments following the recommendations of Mayer and Moreno (2003). These segments were designed to fit on the screen, such that they began and ended on a single screen, but contained completed explanations and paragraphs. TS2 had 14 screens. However, they were longer that the third treatment (TS3) which was the short segmentation treatment. This final text treatment followed the advice of numerous researchers of modality effect (Mayer, 2005; Spanjers et al., 2012; Sung & Mayer, 2013) who determined that short blurbs of text are better for learning (Mayer & Moreno, 2002). TS3 showcased 1-3 sentence segments (no longer) per screen. This rule was applied even when a definition or explanation was longer than three sentences. In these instances, the thoughts were cut into pieces no longer than two to three sentences. This left ample screen real estate around the text. This treatment had 37 screens, many more screens that it's two counterparts. While the simplicity of the design did not allow for much cuing, the navigation acted as a cue, which the research finds assists in limiting split attention by helping the learner connect essential elements (T.-C. Liu et al., 2013, 2012). In all treatments, an arrow cued the learners, in the case of laptops, where to click to proceed, and in the case of smartphones, which direction to swipe to proceed (T.-C. Liu et al., 2013, 2012).



This has many implications for chemistry in aqueous solutions (especially for biochemistry). Interactions of molecules and solubility are greatly affected by their charge state. As we protonate or deprotonate compounds their charges, interactions, and solubility will all be changing. The solubility of drug compounds can change dramatically as the pH changes as charged compounds tend to stay in solution (blood) while neutral molecules are absorbed into tissue. This can affect how they are taken up by different regions of the body. Or dramatic difference in drug compounds given orally vs intravenously since stomach acid is dramatically more acidic than blood. Similarly, the structure of proteins can be altered by changing the protonation state of amino-acid residues. As a consequence, the pH in biochemical systems is carefully buffered to be maintained at particular values as fluctuations in pH would have large consequences on protein structure and function.

Polyprotic Acids
Polyprotic acids are acids with more than one acidic proton. There is a specific equilibrium for each proton coming off of the acid. The equilibrium constants for these protons are ranked by strength. Often the strengths of

Polyprotic Acids
Polyprotic acids are acids with more than one acidic proton. There is a specific equilibrium for each proton coming off of the acid. The equilibrium constants for these protons are ranked by strength. Often the strengths of each proton are well separated, but for many compounds there are multiple protons with very similar equilibrium states.

The equilibria for polyprotic acids are very simply when they are put into water (with nothing else). In this case, only one proton (the one with the largest Ka dissociates to any large extent. These can then be treated essentially as weak acids with only one proton. The other protons in compound will generally all be essentially 100% in their protonated state.

Polyprotic Acids
Polyprotic acids are acids with more than one acidic proton. There is a specific equilibrium for each proton coming off of the acid. The equilibrium constants for these protons are ranked by strength.

TS1	TS2	TS3
continuous text	medium text segmentation	small text segmentation

Figure 3.1. Text segmentation samples. Using the smartphone portrait treatments.

Validation of text segmentation

In order to validate the segmentation of the text, I showed the three segments pieces to the Chemistry faculty, who approved the segments.

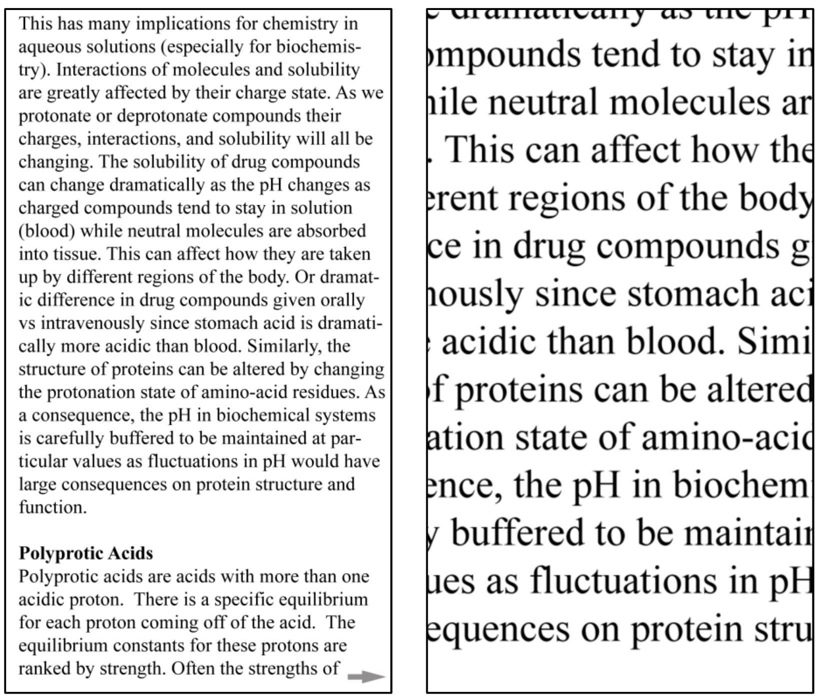
Control variables

To ensure that the experiment was as balanced as possible, I held several variables constant in all treatments. These were based on suggestions from the literature.

No sound or decoration. To maintain focus on only the treatment content and to avoid extraneous load (Chandler & Sweller, 1991; Mayer, 2009; Sung & Mayer, 2013; Sweller et al., 2011), the only thing on the screen was the text and any necessary navigational buttons. There was no sound or background music (Brunken et al., 2003), and there was no decoration (Mayer & Fiorella, 2014), which have both been shown to cause cognitive overload. This is in line with the coherence principle (Mayer et al., 1996; Mayer & Chandler, 2001), namely that all visual and auditory material is pertinent to the topic of learning.

No scrolling navigation. As scrolling has been found to create split attention effect, there was no scrolling in the modules (Churchill, 2011; Churchill & Hedberg, 2008; Luong & McLaughlin, 2009). Additionally, because the literature recommends avoiding excessive swipes, taps, or clicks (Sanchez & Goolsbee, 2010; Seraj & Wong, 2014), there was minimum interaction within the treatments applications. In the laptop module, pagination occurred via right/left arrows at the bottom right and left screen corners respectively. In the mobile applications, navigation occurred via left/right swipe.

No zooming. Zooming has been shown to increase cognitive load in cases when the zoom is learner-controlled (Churchill, 2011; Luong & McLaughlin, 2009; Maniar et al., 2008). Particularly in the case of mobile display text, zooming creates a need to scroll (Maniar et al., 2008) up and down and sometimes left and right to view the text (Figure 3.2). Therefore, the applications were designed in a way that prevented zooming.



Regular screen Zoomed in screen

Figure 3.2. Zooming sample from smartphone screen.

Text size. Sanchez and Goolsbee (2010) found that smaller font produced better overall retention than larger font on small screens, in part because it limited the need to scroll. Though earlier findings suggest that inter-character and inter-line spacing increases recall (Chen & Chien, 2005), adding these buffers would increase the length of text on a small screen device and require either more scrolling or more pages to navigate through. Therefore, all text was kept the same size visually (i.e., similar sized text when devices were held up next to one another) and with the same formatting (in terms of inter-line and character spacing) across treatment groups and devices.

Learner control. Finally, as noted numerous times in the literature, giving the learner control over the learning pace (specifically) has proven to decrease cognitive load (Hassanabadi et al., 2011; Mayer & Chandler, 2001; Schmidt-Weigand et al., 2010; Schüler et al., 2012; Spanjers et al., 2012; Sung & Mayer, 2013; Tabbers, 2002). Therefore, all treatments were learner-paced, meaning the learner could move forward when they were ready. Additionally, they were able to move back to previous screens as needed.

Development of web module and mobile application

The study called for the development of web and mobile applications to deliver the text segmentation treatments, survey questions, and measurement questionnaires. To ensure complete control over the treatment delivery, and to report on the complete development experience, I opted to originally create the learning modules for the laptop and smartphones. Doing so entailed creating one web delivered module and two separate mobile applications, one for iOS and one for Android.

I began by listing and organizing the application pieces required for the complete application. This included clarifying the purpose for the application, identifying the target audience, listing the sections needed and their sequence, and determining the general development timeline.

Next, I built a wire frame, or outline of the application flow (see Figure 3.3). I intentionally kept the design simple and the flow straight-forward to maintain the purpose of the research so as to avoid adding extraneous material or graphics. The application was somewhat complicated from a programming perspective. Mainly, this is due to the built-in instrument items, treatment randomization, and data collection capabilities.

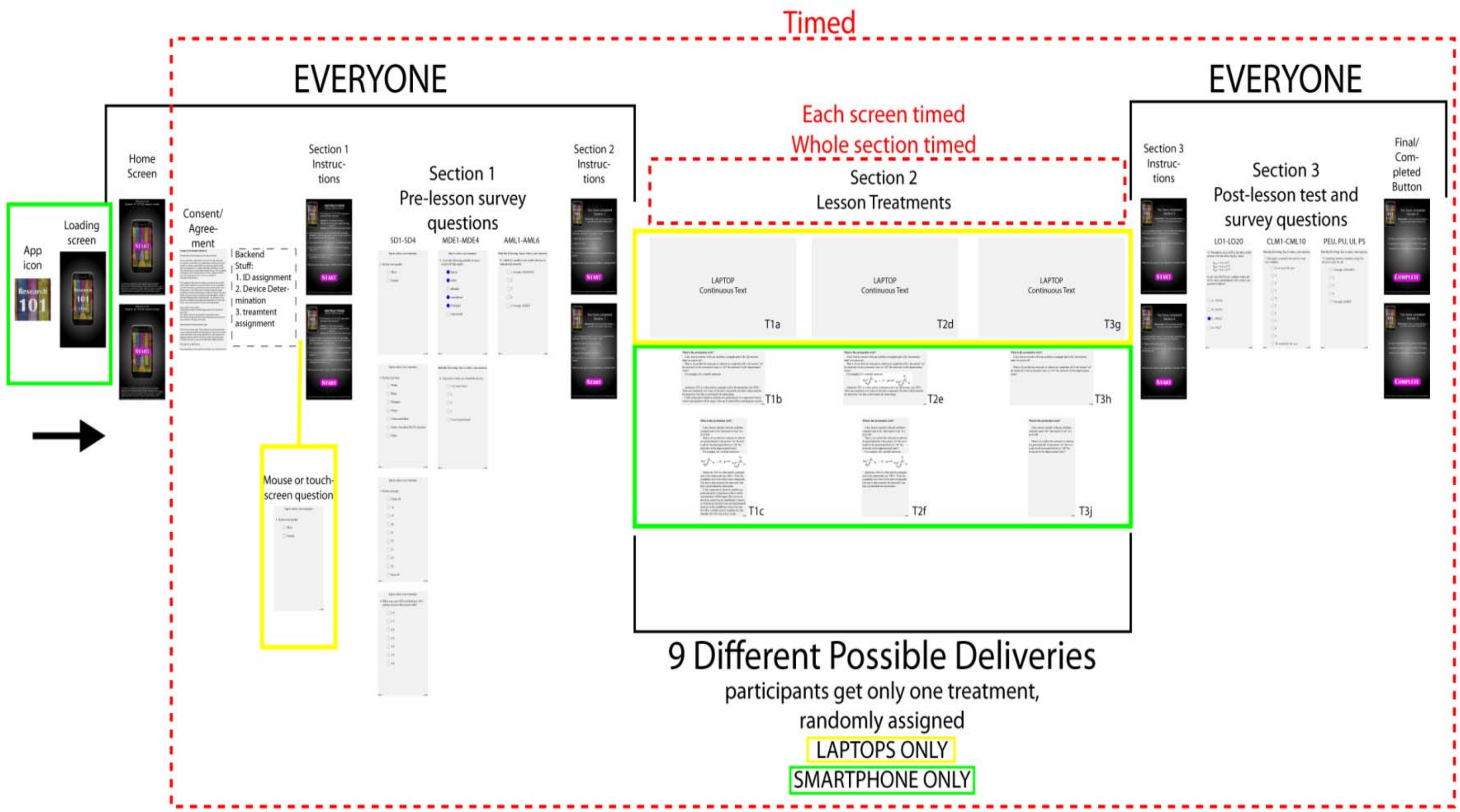


Figure 3.3: Application wireframe.

My professional experience in mobile application development is that design and development tend to overlap given the hurdles experienced when developing on a third party platform (iOS/Android). For example, my study called for some landscape and some portrait treatments. In this case, the landscape views only occurred during the actual text treatment – all other parts of the application were in portrait orientation. Apple has a sticky rule about screen orientation in certain applications that would have made "locking" the screen in landscape for only part of the application impossible. It was agreed (with my iOS developer) that to control for these variables, the best option was to provide the text as images. While this did not largely alter the design, it did make for considerably more design work and required more graphical assets be created.

There are several safeguards and interactions built into the applications to maximize the efficiency of data collection. First, the applications were not be "active" until the day of the study, so that participants were not be able to access the treatments prior to their class period, even if they download the app ahead of time. Second, they were not able to leave the application once the session started. If they did leave the application, a notice alerted them that they would not be able to return once the screen is exited. Finally, the applications automatically timed the whole visit to the module, as well as the collected time-on-task for each screen of the actual text treatments. Additionally, the application recorded the number of visits to each treatment screen, so that individual interactions within the treatment were captured for further assistance with analysis.

Given the constraints of Apple development requirements, it was recommended to create the iOS application before Android. This way, the Android developer was able to copy the completed iPhone application without having to retrofit both apps. As for the web version, the text treatments variable will remain constant, but to fill the laptop screen appropriately, some alterations needed to be made to the continuous text treatment.

I worked with three separate programmers to code the applications. All applications fed into a database where the data was aggregated and stored. The development process was long and detailed and cost around $3,000 (see Appendix E for more details about the development process). Each programmer followed specific instructions based on documentation that was created to both describe the application UX/UI and the code transfer required for accurate database transfer. Once completed, the mobile applications were downloadable for free from the Google Play and Apple App Enterprise. The web version was accessible using any web browser.

Quality-assurance and beta-testing

Prior to the actual data collection, I ran numerous tests on the three applications to ensure that they are in proper working order, which included making sure that all questions, text segment treatments, database interaction and collection, and data spreadsheet generation were properly functioning.

Measurement

This study used three main measurements, as well as a demographic and mobile learning profile survey. The demographic and mobile learning profile (DMLP) was administered before the treatments (Appendix A). It assisted in generally defining the participant groups demographically and to assess the experience with and perception of mobile device and mobile learning. This survey was a series of sub-surveys planned to collect participant on socio-demographic information (gender, race, and age) (SD), as well as assess mobile device experience (MDE) and attitude towards mobile learning (AML). The MDE and AML surveys were borrowed from Molina et al. (2014), who conducted a study very similar to this study. Their study compared screen display sizes between PCs, tablets, and smartphones. They used these surveys to compare the participant groups in terms of mobile learning profiles (p. 480).

The MDE survey contained four items to gauge participant experience, ownership and expertise with mobile devices (Molina et al., 2014). MDE1 was added to the survey to determine how many mobile devices each student owns. Statistically on average, college students own seven mobile devices (ICEF Monitor, 2014). Participants were asked to select all that apply. As this item was not a numeric value, it therefore was not be calculated in the mean. The survey measured student experience using mobile devices (MDE2), experience with smartphones specifically (MDE3), and experience with mobile learning environments (MDE4). The questions were rated using a 5-point Likert scale, where five meant well experienced and one meant little to no experience. Molina et al. used the mean score of all survey questions (in this case MDE2-4) to determine mobile device experience, with five meaning a lot of experience and 1 meaning little to no experience.

The AML survey was created to measure participant attitude towards mobile devices for use in educational contexts (AML1), for use in studying (AML2), the use of smartphones specifically in educational contexts (AML3), and the use of smartphones specifically in study (AML4). It also measured participant preference for studying with desktop computers (AML5), and their preferences for studying with printed material (AML6). The questions were rated using a 5-point Likert scale for how much they agree with the statements. Molina et al. used the mean score of the survey questions to determine attitude towards mobile learning, with five representing a positive attitude and 1 representing a negative attitude.

The post-treatment measures included the learning outcomes (LO) test, the cognitive load measurement (CLM), and the user perception survey (UPS). Learning outcomes measured whether or not participants could recall the content following each treatment. However, learning recall offered only one point of reference for determining if a particular treatment was successfully designed (text segmentation and text treatment) and/or was advantageously delivered given the display size and orientation (Churchill & Hedberg, 2008; Kim & Kim, 2012; Molina et al., 2014). Measuring for cognitive load provided perspective on participant experience learning with each treatment by demonstrating whether students were cognitively overloaded, under loaded, or remained successfully in the ZPD (Schnotz & Bannert, 2003; Schnotz & Kürschner, 2007). Positive user perception has been demonstrated by the literature as a viable gauge of total mobile learning success (Hwang et al., 2011; Sanchez & Goolsbee, 2010; Seraj & Wong, 2014; Terras & Ramsay, 2012; Traxler, 2005; Valk et al., 2010; Wang et al., 2009; Yau & Joy, 2010). It is thus important that the treatments not only produced positive learning outcomes and minimize cognitive load, but also were viewed positively by the participants.

The LO test was a fifteen-question multiple choice test designed to measure immediate learning recall of the chemistry material (Appendix B). A search to find a pre-existing empirically validated scale on protonation state was unsuccessful. The next best option was to procure a test that was approved by the subject matter experts as an accurate measure of the learning material. The LO test was written by the Chemistry faculty for this particular material and had been used for the course the last few years. Both the content and the associated test questions were reviewed and approved by the chemistry faculty. This measure was not empirically validated for the study.

Given that an empirically validated scale could not be located and given that the study is already working at the margins of the class period, I opted to forgo comparing pre- and post-tests to measure learning gains. The intention of this test was to measure learning outcomes, in terms of content recall. It was used to compare the treatments as learning tools, with higher scores signifying better learning than lower scores.

The CLM instrument consisted of ten self-reporting, 10-point rating scale items (Appendix C). The instrument was borrowed from Leppink, Paas, Vleuten, Gog and Merriënboer (2013). This particular scale was recently developed to measure and distinguish between intrinsic cognitive load (ICL), extraneous cognitive load (ECL) and germane cognitive load (ECL), as opposed to generally measuring cognitive load. It measures the complexity of the activity (ICL), the instructions and explanations (ECL), and the enhancement of knowledge given the material (GCL).

Leppink et al. conducted four separate experiments on the scale to assess reliability and validity, as well as compared it in study two and four to the widely used scales of Paas (1992) which measures cognitive load generally, Ayres (2006) which measures ICL, Cierniak et al. (2009) which measures ECL, and Salomon (1984) which measures GCL. With each experiment, they measured whether items 1-3 measure the "complexity of subject matter" (ICL), whether items 4-6 measure "negative characteristics of instructions and explanations" (ECL), and whether items 7-10 measure the extent to which "intrusions and explanations contribute to learning" (GCL), (Leppink, Paas, Vleuten, Gog, & Merriënboer, 2013, p. 1060).

The experiments proved both the reliability and validity of the scale on its own and compared to the earlier created scales of Paas, Ayres, and Pachman (2008), Cierniak et al. (2009), and Salomon (1984). In one experiment using graduate level statistics content, the reliability analysis revealed Cronbach's alpha values of .81 for items 1-3, .75 for items 4-6, and .82 for items 7-10 (Leppink et al., 2013, p. 1061). In a second experiment using higher-education psychology content, the reliability analysis revealed Cronbach's alpha values of .85 for items 1-3, .80 for items 4-6, and .81 for items 7-10

(Leppink et al., 2013, pp. 1062, 1065). In a third experiment using both higher-education psychology content for one group and higher-education health sciences content for a second group, the reliability analysis revealed Cronbach's alpha values of .88 for items 1-3, .81 for items 4-6, and .93 for items 7-10 (Leppink et al., 2013, pp. 1063, 1065). In a fourth experiment using higher-education inferential statistics content, the reliability analysis revealed Cronbach's alpha values of .86 for items 1-3, .71 for items 4-6, and .94 for items 7-10 (Leppink et al., 2013, p. 1066). The consistent reliability scores, in addition to the varied content used to test the scale signaled it a good cognitive load scale for this study.

To make the CLM scale applicable to this study, I added the word "chemistry" in front of the word "formulas" in items CLM2 and CLM9. Additionally, I deleted the word "statistics" in CLM8 and added "protonation state."

The final scale, the user perception scale (UPS) was made up of four smaller scales. The first three scales are based on the Technology Acceptance Model (TAM) (Davis, 1993; Venkatesh et al., 2003). TAM assumes that perceived ease of use (PEU) and perceived usefulness (PU) of the technology influence a user's behavior and attitude toward using the technology, called usage intentions (UI) (Davis, 1993; Venkatesh et al., 2003; Gardner & Amoroso, 2004; Molina et al., 2014; Shroff et al., 2011). This in turn affects actual use. TAM is used to assess acceptance of educational resources and systems (Molina et al., 2014, p. 477). The scale used in this study was taken from Molina et al. Their scale was based on the subjective technology acceptance questionnaires of Davis. I opted to use this particular scale because the study conducted by Molina et al. closely related to this study, and as such, required no alterations.

The final four questions in the UPS survey pertain specifically to perceived satisfaction (PS). This scale was also taken from Molina et al. I chose these because they ask participants directly about their satisfaction and helped me better understand my overall findings. I made no grammatical or word changes to these four questions.

RESEARCH PROCEDURES

In the weeks prior to the days when data was collected, the Chemistry faculty agreed to administer a brief survey to determine how many students have both laptops and smartphones, and which percentage of those smartphones are iPhones, Androids, or other. This information gave me an idea of how many participants and devices we would have in each group.

Data collection was scheduled for Friday, March 6th, 2015 (MWF classes), and Tuesday, March 10th, 2015 (TTH classes). Originally, data collection was scheduled for March 5th and 6th; however, the university cancelled classes on March 5th due to inclement weather and the TTH data collection was moved to the following Tuesday. This was when the content was scheduled in the syllabus. On the Tuesday and Wednesday (March 3nd and 4rd) ahead of those days, I instructed the classes to download the mobile applications and bring their laptops to the next class day. The applications were downloadable, but not "live" until class day, this ensured that participants were not able to view the application until the study commenced. I also briefly explained who I was and what the general plan was so that we did not have to spend time doing that during data collection.

Data collection

Data was collected on March 6th and 10th in the Chemistry classes. By collecting data for two days, I maximized participant numbers by attending all participating MWF and TTH classes.

Each class was randomly split into three sections: laptops, smartphone landscape, and smartphone portrait. As students arrived to class on the specific day, they were assigned a device group (either laptop or smartphone) in the order they arrived. The smartphone group was randomly split into the landscape and portrait groups once they signed into the application. Therefore, to ensure the participants were evenly split into three groups, I assigned two students to the smartphone group for every one in the laptop group. For example, student one was assigned to the laptop group, student two was assigned to the smartphone group, student three was assigned to the smartphone group, student four was assigned to the laptop group, and so on. If a student did not have the necessary equipment, they were reassigned to a group for which they did have a device. For example, if a student had a Microsoft Windows phone for which there was no mobile application available, they were instead assigned to the laptop group. The next assignments were adjusted accordingly.

Those participants using smartphones accessed the content through the dedicated applications accessible via the Apple App Enterprise or the Google Play Store. They were required to download the application for free to their smartphones. Those participants using laptops accessed the content module via the web. Participants were first and foremost required to read the study agreement, which followed the approved Internal Review Board parameters. Accordingly, participation was voluntary. If a potential participant declined to complete the study, they were not given access to the digital material. The system was not set up to record the number of students who declined participation. However, given class counts and matching participant numbers, the great majority of students did participate. All applications communicated with the database to randomly assign one of the three text treatments, such that as participants agreed to participate, they were assigned a random participant ID and a text treatment in sequential order of login (the applications handled this). All data was aggregated in the database for statistical analysis.

Participants were given minimal instructions verbally, as the instructions and participant agreement forms, etc., were all housed within the applications. Once the pre-surveys were completed, the students worked independently on their treatment modules until they finished. The activity ended with the post-treatments instruments (LO, CLM, UPS). The applications took no more than 35 minutes, which fit inside of the shorted MWF course times.

QUANTITATIVE DATA ANALYSIS

Before analyzing my data, I first tested the instruments for internal consistency using Cronbach's alpha. I also ran descriptive analyzes and produce associated tables and or graphs (means, standard deviation, etc.).

Next, I conducted ANOVA on each of the three groups to determine possible associations between the independent variables and instrument results (Table 3.2). The first set of research questions (RQ1a-c) asked if mobile device display size and orientation has an effect on (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception of a digitally delivered chemistry text lesson. To answer RQ1a, I ran a one-way ANOVA to determine if there was a difference in test scores (LO) by device (LT, SML, SMP). To answer RQ1b, I ran a one-way ANOVA on each ICL, ECL, and GCL to determine if there was a difference in cognitive load by device. To answer RQ1c, I ran a one-way ANOVA on each PEU, PU, UI, and PS to determine if there was a difference in user perspective by device.

Table 3.2.

Plan for Statistical Analysis

Instruments	Device Treatments			Text Segmentation Treatments		
	LT	SML	SMP	TS1	TS2	TS3
LO	One-Way ANOVA (RQ1a)			One-Way ANOVA (RQ2a)		
	Two-Way ANOVA (comparing all treatments) (RQ3a)					
CLM	One-Way ANOVA(s) (RQ1b)			One-Way ANOVA(s) (RQ2b)		
	Two-Way ANOVA (comparing all treatments)(s) (RQ3b)					
UPS	One-Way ANOVA(s) (RQ1c) for PEU, PU, UI, and PS			One-Way ANOVA(s) (RQ2c) for PEU, PU, UI, and PS		
	Two-Way ANOVA(s) (comparing all treatments) (RQ3c) for PEU, PU, UI, and PS					

Research design:
9 treatment groups (3x3 design): T1a-T3j

Independent variables:
Device treatments: laptop (LT), smartphone landscape (SML), smartphone portrait (SMP)
Text segmentation treatments: continuous text (TS1), medium segmented text (TS2), small segmented text (TS3)

Dependent variables:
Learning outcome (recall test) (LO), cognitive load measurement (CLM), user perception survey (USP)

Research questions:
RQ1 (mobile device comparison): Do mobile display size and orientation affect (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception of a digitally delivered chemistry text lesson?
RQ2 (text segmentation comparison): How do digitally continuous text, medium text segments, and short text segments compare in terms of (a) learning outcomes of a digitally delivered chemistry text lesson, (b) maximizing cognitive resources for a digitally delivered chemistry text lesson, and (c) influencing user perception of a digitally delivered chemistry text lesson?
RQ3 (mobile device and segmentation interaction): Do text segmentation and mobile screen display size/orientation affect (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception digitally delivered chemistry text lesson?

The second set of research questions (RQ2a-c) asked if digitally continuous text, medium text segments, and short text segments compare in terms of (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception of a digitally delivered chemistry text lesson. To answer RQ2a, I ran a one-way ANOVA to determine if there was a difference in test scores (LO) by text segmentation (TS1, TS2, TS3). To answer RQ2b, I ran a similar test to determine if there was a difference in cognitive load by text segmentation. To answer RQ2c, I ran a one-way ANOVA on each PEU, PU, UI, and PS to determine if there was a difference in user perspective by text segmentation.

The third set of research questions (RQ3a-c) asked if there an interaction affect between text segmentation and screen display size and orientation on (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception of a digitally delivered chemistry text lesson. To answer RQ3a, I ran a two-way ANOVA to determine if there was an interaction between mobile device (LT, SML, SMP) and text segmentation (TS1, TS2, TS3)on test scores (LO). To answer RQ3b, I ran a similar test to determine if there was an interaction between mobile device and text segmentation on cognitive load. To answer RQ3c, I ran a two-way ANOVA on each PEU, PU, UI, and PS to determine if there was an interaction between mobile device and text segmentation on user perspective.

If statistical significance was found anywhere, I measured for effect size and ran appropriate post-hoc tests to determine how big the differences were and what variables were involved.

TIMELINE OF ACTIVITIES

The timeline of activities for this study was as follows:

Table 3.3.

Timeline of Data Collection Activities

	Task	Study prep		MWF – 1 hour classes March 6th												TTH – 1.5 hour classes March 10th																	
		3/3	3/4	:05	:10	:15	:20	:25	:30	:35	:40	:45	:50	:55	:60	:05	:10	:15	:20	:25	:30	:35	:40	:45	:50	:55	:60	:05	:10	:15	:20	:25	:30
1	Pre-study preparation																																
Data collection days:																																	
2	Random assignment																																
3	Intro and instruction																																
Application delivery:																																	
4	IRB agreement																																
Pre-treatment:																																	
5	DMLP																																
Treatments:																																	
6	Treatments																																
Post-treatment:																																	
7	PO																																
8	CLM																																
9	UPS																																
10	Activity concludes																																

This opportunity for substantial quantitative research was unique for mobile learning research. With all three applications well-developed, the data provided numerous opportunities for additional papers and will be a springboard for future research. As a gesture of appreciation, I have agreed to allow the faculty of the College of Natural Science to use these applications, as developed at the time of research, for any future research delivered via mobile application.

Chapter 4: Results

Using a quantitative research approach, this research examined the relationship between mobile device screen display size and orientation and text segmentation for learning. This chapter begins by describing the participants from a demographic perspective and is followed by research results organized by the overarching research questions:

When specific formatting variables are held constant (variables explained in materials section below):

RQ1 (*mobile device comparison*): Do display size and orientation affect

A: learning outcomes of a digitally delivered chemistry text lesson?

B: cognitive load of a digitally delivered chemistry text lesson?

C: user perception of a digitally delivered chemistry text lesson?

RQ2 (*text segmentation comparison*): Do digitally continuous text, medium text segments, and short text segments compare in terms of

A: learning outcomes of a digitally delivered chemistry text lesson?

B: minimizing cognitive load for a digitally delivered chemistry text lesson?

C: influencing user perception of a digitally delivered chemistry text lesson?

RQ3 (*mobile device and segmentation interaction*): Do text segmentation and screen display size and orientation affect

A: learning outcomes of a digitally delivered chemistry text lesson?

B: cognitive load of a digitally delivered chemistry text lesson?

C: user perception of a digitally delivered chemistry text lesson?

PARTICIPANT DEMOGRAPHICS

The sample group of participants was amassed from a higher education, undergraduate chemistry course. In total, four classes participated, each with well over 100 students enrolled (Table 4.1). The data was collected in the 2015 spring semester, during the class periods of the classes included. In total, 950 entries were recorded. However, of those 179 entries were debunked, meaning the scores and times for that participant were not recorded in the database. This may have occurred for several reasons, including: (a) if a participant exited and reentered the module, it would have created a new user ID for them, (b) in some cases, the device connectivity was spotty and therefore after a certain point, information was either missed, or no longer transferred to the server. If data for a single participant did not include scores and times for all three dependent measures, I excluded that participant from the analysis. After cleaning the data accordingly, there were a total of 771 participants (N=771).

Table 4.1

Chemistry 302 Participant Class Breakdown

Class#	Day	Time	Total participants
50203	Friday, March 6, 2015	1:00-2:00	221
50150	Tuesday, March 10, 2015	9:30-11:00	202
50155	Tuesday, March 10, 2015	11:00-12:30	201
50160	Tuesday, March 10, 2015	12:30-2:00	147

Participant demographic and mobile learning profile

The demographic and mobile learning profile (DMLP) (Appendix A) was administered immediately before the treatments. It consisted of a series of questions and sub-surveys. The SD questions collected socio-demographic information, including gender, race, age, and GPA (Figure 4.1). In total, there were 336 males and 427 females, with 8 participants not responding (SD1). The participant racial breakdown showed that a majority of the participants (90%) were white, Hispanic, or Asian. The participant group included 3% black students, 5% from other groups, and 2% (thirteen participants) did not log their race (SD2). Eighteen and Nineteen year olds comprised 79% of the participant group. Of the remaining participants, 19% were twenty years or older, while 1% were under eighteen. Four did not provide their age (SD3). Finally, 81% of participants had a grade point average (GPA) of 3.0 or higher (SD4), which fits with the Chemistry faculty's assessment that because the students must first pass Chemistry 301, those students who are either not interested in chemistry or who suffer poor grades do not often continue with Chemistry 302.

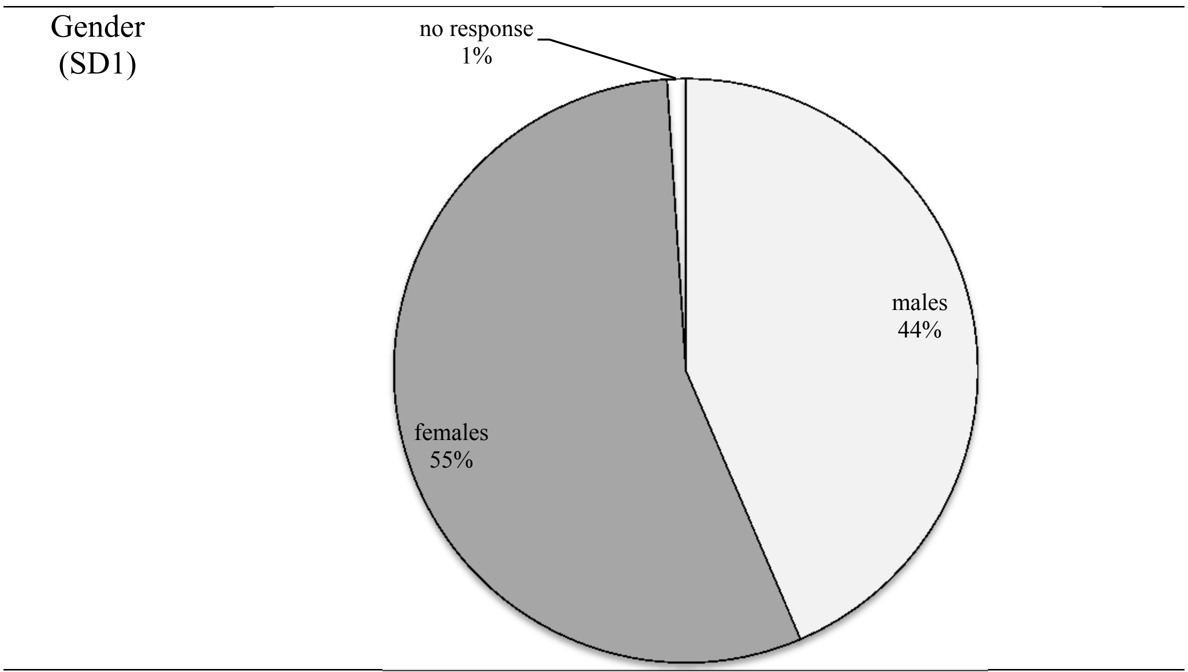
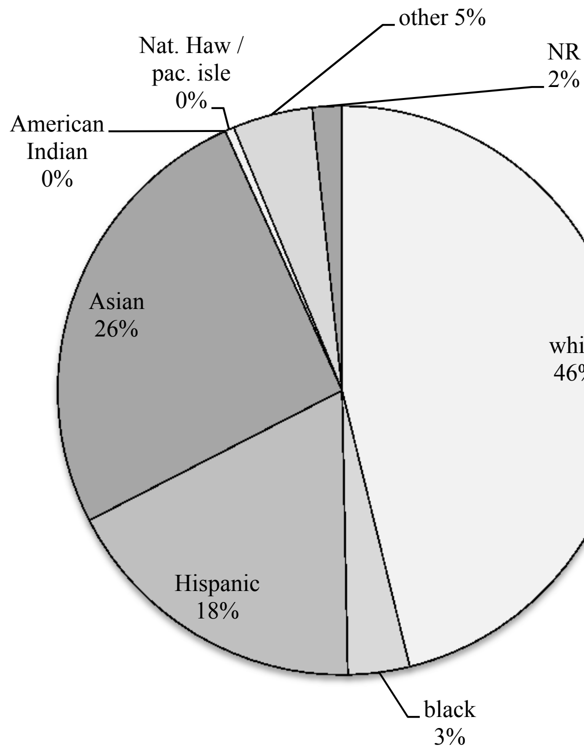


Figure 4.1. Socio-demographics findings for gender, race, age, and GPA

Race
(SD2)



Age
(SD3)

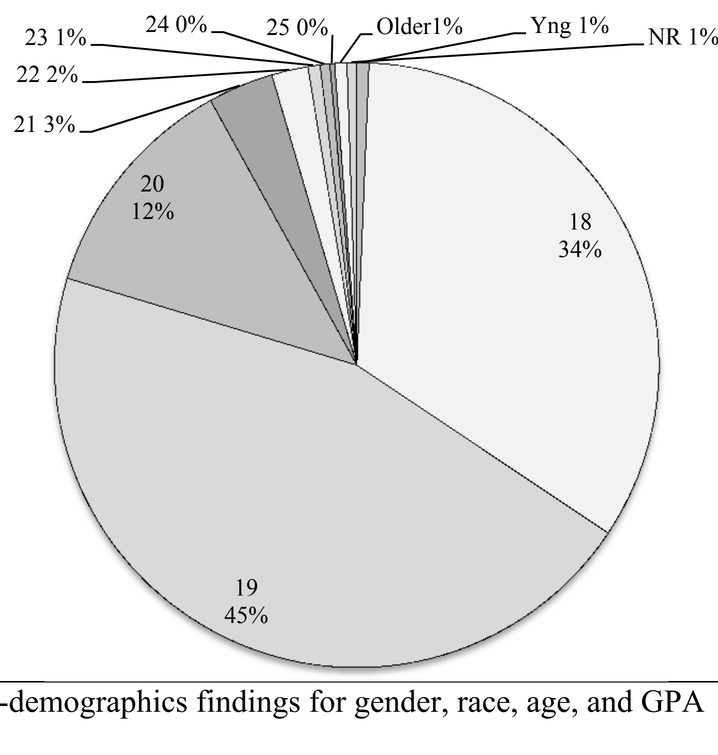


Figure 4.1 (cont.) Socio-demographics findings for gender, race, age, and GPA

GPA (SD4)

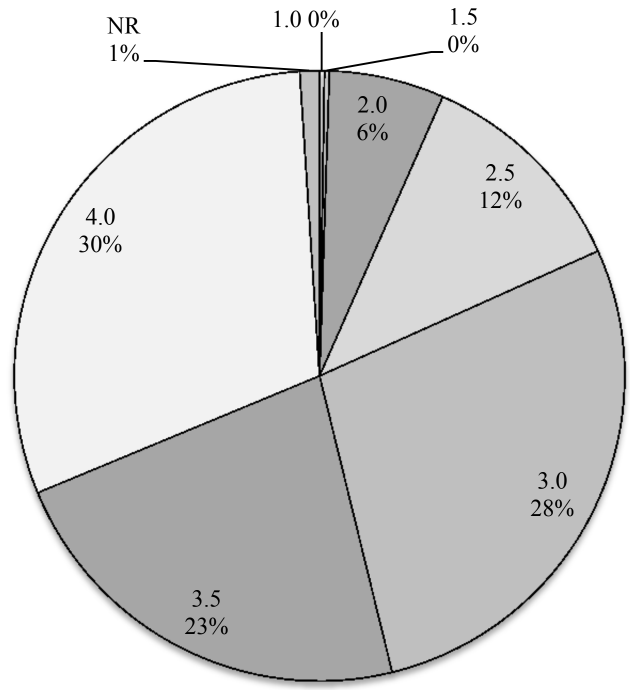
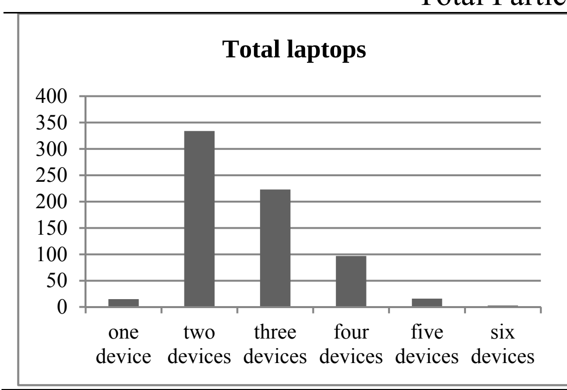


Figure 4.1. (cont.) Socio-demographics findings for gender, race, age, and GPA

The mobile device experience (MDE) survey contained four items to gauge participant experience, ownership, and expertise with mobile devices (Molina et al., 2014). MDE1 was a multiple select question included to determine if the participants' device ownership was consistent with statistics (Ericsson, 2015) on mobile device ownership (Figure 4.2). Nearly 90% of participants owned laptops and 97% owned smartphones. Only 35% owned tablets or eReaders. Nearly 90% of participants owned more than one mobile device. Of those who owned more than one device, 98.54% owned laptops and 99.12% owned smartphones.

Code	Mobile device ownership	Participants
0	no response	3
1	laptop	15
2	tablet	1
4	smartphone	67
6	smartwatch	1
12	laptop, tablet	3
14	laptop, smartphone	328
15	laptop, iPod	3
24	tablet, smartphone	8
34	eReader, smartphone	1
46	smartphone, smartwatch	1
124	laptop, tablet, smartphone	126
134	laptop, eReader, smartphone	17
145	laptop, smartphone, iPod	79
146	laptop, smartphone, smartwatch	1
245	tablet, smartphone, iPod	1
1234	laptop, tablet, eReader, smartphone	6
1245	laptop, tablet, smartphone, iPod	72
1246	laptop, tablet, smartphone, smartwatch	2
1345	laptop, eReader, smartphone, iPod	12
1346	laptop, eReader, smartphone, smartwatch	2
1456	laptop, smartphone, iPod, smartwatch	3
12345	laptop, tablet, eReader, smartphone, iPod	14
12456	laptop, tablet, smartphone, iPod, smartwatch	2
123456	laptop, tablet, eReader, smartphone, iPod, smartwatch	3
	Total Participants	771



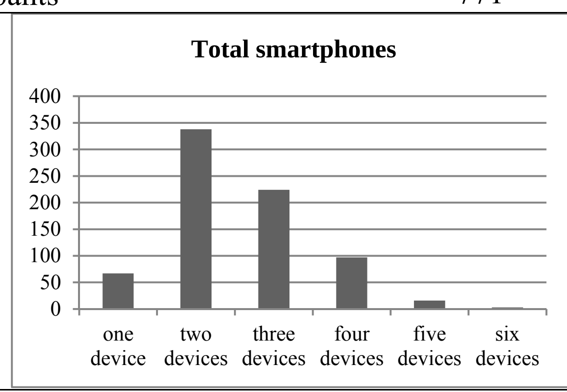


Figure 4.2. Mobile device ownership.

The MDE survey additionally measured student experience using mobile devices (MDE2), experience with smartphone devices (MDE3), and experience with mobile learning environments (MDE4). The questions were rated using a 5-point Likert scale, where '5' meant "well experienced" and '1' meant "little to no experience." Molina et al. (2014) used the mean score of all survey questions (in this case MDE2-4) to determine mobile device experience of the participants, with '5' meaning a lot of experience and '1' meaning little to no experience (Figure 4.3). The mean score was 4.27, suggesting that the participant group as a whole had significant experience using mobile devices.

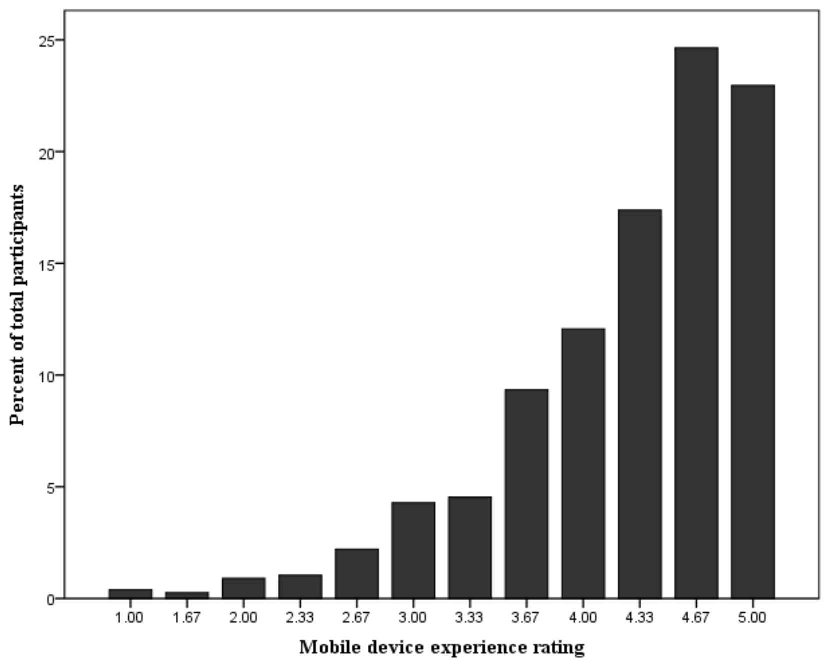
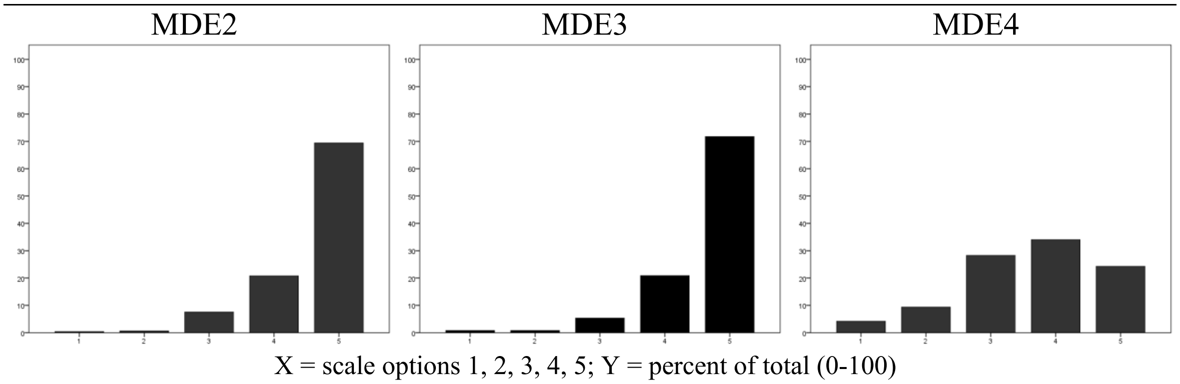


Figure 4.3. Mobile device experience (MDE) summary. Rating on a scale of 1 for "no experience" to 5 or "well experienced."

In looking at the individual items of MDE, it can be determined that while participants had ample experience with mobile devices, and smartphones specifically, the score for mobile learning was slightly less (Figure 4.4). In this context, mobile devices refer to all devices that allow mobility with simultaneous connectivity.



Mobile device experience survey items:
MDE2 Experience in the use of mobile devices.
MDE3 Experience in the use of a smartphone device.
MDE4 Experience in the use of mobile learning tools.

Figure 4.4. Mobile device experience survey results per individual item. Rating on a scale of 1 for "no experience" to 5 or "well experienced."

The final DMLP section assessed participant attitude towards mobile learning (AML). The AML survey measured participant attitude towards mobile devices for use in educational contexts (AML1), for use in studying (AML2), for use of smartphones specifically in educational contexts (AML3), and for use of smartphones specifically in study (AML4). It also measured participant preference for desktop computers (AML5), and for printed material (AML6). The questions were rated using a 5-point Likert scale for how much they agree with the statements, with '5' representing "strongly agree" and '1' representing "strongly disagree." Molina et al. used the mean score of the survey questions to determine attitude towards mobile learning, with five representing a positive attitude and 1 representing a negative attitude (Figure 4.5).

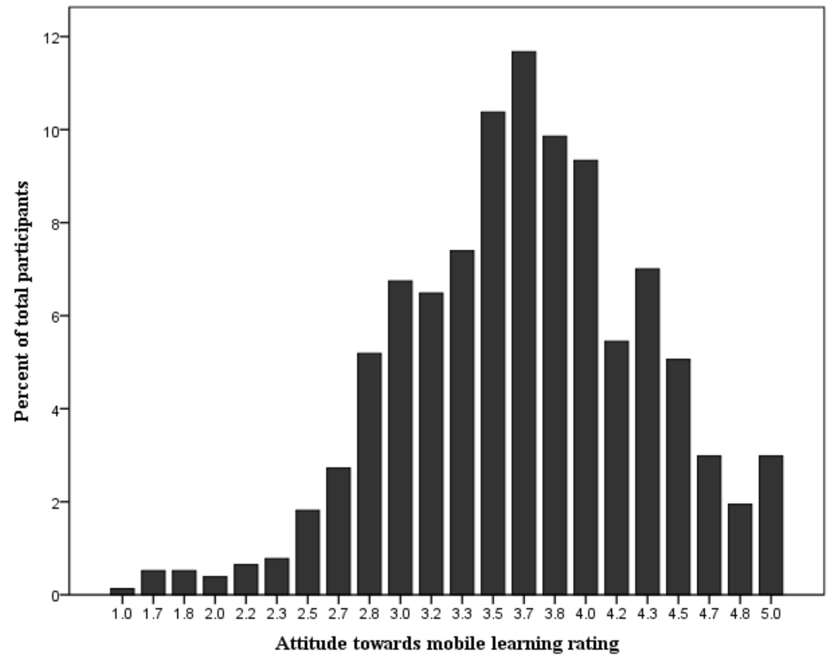
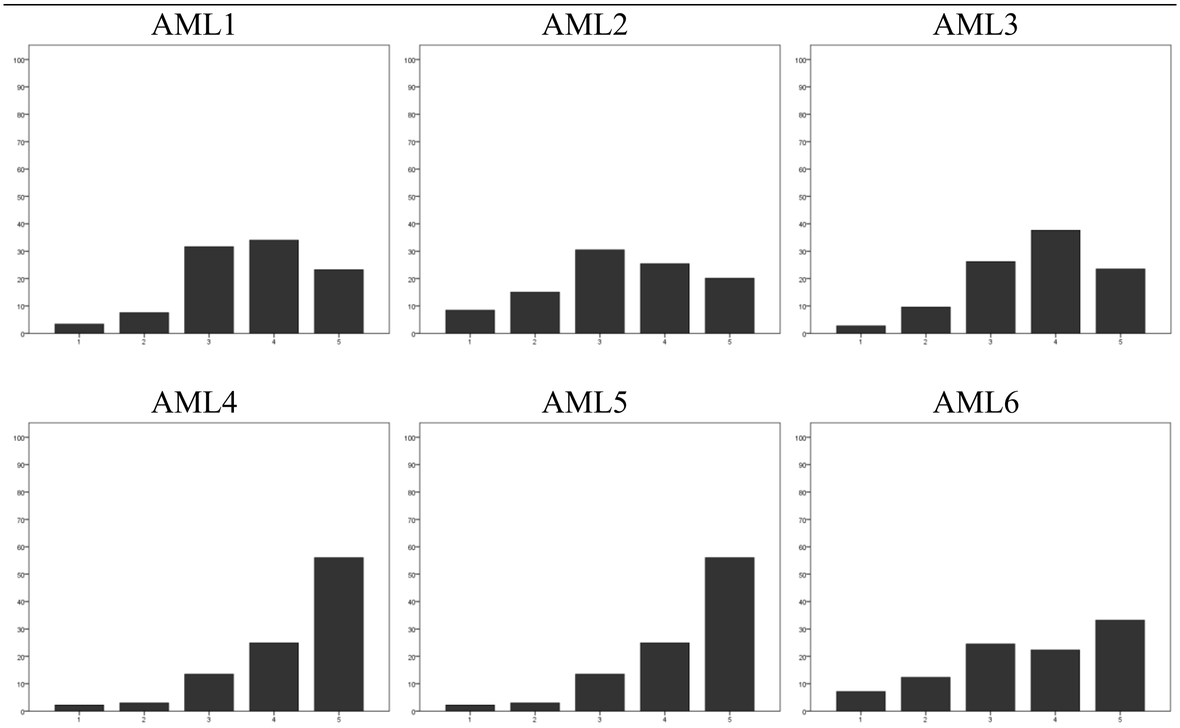


Figure 4.5. Attitude towards mobile learning (AML) summary. Rating on a scale of 1 for "strongly disagree" to 5 or "strongly agree."

The mean score was 3.66, suggesting that the participant group as a whole had relatively neutral attitudes towards using mobile devices for learning, leaning slightly towards agreement in its use. In examining the individual items of AML, while students do think that mobile devices are useful in educational contexts and for studying, there remains still a propensity towards using desk top and printed materials for study (Figure 4.6).



X = scale options 1, 2, 3, 4, 5; Y = percent of total (0-100)

Attitude toward mobile learning survey items:

AML1	I think it's useful to use mobile devices in educational contexts.
AML2	I think it's useful to use mobile devices to study.
AML3	I think it's useful to use smartphones and tablets in educational contexts.
AML4	I think it's useful to use smartphones and tablets to study.
AML5	I prefer to use a desktop computer or laptop to study.
AML6	To study, I prefer to print the material.

Figure 4.6. Attitude toward mobile learning survey results per individual item. Rating on a scale of 1 for "strongly disagree" to 5 or "strongly agree."

INSTRUMENT RELIABILITY TESTING

The post-treatment, dependent measures of this study included the learning outcomes (LO) test, the cognitive load measurement (CLM), and the user perception survey (UPS). Cronbach's alpha reliability coefficient was calculated to determine reliability for each of these scales before further statistical analysis was run. Cronbach's alpha reliability coefficient normally ranges between 0 and 1, where the closer the alpha is to 1, the greater the internal consistency of the scale items. George and Mallery (2005) suggest that guidelines for determining internal consistency using Cronbach's alpha are "_ > .9 – Excellent, _ > .8 – Good, _ > .7 – Acceptable, _ > .6 – Questionable, _ > .5 – Poor, and _ < .5 – Unacceptable" (p. 231). Others consider lower alphas to still be acceptable, especially in early stages of research (Nunnally, 1978). For reliability analysis in this study, the scales varied in terms of prior empirical testing. The LO scale was created for this study specifically by the chemistry faculty. The CLM and UPS were both taken from previous studies, in which reliability tests revealed the internal consistency of the scales were reliable.

LO measured whether or not participants were able to recall the protonation state content following each treatment. It was used to compare the treatments as learning tools, with higher scores signifying better learning than lower scores. The LO scale consisted of 15 items. The total score was reported as a percentage of total correct ranging from 100 for all correct to zero for none correct. Given this was not previously empirically validated, and given it was an expert approved measure of content recall, no reliability statistics were administered.

Cognitive load measurement (CLM) reliability statistics

Measuring for cognitive load provided perspective on participant experience learning with each treatment by demonstrating whether students were cognitively overloaded, under loaded, or remained successfully in the ZPD (Schnotz & Bannert, 2003; Schnotz & Kürschner, 2007). The CLM instrument was borrowed from Leppink et al., (2013). This particular scale measured the complexity of the activity (intrinsic cognitive load, ICL), the instructions and explanations (extraneous cognitive lead, ECL), and the enhancement of knowledge given the material (germane cognitive load, GCL).

The ten-item scale was broken down into three subscales (Table 4.2). Items 1-3 (ICL) measured the “complexity of subject matter” (Leppink et al., 2013). The ICL subscale reliability analysis revealed Cronbach’s alpha value 3 items (α = .87). Items 4-6 (ECL) measured “negative characteristics of instructions and explanations” (Leppink et al., 2013). The ECL subscale reliability analysis revealed Cronbach’s alpha value 3 items (α = .88). Finally, items 7-10 (GCL) measured the extent to which “intrusions and explanations contribute to learning” (Leppink et al., 2013). The GCL subscale reliability analysis revealed Cronbach’s alpha value 4 items (α = .94). The reliability findings for the CLM were consistent with those of Leppink et al., indicating that the CLM had high intrinsic reliability and was therefore a good measure of cognitive load (Field, 2013; George & Mallery, 2005; Leppink et al., 2013).

Table 4.2

Cognitive Load Measurement (CLM) Reliability Statistics

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Intrinsic Cognitive Load (CLMICL) Subscale	0.87	0.87	3
Extraneous Cognitive Load (CLMECL) Subscale	0.88	0.88	3
Germane Cognitive Load (CLMGCL) Subscale	0.94	0.94	4

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Intrinsic Cognitive Load (CLMICL) Subscale					
CLM1. The topics covered in the activity were very complex.	9.88	20.59	0.74	0.55	0.83
CLM2.The activity covered chemistry formulas that I perceived as very complex.	10.89	18.06	0.74	0.55	0.83
CLM3. The activity covered concepts and definitions that I perceive as very complex.	10.40	17.91	0.78	0.61	0.79
Extraneous Cognitive Load (CLMECL) Subscale					
CLM4. The instructions and/or explanations during the activity were very unclear.	6.18	24.03	0.75	0.60	0.86
CLM5. The instructions and/or explanations were, in terms of learning, very unclear.	6.08	22.50	0.85	0.71	0.77
CLM6. The instruction and/or explanations were full of unclear language.	6.67	24.98	0.74	0.58	0.87
Germane Cognitive Load (CLMGCL) Subscale					
CLM7. The activity really enhanced my understanding of the topics covered.	14.86	48.20	0.86	0.77	0.92
CLM8. The activity really enhanced my knowledge and understanding of protonation state.	14.55	46.59	0.89	0.81	0.91
CLM9. The activity really enhanced my understanding of the chemistry formulas covered.	15.21	50.61	0.80	0.65	0.94
CLM10. The activity really enhanced my understanding of the concepts and definitions.	14.65	48.82	0.87	0.76	0.92

User perception scale (UPS) reliability statistics

As positive user perception has been demonstrated by the literature as a viable gauge of total mobile learning success (Hwang et al., 2011; Sanchez & Goolsbee, 2010; Seraj & Wong, 2014; Terras & Ramsay, 2012; Traxler, 2005; Valk et al., 2010; Y.-S. Wang et al., 2009; Yau & Joy, 2010), the user perception scale (UPS) was used as a final measure for the study (Table 4.3). UPS consisted of four subscales. The first three subscales (perceived ease of use, PEU; perceived use, PU; and usage intentions, UI) were based on the Technology Acceptance Model (TAM) (Davis, 1993; Venkatesh et al., 2003), which is used to assess acceptance of educational resources and systems (Molina et al., 2014, p. 477). The PEU subscale reliability analysis revealed Cronbach's alpha value 3 items (α = .87). The PU subscale reliability analysis revealed Cronbach's alpha value 3 items (α = .93). The PEU subscale reliability analysis revealed Cronbach's alpha value 2 items (α = .93).

The final UPS subscale (perceived satisfaction, PS), measured participant satisfaction with using the mobile device (Molina et al. 2014). The PS subscale reliability analysis revealed Cronbach's alpha value 4 items (α = .94). The reliability findings for the UPS scale suggested each subscale had high intrinsic reliability and was therefore a good measure of user perceptions (Molina, et al., 2014).

Table 4.3

User Perception Survey (UPS) Reliability Statistics

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Perceived Ease of Use (PEU) Subscale	0.87	0.87	3
Perceived Use (PU) Subscale	0.93	0.93	3
Use Intentions (UI) Subscale	0.93	0.93	2
Perceived Satisfaction (PS) Subscale	0.94	0.94	4

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Perceived Ease of Use (PEU) Subscale					
PEU1. Studying learning materials using this device is easy for me.	7.01	5.42	0.75	0.57	0.82
PEU2. My interaction with this device has been flexible, direct, and fluid.	6.61	5.95	0.73	0.53	0.85
PEU3. Overall, I believe that this learning environment is easy to use.	6.75	5.33	0.79	0.62	0.79
Perceived Use (PU) Subscale					
PU1. I think that the use of this type of device could help me in my learning tasks.	6.35	6.52	0.86	0.75	0.89
PU2. Using this device enables me to accomplish study tasks more quickly.	6.39	6.58	0.83	0.68	0.92
PU3. Overall, I find that using this device is a useful studying tool.	6.27	6.40	0.88	0.78	0.88
Use Intentions (UI) Subscale					
UI1. I intend to use this device for studying in the future.	3.09	1.87	0.87	0.75	.
UI2. I would recommend the use of this device for study.	3.04	2.00	0.87	0.75	.
Perceived Satisfaction (PS) Subscale					
PS1. I am satisfied with accessing learning contents using this device.	9.07	13.97	0.86	0.77	0.92
PS2. I am satisfied with the interaction with this device for studying.	9.08	14.07	0.87	0.78	0.92
PS3. I think that using this device for learning could be motivating.	9.43	13.86	0.83	0.71	0.93
PS4. I like using this device for studying.	9.35	13.17	0.86	0.75	0.92

ANALYSIS OF VARIANCE RESULTS

The research design called for conducting ANOVA on each of the three research question groups to determine possible associations between the independent and dependent variables (Table 4.4). The first set of research questions (RQ1a-c) asked if mobile device display size and orientation has a main effect on (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception of a digitally delivered chemistry text lesson. To answer RQ1a, I ran a one-way ANOVA to determine if there was a main effect of device (LT, SML, SMP) on learning outcomes (LO). To answer RQ1b, I ran a one-way ANOVA to determine if there was a main effect of device on cognitive load (ICL, ECL, and GCL) To answer RQ1c, I ran a one-way ANOVA to determine if there was a main effect of device on user perception (PEU, PU, UI, and PS).

Table 4.4

Plan for Statistical Analysis

<table>
<tr><th></th><th></th><th colspan="3">Device Treatments</th><th colspan="3">Text Segmentation Treatments</th></tr>
<tr><th></th><th></th><th>LT</th><th>SML</th><th>SMP</th><th>TS1</th><th>TS2</th><th>TS3</th></tr>
<tr><td rowspan="6">Instruments</td><td rowspan="2">LO</td><td colspan="3">One-Way ANOVA (RQ1a)</td><td colspan="3">One-Way ANOVA (RQ2a)</td></tr>
<tr><td colspan="6">Two-Way ANOVA (comparing all treatments) (RQ3a)</td></tr>
<tr><td rowspan="2">CLM</td><td colspan="3">One-Way ANOVA(s) (RQ1b)</td><td colspan="3">One-Way ANOVA(s) (RQ2b)</td></tr>
<tr><td colspan="6">Two-Way ANOVA (comparing all treatments)(s) (RQ3b)</td></tr>
<tr><td rowspan="2">UPS</td><td colspan="3">One-Way ANOVA(s) (RQ1c)
for PEU, PU, UI, and PS</td><td colspan="3">One-Way ANOVA(s) (RQ2c)
for PEU, PU, UI, and PS</td></tr>
<tr><td colspan="6">Two-Way ANOVA(s) (comparing all treatments) (RQ3c)
for PEU, PU, UI, and PS</td></tr>
</table>

Research design:
9 treatment groups (3x3 design): T1a-T3j

Independent variables:
Device treatments: laptop (LT), smartphone landscape (SML), smartphone portrait (SMP)
Text segmentation treatments: continuous text (TS1), medium segmented text (TS2), small segmented text (TS3)

Dependent variables:
Learning outcome (recall test) (LO), cognitive load measurement (CLM), user perception survey (USP)

Research questions:
RQ1 (mobile device comparison): Do mobile display size and orientation affect (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception of a digitally delivered chemistry text lesson?
RQ2 (text segmentation comparison): Do digitally continuous text, medium text segments, and short text segments compare in terms of (a) learning outcomes of a digitally delivered chemistry text lesson, (b) minimizing cognitive load for a digitally delivered chemistry text lesson, and (c) influencing user perception of a digitally delivered chemistry text lesson?
RQ3 (mobile device and segmentation interaction): Do text segmentation and mobile screen display size/orientation affect (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception digitally delivered chemistry text lesson?

The second set of research questions (RQ2a-c) ask if there was a main effect of digitally continuous text, medium text segments, and short text segments compare on (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception of a digitally delivered chemistry text lesson. To answer RQ2a, I ran a one-way ANOVA to determine if there was a main effect of text segmentation (TS1, TS2, TS3) on test scores (LO). To answer RQ2b, I ran a similar test to determine if there was a main effect of text segmentation on cognitive load (ICL, ECL, and GCL). To answer RQ2c, I ran a one-way ANOVA to determine if there was a main effect of text segmentation on user perception (PEU, PU, UI, and PS).

The third set of research questions (RQ3a-c) asked if there was an interaction effect between text segmentation and screen display size and orientation on (a) learning outcomes of a digitally delivered chemistry text lesson, (b) cognitive load of a digitally delivered chemistry text lesson, (c) user perception of a digitally delivered chemistry text lesson. To answer RQ3a, I ran a two-way ANOVA to determine if there was an interaction effect between device (LT, SML, SMP) and text segmentation (TS1, TS2, TS3) on test scores (LO). To answer RQ3b, I ran a similar test to determine if there was an interaction effect between device and text segmentation on cognitive load (ICL, ECL, and GCL). To answer RQ3c, I ran a final two-way ANOVA to determine if there was an interaction effect between device and text segmentation on user perception (PEU, PU, UI, and PS).

An alpha level of .05 was used for all analyses. Effect sizes were calculated using Omega squared. A measure of the strength of the association between the independent variable and then dependent variable in ANOVA is ω^2, omega squared. Omega squared indicates the proportion of the total variance in the dependent variable that is accounted for by the levels of the independent variable. This is analogous to the coefficients of determination (r^2). For this study, omega squared values of .01, .06, and .14, generally represent small, medium, and large effect sizes (Kirk, 1996).

Treatment group participants (N)

The participants (N = 771) were randomly split into mobile device groups and text segmentation groups. There were two independent variables in this study: mobile device and text segmentation. The independent variable mobile device was split into three subgroups: laptop (LT), smartphone landscape (SML), and smartphone portrait (SMP). The independent variable text segmentation split into three subgroups: continuous text (TS1), medium text segments (TS2), and small text segments (TS3).

As the participants entered the room for data collection, they were separated into two mobile device groups: laptops (LT), and smartphones. One laptop was assigned for every two smartphones. The smartphone group was then randomly split (via the application) into smartphone landscape (SML) and smartphone portrait (SMP). This made up the three mobile device groups (Table 4.5).

There was some inconsistency in assignment due to a few factors. First, if a student arrived in class when a certain device was assigned and they did not have that specific device, they were switched with the next person to arrive who did have that device. Additionally, if a student had a smartphone that did not support either iOS or Android (like a Microsoft phone), they were automatically assigned to the laptop group. Next, because the server was inundated, even if they had the correct device, not all participants were able to download the application, requiring devices be swapped. Finally, some of the participants opted of their own accord to swap devices, from laptop to smartphone and vice versa.

Table 4.5

Independent Variable: Mobile Device Frequencies

	Frequency	Percent	Valid Percent	Cumulative Percent
LT	292	37.9	37.9	37.9
SML	234	30.4	30.4	68.2
SMP	245	31.8	31.8	100.0
Total	771	100.0	100.0	

The number of participants in these instances was relatively low. However, these factors in addition to the participant data that was not captured by the database (from the 950 original ids assigned) created a slight discrepancy in the distribution of the mobile device groups (N_{LT} 292, N_{SML} = 234, N_{SMP} = 245). Given the participant numbers were well over the widely accepted 30 per group (Fields, 2013), these discrepancies were not expected to influence statistical outcomes.

There were three subgroups of the text segmentation independent variable: continuous text (TS1), medium text segments (TS2), and small text segments (TS3). Participants in the laptop and smartphone groups were randomly assigned to a text segmentation group (Table 4.6). This was executed for the laptop group by order of those who clicked ‘yes,’ to the participation agreement, such that of every three participants using a laptop one was assigned TS1, one to TS2, and one to TS3 in order.

Table 4.6

Independent Variable: Text Segmentation Frequencies

	Frequency	Percent	Valid Percent	Cumulative Percent
TS1	262	34.0	34.0	34.0
TS2	271	35.1	35.1	69.1
TS3	238	30.9	30.9	100.0
Total	771	100.0	100.0	

A similar process was executed for the smartphone group, however, to also split the smartphone group into landscape and portrait respectively, smartphone participants were assigned in order to SML/TS1, SMP/TS1, SML/TS2, SMP/TS2, SMP/TS3, and SML/TS3. The resulting group numbers were $N_{TS1} = 262$, $N_{TS2} = 271$, $N_{TS3} = 238$. Combined together, there were a total of nine treatment in the 3x3 research design (Figure 4.7).

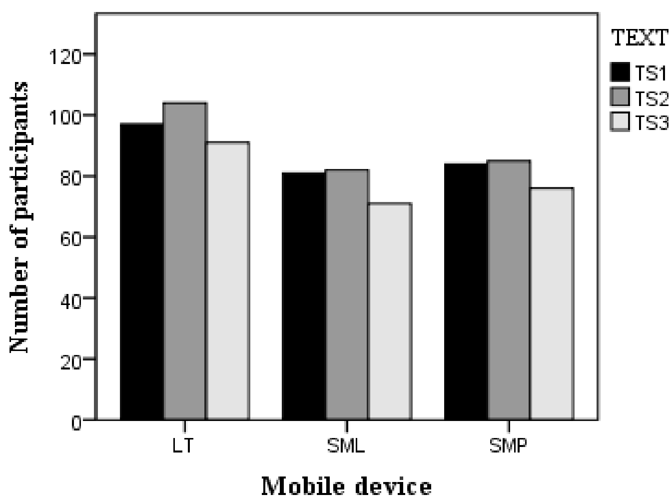


Figure 4.7. Mobile device by text segmentation. Note: Each bar from left to right designates each of nine treatment groups (3x3 research design).

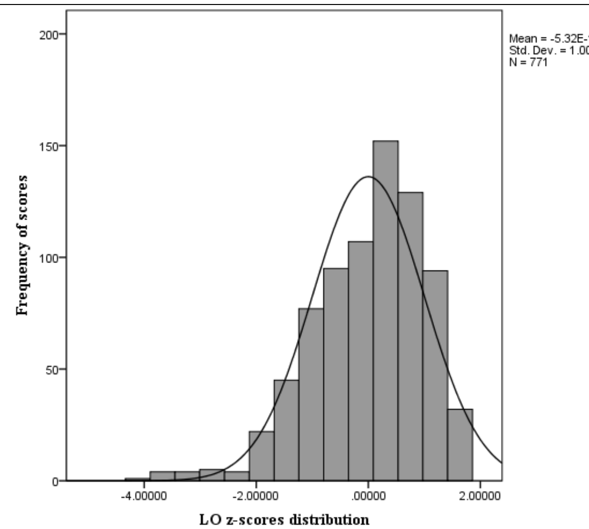
Assumptions of ANOVA

To reduce the bias in the sample, assumptions are required to run a successful ANOVA. These include assumptions of independence, normality, and homogeneity of variance. The assumption of independence was met because the participants in each group were in no way dependent on one another, each interacting with their own device and treatment, working at their own pace. Additionally, they were assigned to the various groups randomly (see Treatment Group Participants (N) section above).

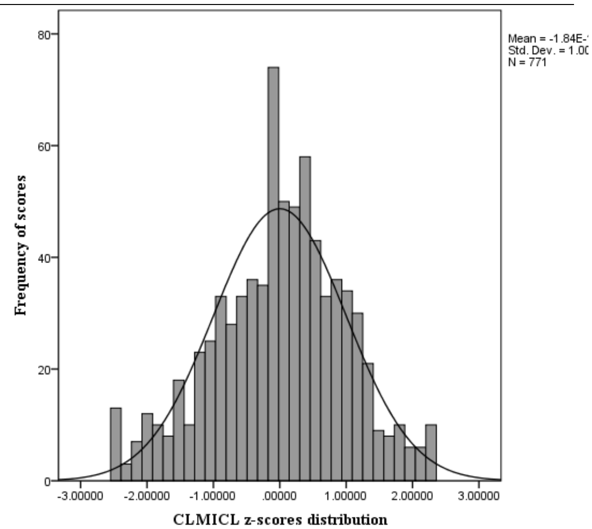
In terms of the normality assumption, the central limit theorem states that when samples are larger than N=30, the sampling distribution will take the shape of a normal distribution regardless of the shape of the population from which the sample was drawn (Lumley, Diehr, Emerson, & Chen, 2002). The size of the sample needed to meet this assumption may vary based on outliers (Fields, 2013). To ensure that outliers, z-scores and histograms of each dependent variable were examined.

On the learning outcomes (LO) test, the 771 participants had a mean score of 75.31 (SD = 15.06). Scores of 66.67, 80.00, and 86.67 represented the 25th, 50th, and 75th percentiles, respectively. Initial examination of z-scores revealed several outliers. 0.6 %, recorded extreme z-scores greater than -3.29. 0.5%, recorded z-scores between -3.29 and -2.58. Together, these scores represented only 1.1% of the data. Further inspection of these cases revealed that these nine scores occurred because the individual incorrectly answered more than 12 items of the 15 item multiple choice test (LO). 0.5% of z-scores were between -1.96 and -2.58. There were no z-scores greater than 1.96. The LO distribution shows the low scores (Figure 4.8). However, the distribution appears otherwise evenly distributed and given the low percentage of extreme z-scores, normality is assumed.

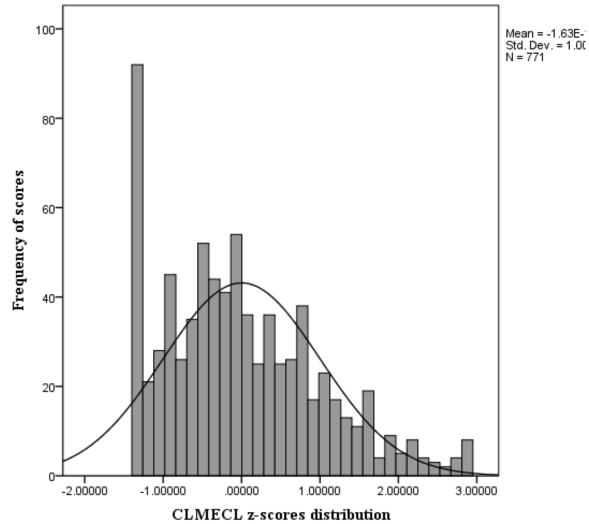
On the cognitive load measurement, for the intrinsic cognitive load subscale (CLMICL), there was a mean score of 5.20 (SD = 2.10). Scores of 4.00, 5.33, and 6.67 represented the 25th, 50th, and 75th percentiles. Initial examination of CLMICL z-scores revealed no outliers. 4.5% had z-scores between than -1.96 and -2.58, while 2.9% had z-scores between than 1.96 and 2.58. A relatively normal distribution was evident (Figure 4.8) and normality is assumed.



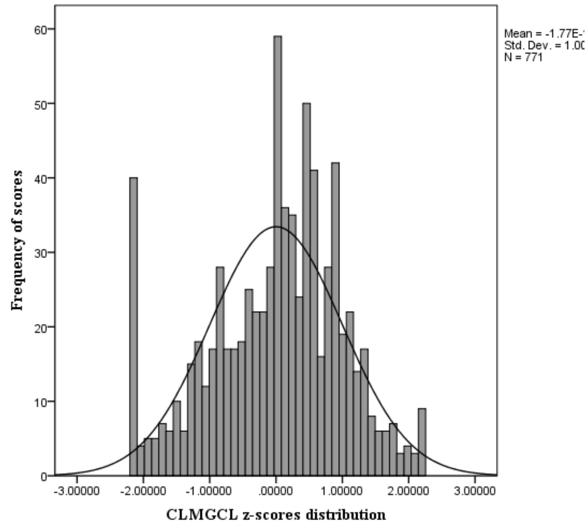
Learning outcomes (LO) distribution.



Intrinsic cognitive load (CLMICL) distribution.



Extraneous cognitive load (CLMECL) distribution.



Germane cognitive load (CLMGCL) distribution.

Figure 4.8. LO, CLMICL, CLMECL, and CLMGCL histograms

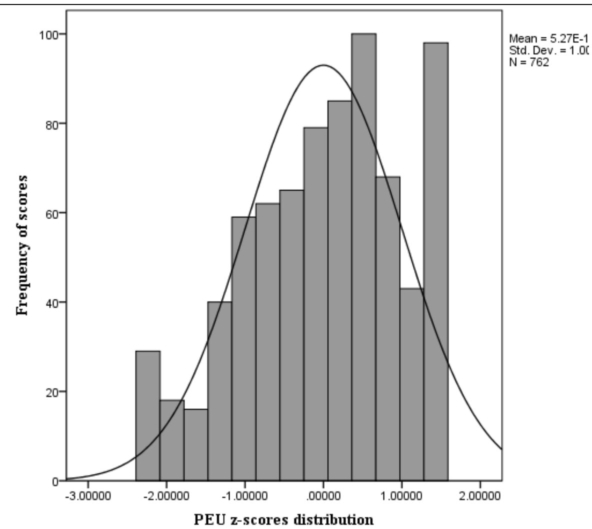
For the extraneous cognitive load subscale (CLMECL), there was a mean score of 3.16 (SD = 2.37). Scores of 1.33, 3.00, and 4.67 represented the 25th, 50th, and 75th percentiles. Initial examination of CLMECL z-scores revealed a few extreme cases. 1.8% had z-scores between 2.58 and 3.29, while 2.5% had z-scores between than 1.96 and 2.58. There were no z-scores lower than -1.96. Ninety-two z-scores were recorded at -1.33 resulting in a positive skewness and highlighting that these participants selected extreme values on the CLMECL items. However, given that these particular z-scores were inside of 95%, given that there were no extreme z-scores, and given the distribution (Figure 4.8) was otherwise normal, normality is assumed.

For the final subscale of the CLM, germane cognitive load (CLMGCL), there was a mean score of 4.94 (SD = 2.30). Scores of 3.50, 5.25, and 6.50 represented the 25th, 50th, and 75th percentiles. Initial examination of CLMGCL z-scores revealed a no extreme cases. However, 5.7% had z-scores between than -1.96 and -2.58, while 2.1% had z-scores between than 1.96 and 2.58. However, given that there were no extreme z-scores, and given the distribution (Figure 4.8) was otherwise normal, normality is assumed.

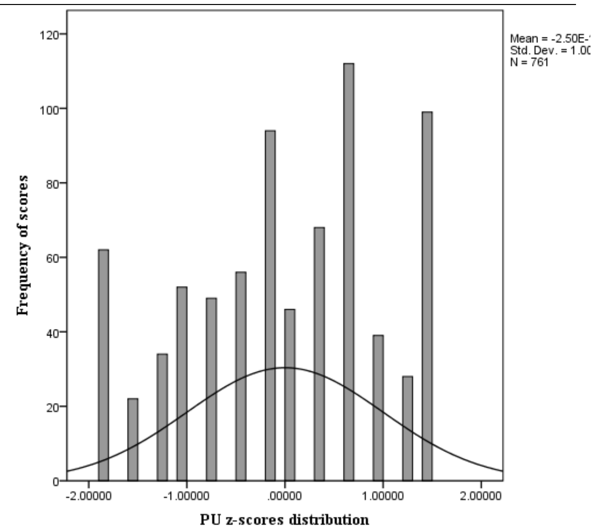
On the four subscales of the user perception survey (UPS), a mean of 3.44 (SD = 1.09) resulted from the perceived ease of use (PEU) subscale, while scores of 2.67, 3.67, and 4.33 represented the 25th, 50th, and 75th percentiles. Initial examination of PEU z-scores revealed no extreme cases, and 3.8% z-scores between than -1.96 and -2.58. There was a slightly negative skew on the distribution (Figure 4.9), however given that there were no extreme z-scores and given the skew was not extreme, normality was assumed.

For the perceived use (PU) subscale, there was a mean score of 3.21 (SD = 1.21). Scores of 2.33, 3.33, and 4.00 represented the 25th, 50th, and 75th percentiles.

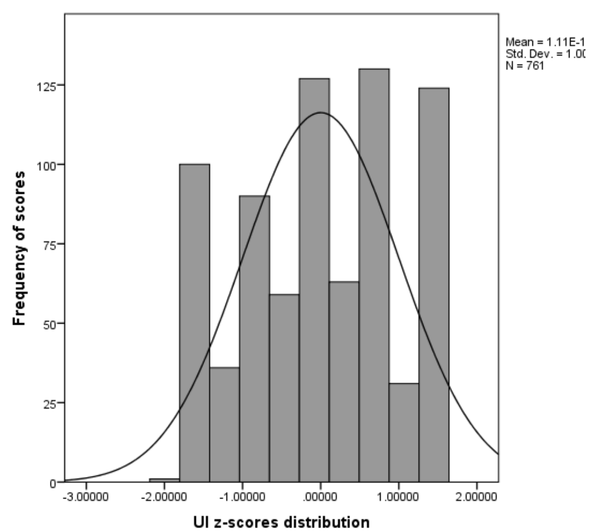
Examination of PU z-scores revealed no z-scores greater or less than ±1.96. Given that the distribution was only slightly negatively skewed, normality was assumed (Figure 4.9).



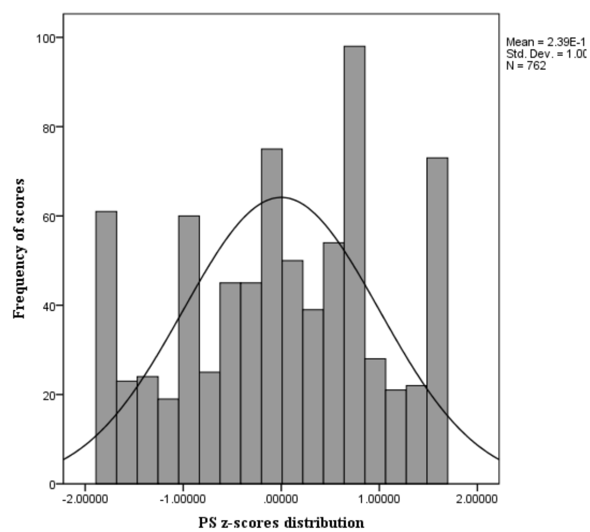
Perceived ease of use (PEU) distribution.



Perceived use (PU) distribution.



Use intentions (UI) distribution.



Perceived satisfaction (PS) distribution.

Figure 4.9. PEU, PU, UI, and PS histograms.

For the use intentions (UI) subscale, there was a mean score of 3.11 (SD = 1.31). Scores of 2.00, 3.00, and 4.00 represented the 25th, 50th, and 75th percentiles.

Examination of UI z-scores revealed no extreme cases, while 0.1%. had z-scores between -1.96 and -2.58. Given the otherwise normal distribution of scores (Figure 4.9), normality was assumed.

For the final subscale of the UPS, perceived satisfaction (PS), there was a mean score of 3.11 (SD = 1.18). Scores of 2.25, 3.25, 4.00 represented the 25th, 50th, and 75th percentiles. Initial examination of PS z-scores revealed no z-scores greater or less than ± 1.96. Given the distribution (Figure 4.9) was otherwise normal, normality was assumed.

Results for research question one (RQ1): Mobile device comparison

To address the gap in literature concerning mobile device comparison when design is tailored specifically to the device, as well as to answer additional questions about smartphone screen display and orientation, RQ1 asked if, when specific formatting variables were held constant, do mobile display size and orientation affect:

RQ1a: learning outcomes of a digitally delivered chemistry text lesson?

RQ1b: cognitive load of a digitally delivered chemistry text lesson?

RQ1c: user perception of a digitally delivered chemistry text lesson?

The independent variable mobile device had three groups, namely laptop (LT), smartphone landscape (SML), and smartphone portrait (SMP). The dependent variables included learning outcomes (LO), intrinsic cognitive load (CLMICL), extraneous cognitive load (CLMECL), germane cognitive load (CLMGCL), perceived ease of use (PEU), perceived use (PU), use intentions (UI), and perceived satisfaction (PS).

Results for RQ1a

To answer RQ1a, a one-way ANOVA was conducted to determine if there was an association in learning outcome test scores (LO) by device (LT, SML, SMP). The sample participants were randomly split into three device groups, LT (N = 292), SML (N = 234), and SMP (N=245).

To first ensure that the homogeneity of variance assumption of the ANOVA was met, Levene's test (Levene, 1960) was used to test that variance of each group was equal. It revealed that the variance was roughly equal F(2, 768) = .129, $p = .879$ and therefore, the assumptions for ANOVA were tenable for this analysis. A one-way ANOVA found no significant effect of mobile device (LT, SML, SMP) on learning outcome (LO), $F(2, 768) = 1.163$, $p = .313$, $\omega^2 = 0$, indicating that the mobile device used did not influence participant performance on the learning outcomes test (Table 4.7). Therefore, the null hypothesis was retained and no post hoc testing was required.

Table 4.7

Summary of ANOVA between Mobile Device and LO

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	527.664	2	263.832	1.163	.313
Within Groups	174182.430	768	226.800		
Total	174710.093	770			

Results for RQ1b

To answer RQ1b, a one-way ANOVA was conducted on each of the cognitive load measurement (CLM) subscales (ICL, ECL, and GCL) to determine if there was an association in cognitive load by device (LT, SML, SMP). The sample participants were randomly split into three device groups, LT (N = 292), SML (N = 234), and SMP (N=245).

Results for analysis of variance between mobile device and intrinsic cognitive load (CLMICL)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 768) = 1.502$, $p = .223$. A one-way ANOVA found no significant effect of mobile device (LT, SML, SMP) on intrinsic cognitive load (CLMICL), $F(2, 768) = .223$, $p = .800$, $\omega^2 = 0$, indicating that the mobile device used did not affect the intrinsic load of the digital material (Table 4.8). Therefore, the null hypothesis was retained and no post hoc testing was needed.

Table 4.8

Summary of ANOVA between Mobile Device and CLMICL

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.976	2	.988	.223	.800
Within Groups	3403.885	768	4.432		
Total	3405.861	770			

Results for analysis of variance between mobile device and extraneous cognitive load (CLMECL)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 768) = .776$, $p = .461$. A one-way ANOVA revealed no significant effect of mobile device (LT, SML, SMP) on extraneous cognitive load (GLMECL), $F(2, 768) = 1.832$, $p = .161$, $\omega^2 = 0$, indicating that the mobile device used did not add extraneous load to the learning material (Table 4.9). Therefore, the null hypothesis was retained and no post hoc testing was required.

Table 4.9

Summary of ANOVA between Mobile Device and CLMECL

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	20.588	2	10.294	1.832	.161
Within Groups	4316.541	768	5.620		
Total	4337.129	770			

Results for analysis of variance between mobile device and germane cognitive load (CLMGCL)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 768) = 1.421$, $p = .242$. A one-way ANOVA found no significant effect of mobile device (LT, SML, SMP) on germane cognitive load, $F(2, 768) = .271$, $p = .763$, $\omega^2 = 0$, indicating that the mobile device used did not affect the germane load of the digital material (Table 4.10). Therefore, the null hypothesis was retained and no post hoc testing was required.

Table 4.10

Summary of ANOVA between Mobile Device and CLMGCL

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.867	2	1.433	.271	.763
Within Groups	4068.796	768	5.298		
Total	4071.663	770			

Results for RQ1c

To answer RQ1c, a one-way ANOVA was conducted on each of the four UPS subscales (PEU, PU, UI, and PS) to determine if there was a difference in user perspective by device (LT, SML, SMP). The sample participants were randomly split into three device groups, LT (N = 289), SML (N = 231), and SMP (N=241).

Results for analysis of variance between mobile device and perceived ease of use (PEU)

Levene's test indicated that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, F(2, 759) = 1.98, $p = .139$. A one-way ANOVA revealed a significant main effect of mobile device on PEU at the $p < .05$ level, $F(2, 759) = 10.751$, $p = .000$, $\omega^2 = .02$.

Table 4.11

Summary of ANOVA between Mobile Device and PEU

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	24.845	2	12.422	10.751	.000
Within Groups	876.980	759	1.155		
Total	901.825	761			

This indicated that the null hypothesis was rejected. Accordingly, the mobile device used had a significant main effect on participant perception of ease of use of learning (Table 4.11). The estimated omega squared ($\omega^2 = .02$) indicated that approximately 2% of the total variation in device on PEU is attributable to difference between the three devices (Kirk, 1996). A boxplot visually illustrates the perceived ease of use score means and variance between and within the mobile device groups (Figure 4.10).

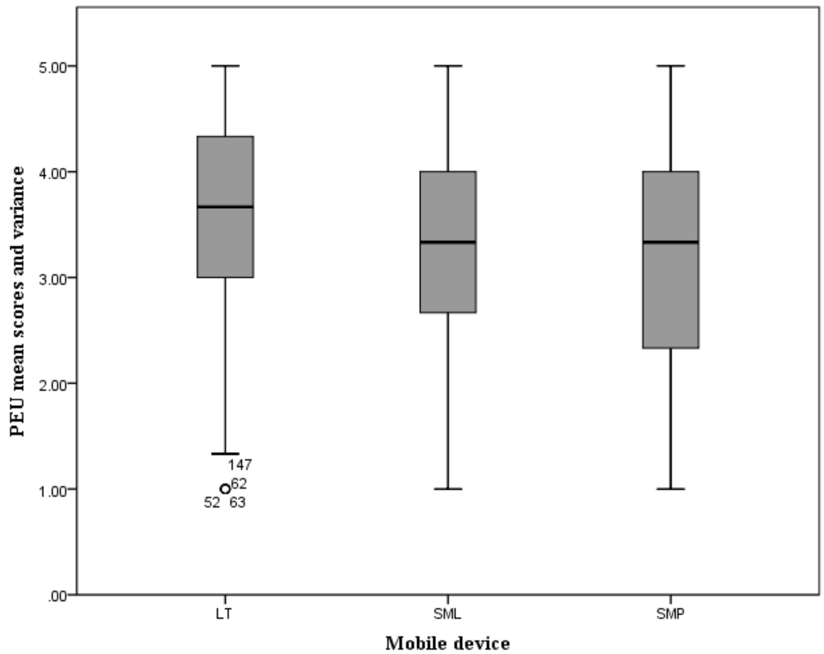


Figure 4.10. Boxplot of mobile device by perceived ease of use.

Pairwise comparisons were used to further analyze differences in means within mobile device groups and because the assumptions of ANOVA were met, post-hoc testing was conducted using Tukey's HSD (Table 4.12). The means and standard deviation for the LT group was M = 3.67, SD = 1.04. The mean and standard deviation for the SML group was M = 3.30, SD = 1.06. The mean and standard deviation for the SMP group was M = 3.29, SD = 1.13. Tukey's HSD revealed that the mean of the LT group was significantly different from the SML group, t (759) = 3.88, p = .000, r = .14. The LT group was also significantly different from the SMP group, t (759) = 4.01, p = .000, r = .14. In both cases, the effect sizes were small. There was no pairwise significance between the SML and SMP groups, t (759) = 0.08, p = .996. This indicated that participants in the sample perceived laptops to be easier to use than smartphones for accessing a digitally delivered chemistry text, regardless of screen display orientation.

Table 4.12

Tukey's Post Hoc between Mobile Device and PEU

(I) DEVICE	(J) DEVICE	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
LT	SML	.36796*	.09487	.000	.1452	.5907
	SMP	.37603*	.09366	.000	.1561	.5960
SML	LT	-.36796*	.09487	.000	-.5907	-.1452
	SMP	.00806	.09888	.996	-.2241	.2403
SMP	LT	-.37603*	.09366	.000	-.5960	-.1561
	SML	-.00806	.09888	.996	-.2403	.2241

*. Significant at the 0.05 level.

Results for analysis of variance between mobile device and perceived use (PU)

Levene's test revealed that the variance of each group was significantly unequal, F(2, 758) = 4.496, p = .011 and the homogeneity of variance assumption of ANOVA was not met. As such, the Welch's F test was used and an alpha level of .05 was used for the subsequent tests (Table 4.13). The one-way ANOVA of the main effect of mobile device on PU revealed a significant effect of mobile device on perceived use (PU), Welch's F(2, 487.256) = 9.782, p = .000, indicating that the mobile device used had a significant effect on the perceived use of learning technology and the null hypothesis was therefore rejected.

Table 4.13

Summary of ANOVA between Mobile Device and PU

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	26.503	2	13.251	9.300	.000
Within Groups	1080.019	758	1.425		
Total	1106.522	760			

The estimated omega squared (ω^2 = .02) indicated that approximately 2% of the total variation in device on PU is attributable to difference between the three devices. A boxplot visually illustrates the perceived use score means and variance between and within the mobile device groups (Figure 4.11).

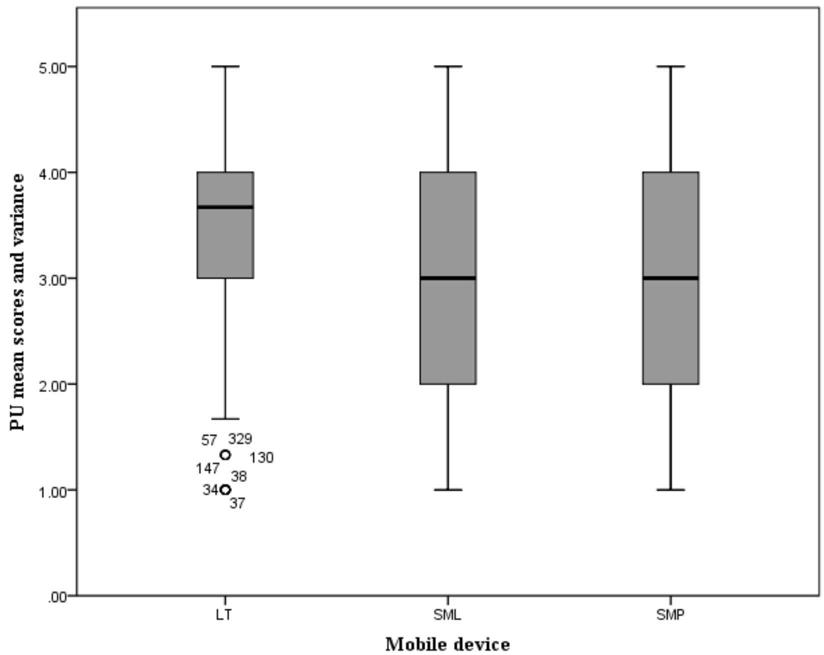


Figure 4.11. Boxplot of mobile device by perceived use.

Post hoc comparisons using the Games-Howell post hoc procedure were conducted to determine which mobile device means differed significantly (Table 4.14). The results indicated that participants who used laptops (M = 3.45, SD = 1.12) ranked perceived use significantly higher on average than participants who used either smartphone landscape (M = 3.06, SD = 1.20) or smartphone portrait (M = 3.07, SD = 1.28) treatments. The effect sizes for these two significant effects were t (758) = 3.81, p = .000, r = .14 and t (758) = 3.59, p = .001, r = .13, respectively. However, there was no pairwise significance between the SML and SMP groups, t (758) = 0.11, p = .993. This indicated that participants in the sample perceived laptops to be more useful than smartphones for accessing a digitally delivered chemistry text, regardless of screen display orientation.

Table 4.14

Games-Howell Post Hoc between Mobile Device and PU

(I) DEVICE	(J) DEVICE	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
LT	SML	.39087*	.10260	.000	.1496	.6321
	SMP	.37817*	.10526	.001	.1307	.6256
SML	LT	-.39087*	.10260	.000	-.6321	-.1496
	SMP	-.01270	.11376	.993	-.2802	.2548
SMP	LT	-.37817*	.10526	.001	-.6256	-.1307
	SML	.01270	.11376	.993	-.2548	.2802

*. Significant at the 0.05 level.

Results for analysis of variance between mobile device and use intentions (UI)

Levene's test indicated that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 758) = 1.63$, $p = .197$. A one-way ANOVA revealed a significant main effect of mobile device on UI at the $p < .05$ level, $F(2, 758) = 31.335$, $p = .000$, $\omega^2 = .07$.

Table 4.15

Summary of ANOVA between Mobile Device and UI

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	98.899	2	49.450	31.335	.000
Within Groups	1196.191	758	1.578		
Total	1295.090	760			

This indicated that the null hypothesis was rejected. Accordingly, the mobile device used had a significant main effect on participant intention to use the learning (Table 4.15). The estimated omega squared (ω^2 = .07) indicated that approximately 7% of the total variation in device on UI is attributable to difference between the three devices (Kirk, 1996). A boxplot visually illustrates the use intentions score means and variance between and within the mobile device groups (Figure 4.12).

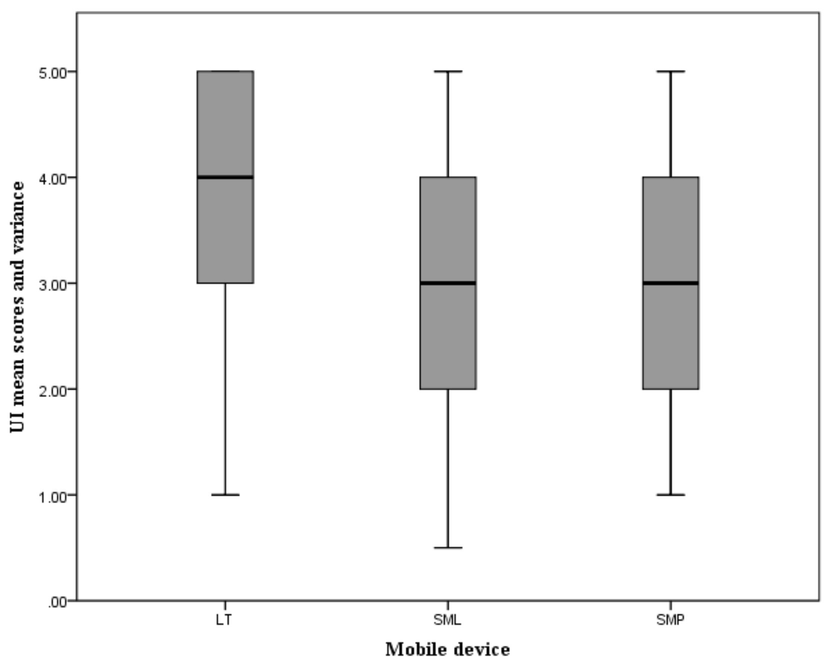


Figure 4.12. Boxplot of mobile device by use intentions.

Pairwise comparisons were used to further analyze differences in means within mobile device groups and because the assumptions of ANOVA were met, post-hoc testing was conducted using Tukey's HSD (Table 4.16). The means and standard deviation for the LT group was M = 3.57, SD = 1.21. The mean and standard deviation for the SML group was M = 2.81, SD = 1.26. The mean and standard deviation for the SMP group was M = 2.83, SD = 1.30. Tukey's HSD revealed that the mean of the LT group was significantly different from the SML group, t (758) = 6.78, p = .000, r = .24. The LT group was also significantly different from the SMP group, t (758) = 6.70, p = .000, r = .24. In both cases, the effect sizes were between small and medium. There was no pairwise significance between the SML and SMP groups, t (758) = 0.16, p = .987. This indicated that participants in the sample had greater intentions to use laptops than for smartphones for accessing a digitally delivered chemistry text, regardless of screen display orientation.

Table 4.16

Tukey's Post Hoc between Mobile Device and UI

(I) DEVICE	(J) DEVICE	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
LT	SML	.75189*	.11087	.000	.4915	1.0122
	SMP	.73379*	.10958	.000	.4765	.9911
SML	LT	-.75189*	.11087	.000	-1.0122	-.4915
	SMP	-.01810	.11567	.987	-.2897	.2535
SMP	LT	-.73379*	.10958	.000	-.9911	-.4765
	SML	.01810	.11567	.987	-.2535	.2897

*. Significant at the 0.05 level.

Results for analysis of variance between mobile device and perceived satisfaction (PS)

Levene's test indicated that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, F(2, 759) = 2.08, p = .126. A one-way ANOVA revealed a significant main effect of mobile device on PS at the $p < .05$ level, $F(2, 759) = 15.126$, $p = .000$, $\omega^2 = .04$.

Table 4.17

Summary of ANOVA between Mobile Device and PS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	40.934	2	20.467	15.126	.000
Within Groups	1027.008	759	1.353		
Total	1067.942	761			

This indicated that the null hypothesis was rejected. Accordingly, the mobile device used had a significant main effect on participant perceived satisfaction (Table 4.17). The estimated omega squared ($\omega^2 = .04$) indicated that approximately 4% of the total variation in device on PS is attributable to difference between the three devices (Kirk, 1996). A boxplot visually illustrates the perceived satisfaction score means and variance between and within the mobile device groups (Figure 4.13).

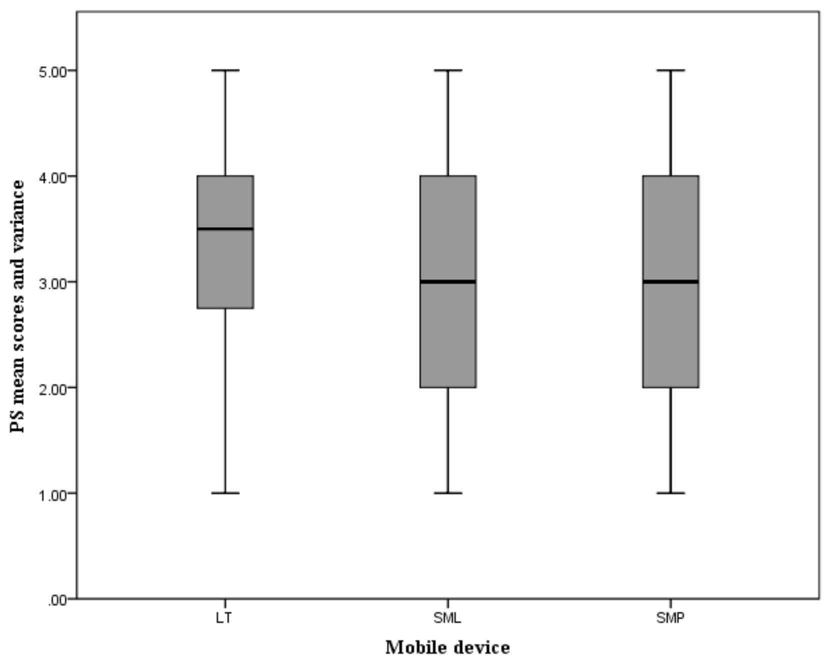


Figure 4.13. Boxplot of mobile device by perceived satisfaction.

Pairwise comparisons were used to further analyze differences in means within mobile device groups and because the assumptions of ANOVA were met, post-hoc testing was conducted using Tukey's HSD (Table 4.18). The means and standard deviation for the LT group was M = 3.41, SD = 1.11. The mean and standard deviation for the SML group was M = 2.91, SD = 1.16. The mean and standard deviation for the SMP group was M = 2.95, SD = 1.22. Tukey's HSD revealed that the mean of the LT group was significantly different from the SML group, t (759) = 4.84, p = .000, r = .17. The LT group was also significantly different from the SMP group, t (759) = 4.51, p = .000, r = .16. In both cases, the effect sizes were small. There was no pairwise significance between the SML and SMP groups, t (759) = 0.37, p = .929. This indicated that participants in the sample had greater perceived satisfaction with laptops than with smartphones for accessing a digitally delivered chemistry text, regardless of screen display orientation.

Table 4.18

Tukey's Post Hoc between Mobile Device and PS

(I) DEVICE	(J) DEVICE	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
LT	SML	.49661*	.10266	.000	.2555	.7377
	SMP	.45756*	.10136	.000	.2195	.6956
SML	LT	-.49661*	.10266	.000	-.7377	-.2555
	SMP	-.03906	.10700	.929	-.2903	.2122
SMP	LT	-.45756*	.10136	.000	-.6956	-.2195
	SML	.03906	.10700	.929	-.2122	.2903

*. Significant at the 0.05 level.

Results for research question two (RQ2): Text segmentation comparison

To address the gap in literature regarding text segmentation characteristics for various screen displays, RQ2 asked if, when specific formatting variables were held constant, do continuous text (TS1), medium text segments (TS2), and short text segments (TS3) compare in terms of:

RQ2a: learning outcomes of a digitally delivered chemistry text lesson?

RQ2b: minimizing cognitive load for a digitally delivered chemistry text lesson?

RQ3c: influencing user perception of a digitally delivered chemistry text lesson?

Results for RQ2a

To answer RQ2a a one-way ANOVA was conducted to determine if there was an association in learning outcomes test scores (LO) by text segmentation (TS1, TS2, TS3). The sample participants were randomly split into three text segmentation groups (N_{TS1}= 262, N_{TS2}= 271, and N_{TS3}=238).

To first ensure that the homogeneity of variance assumption of the ANOVA was met, Levene's test (Levene, 1960) was used to test that variance of each group was equal. It revealed that the variance was roughly equal F(2, 768) = .128, p = .880 and therefore, the assumptions for ANOVA were tenable for this analysis. A one-way ANOVA found no significant effect of text segmentation (TS1, TS2, TS3) on learning outcomes (LO). There was no significant effect of text segmentation on learning outcome, $F(2, 768) = 0.703$, $p = .495$, $\omega^2 = 0$, indicating that the text segmentation used did not directly affect participant performance on the learning outcomes test (Table 4.19). Therefore, the null hypothesis was retained and no post hoc testing was required.

Table 4.19

Summary of ANOVA between Text Segmentation and LO

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	319.204	2	159.602	.703	.495
Within Groups	174390.889	768	227.071		
Total	174710.093	770			

Results for RQ2b

To answer RQ2b, a one-way ANOVA was conducted on each of the cognitive load measurement (CLM) subscales (ICL, ECL, and GCL) to determine if there was an association in cognitive load by text segmentation (TS1, TS2, TS3). The sample participants were randomly split into three text segmentation groups (N_{TS1}= 262, N_{TS2}= 271, and N_{TS3}=238).

Results for analysis of variance between text segmentation and intrinsic cognitive load (CLMICL)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 768) = .310$, $p = .734$. A one-way ANOVA found no significant effect of text segmentation (TS1, TS2, TS3) on intrinsic cognitive load (CLMICL), $F(2,768) = 2.341$, $p = .097$, $\omega^2 = 0$, indicating that the text segmentation accessed did not affect the intrinsic load of the digital material (Table 4.20). Therefore, the null hypothesis was retained and no post hoc testing was needed.

Table 4.20

Summary of ANOVA between Text Segmentation and CLMICL

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	20.640	2	10.320	2.341	.097
Within Groups	3385.221	768	4.408		
Total	3405.861	770			

Results for analysis of variance between text segmentation and extraneous cognitive load (CLMECL)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 768) = 1.330$, $p = .265$. A one-way ANOVA found no significant effect of text segmentation (TS1, TS2, TS3) on extraneous cognitive load (CLMECL), $F(2,768) = .419$, $p = .658$, $\omega^2 = 0$, indicating that the text segmentation accessed did not create extraneous load (Table 4.21). Therefore, the null hypothesis was retained and no post hoc testing was needed.

Table 4.21

Summary of ANOVA between Text Segmentation and CLMECL

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.723	2	2.361	.419	.658
Within Groups	4332.406	768	5.641		
Total	4337.129	770			

Results for analysis of variance between text segmentation and germane cognitive load (CLMGCL)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 768) = .235$, $p = .791$. A one-way ANOVA found no significant effect of text segmentation (TS1, TS2, TS3) on germane cognitive load (CLMGCL), $F(2,768) = 1.164$, $p = .313$, $\omega^2 = 0$, indicating that the text segmentation accessed did not affect the germane load of the digital material (Table 4.22). Therefore, the null hypothesis was retained and no post hoc testing was needed.

Table 4.22

Summary of ANOVA between Text Segmentation and CLMGCL

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	12.306	2	6.153	1.164	.313
Within Groups	4059.357	768	5.286		
Total	4071.663	770			

Results for RQ2c

To answer RQ2c, a one-way ANOVA was conducted on each of the user perception survey (UPS) subscales (PEU, PU, UI, and PS) to determine if there was an association in cognitive load by text segmentation (TS1, TS2, TS3). The sample participants (N = 762)[2] were randomly split into three device groups (N_{TS1}= 256/257, N_{TS2}= 269, and N_{TS3}=236).

[2] Although there were a total of 771 participants, 9 were missing data for the PEU subscale, 10 were missing data for the PU subscale, 10 were missing data for the UI subscale, and 9 were missing data from the PS subscale. As these were all the same participants, it can be speculated that for whatever reason, communication with the database was discontinued at this point.

Results for analysis of variance between text segmentation and perceived ease of use (PEU)

Levene's test indicated that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, F(2, 759) = .455, p = .634. A one-way ANOVA revealed a significant main effect of text segmentation on PEU at the $p < .05$ level, $F(2, 759) = 3.807$, $p = .023$, $\omega^2 = .01$.

Table 4.23

Summary of ANOVA between Text Segmentation and PEU

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.956	2	4.478	3.807	.023
Within Groups	892.868	759	1.176		
Total	901.825	761			

This indicated that the null hypothesis was rejected. Accordingly, the text segmentation accessed had a significant main effect on participant perceived ease of use of learning technology (Table 4.23). The estimated omega squared ($\omega^2 = .01$) indicated that approximately 1% of the total variation in text on PEU is attributable to difference between the three segmentation types (Kirk, 1996). A boxplot visually illustrates the perceived ease of use score means and variance between and within the text segmentation groups (Figure 4.14).

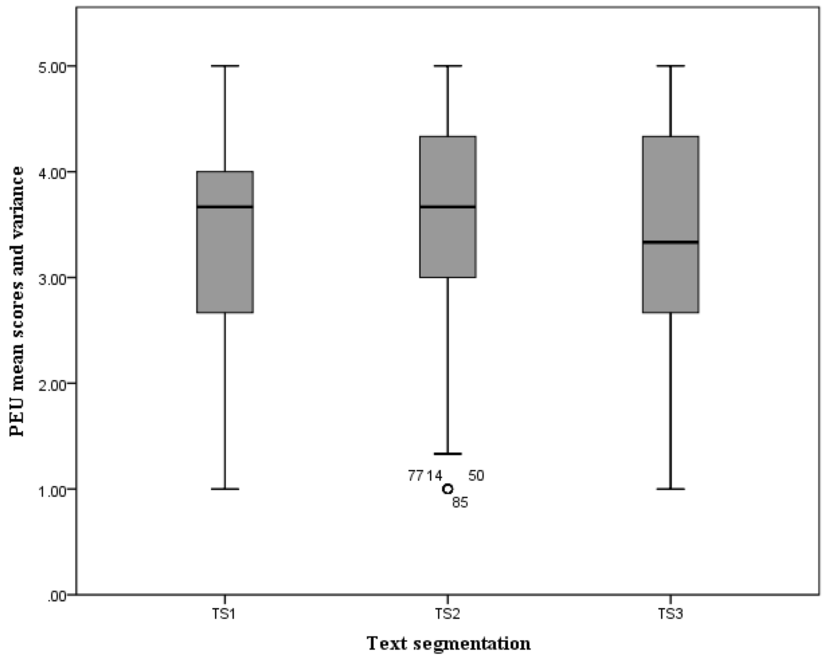


Figure 4.14. Boxplot of text segmentation by perceived ease of use.

Pairwise comparisons were used to further analyze differences in means within text segmentation groups and because the assumptions of ANOVA were met, post-hoc testing was conducted using Tukey's HSD (Table 4.24). The means and standard deviation for the TS1 group was M = 3.36, SD = 1.08. The mean and standard deviation for the TS2 group was M = 3.58, SD = 1.07. The mean and standard deviation for the TS3 group was M = 3.35, SD = 1.10. Tukey's HSD revealed that the mean of the TS2 group was significantly different from the TS1 group, t (759) = 2.36, p = .049, r = .09. The TS2 group was also significantly different from the TS3 group, t (759) = 2.38, p = .046, r = .09. In both cases, the effect sizes were small. There was no pairwise significance between the TS1 and TS3 groups, t (759) = 0.08, p = .997. This indicated that participants in the sample perceived medium text segments to be easier to use than either continuous text or small text segments.

Table 4.24

Tukey's Post Hoc between Text Segmentation and PEU

(I) DEVICE	(J) DEVICE	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
TS1	TS2	-.22313*	.09461	.049	-.4453	-.0010
	TS3	.00759	.09779	.997	-.2220	.2372
TS2	TS1	.22313*	.09461	.049	.0010	.4453
	TS3	.23072*	.09674	.046	.0035	.4579
TS3	TS1	-.00759	.09779	.997	-.2372	.2220
	TS2	-.23072*	.09674	.046	-.4579	-.0035

*. Significant at the 0.05 level.

Results for analysis of variance between text segmentation and perceived use (PU)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 258) = .762$, $p = .467$. A one-way ANOVA found no significant effect of text segmentation (TS1, TS2, TS3) on perceived use (PU), $F(2,758) = 1.469$, $p = .231$, $\omega^2 = 0$, indicating that the text segmentation accessed did not affect the perceived use of the learning technology (Table 4.25). Therefore, the null hypothesis was retained and no post hoc testing was needed.

Table 4.25

Summary of ANOVA between Text Segmentation and PU

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.272	2	2.136	1.469	.231
Within Groups	1102.250	758	1.454		
Total	1106.522	760			

Results for analysis of variance between text segmentation and use intentions (UI)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 758) = 1.410$, $p = .245$. A one-way ANOVA found no significant effect of text segmentation (TS1, TS2, TS3) on use intentions (UI), $F(2,758) = 1.544$, $p = .214$, $\omega^2 = 0$, that the text segmentation used did not affect use intentions of the learning technology (Table 4.26). Therefore, the null hypothesis was retained and no post hoc testing was required.

Table 4.26

Summary of ANOVA between Text Segmentation and UI

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.256	2	2.628	1.544	.214
Within Groups	1289.835	758	1.702		
Total	1295.090	760			

Results for analysis of variance between text segmentation and perceived satisfaction (PS)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(2, 759) = .398$, $p = .672$. A one-way ANOVA found no significant effect of text segmentation (TS1, TS2, TS3) on perceived satisfaction (PS), $F(2, 759) = 1.476$, $p = .229$, $\omega^2 = 0$, indicating that the text segmentation used did not affect overall perceived satisfaction from the learning technology (Table 4.27). Therefore, the null hypothesis was retained and no post hoc testing was required.

Table 4.27

Summary of ANOVA between Text Segmentation and PS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.138	2	2.069	1.476	.229
Within Groups	1063.804	759	1.402		
Total	1067.942	761			

Results for research question three (RQ3): Interaction effects

To address possible interactions between the mobile device (LT, SML, SMP) and text segmentation (TS1, TS2, TS3), RQ31 asked if, when specific formatting variables were held constant, do text segmentation and screen display size and orientation affect:

RQ3a: learning outcomes of a digitally delivered chemistry text lesson?

RQ3b: cognitive load of a digitally delivered chemistry text lesson?

RQ3c: user perception of a digitally delivered chemistry text lesson?

The three mobile device groups were laptop (LT), smartphone landscape (SML), and smartphone portrait (SMP). The three text segmentation groups were continuous text (TS1), medium text segments (TS2), and short text segments (TS3).

Results for RQ3a

To answer RQ3a, a two-way factorial ANOVA was conducted to determine if there was an interaction between mobile device and text segmentation on learning outcome (LO) test scores. The sample participants (N=771) were randomly split into the three mobile device groups (N_{LT} = 292, N_{SML} = 234, and N_{SMP} = 245) and three text segmentation groups (N_{TS1} = 262, N_{TS2} = 271, N_{TS3} = 238).

To first ensure that the homogeneity of variance assumption of the ANOVA was met, Levene's test (Levene, 1960) was used to test that variance of each group was equal.

It revealed that the variance was roughly equal $F(8, 762) = .736$, $p = .660$ and therefore, the assumptions for ANOVA were tenable for this analysis. The two-way factorial ANOVA found no significant main effect of mobile device on learning outcomes (LO) test scores, $F(8, 762) = 1.162$, $p = .313$, $\omega^2 = 0$. There was also non-significant main effect of text segmentation on LO test scores, $F(8, 762) = .688$, $p = .503$, $\omega^2 = .24$. Finally, there were no significant interaction effects between mobile device and text segmentation on LO test scores, $F(8, 762) = .411$, $p = .801$, $\omega^2 = .89$. This indicated that the mobile device and text segmentation used did not affect learning outcomes (Table 4.28). Therefore, the null hypothesis was retained and no post hoc testing was required.

Table 4.28

Summary of ANOVA between Mobile Device and Text Segmentation on LO

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	1211.593[a]	8	151.449	.665	.722	.007
Intercept	4312436.643	1	4312436.643	18940.087	.000	.961
DEVICE	529.059	2	264.529	1.162	.313	.003
TEXT	313.206	2	156.603	.688	.503	.002
DEVICE * TEXT	374.448	4	93.612	.411	.801	.002
Error	173498.500	762	227.688			
Total	4547910.742	771				
Corrected Total	174710.093	770				

a. R Squared = .007 (Adjusted R Squared = -.003)

Results for RQ3b

To answer RQ3a, a two-way factorial ANOVA was conducted to determine if there was an interaction between mobile device and text segmentation on cognitive load. The cognitive load measurement (CLM) had three subscales: Intrinsic cognitive load (CLMICL), extraneous cognitive load (CLMECL), and germane cognitive load

(CLMGCL), therefore, three separate ANOVAs were performed. The sample participants (N=771) were randomly split into the three mobile device groups (N_{LT} = 292, N_{SML} = 234, and N_{SMP} = 245) and three text segmentation groups (N_{TS1} = 262, N_{TS2} = 271, N_{TS3} = 238).

Results for analysis of variance between mobile device and text segmentation on intrinsic cognitive load (CLMICL)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(8, 762) = 2.029$, $p = .041$[3] and therefore, the assumptions for ANOVA were tenable for this analysis. The two-way factorial ANOVA found no significant main effect of mobile device on intrinsic cognitive load (CLMICL), $F(8, 762) = .154$, $p = .857$, $\omega^2 = 0$. There was also non-significant main effect of text segmentation on CLMICL, $F(8, 762) = .2.303$, $p = .101$, $\omega^2 = .52$. Finally, there were no significant interaction effects between mobile device and text segmentation on CLMICL, $F(8, 762) = 2.023$, $p = .089$, $\omega^2 = .82$. This indicated that the mobile device and text segmentation used did not affect the intrinsic load of the digital material (Table 4.29). Therefore, the null hypothesis was retained and no post hoc testing was required.

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[3] Though Levene's was violated for this two-way ANOVA, because significance was very close to .05 and because there was no significance found and effect sizes were relatively small, I opted not to conduct further testing on this specific ANOVA.

Table 4.29

Summary of ANOVA between Mobile Device and Text Segmentation on CLMICL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	58.227a	8	7.278	1.657	.105	.017
Intercept	20476.619	1	20476.619	4660.960	.000	.859
DEVICE	1.356	2	.678	.154	.857	.000
TEXT	20.235	2	10.117	2.303	.101	.006
DEVICE * TEXT	35.542	4	8.885	2.023	.089	.011
Error	3347.633	762	4.393			
Total	24223.874	771				
Corrected Total	3405.861	770				

a. R Squared = .017 (Adjusted R Squared = .007)

Results for analysis of variance between mobile device and text segmentation on extraneous cognitive load (CLMECL)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(8, 762) = 1.592$, $p = .123$ and therefore, the assumptions for ANOVA were tenable for this analysis. The two-way factorial ANOVA found no significant main effect of mobile device on extraneous cognitive load (CLMECL), $F(8, 762) = 1.607$, $p = .201$, $\omega^2 = 1.15$. There was also non-significant main effect of text segmentation on CLMECL, $F(8, 762) = .498$, $p = .608$, $\omega^2 = 0$. Finally, there were no significant interaction effects between mobile device and text segmentation on CLMECL, $F(8, 762) = 1.211$, $p = .304$, $\omega^2 = .80$. This indicated that the mobile device and text segmentation used did not affect the extraneous load of the digital material (Table 4.30). Therefore, the null hypothesis was retained and no post hoc testing was required.

Table 4.30

Summary of ANOVA between Mobile Device and Text Segmentation on CLMECL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	52.458a	8	6.557	1.166	.317	.012
Intercept	7568.657	1	7568.657	1346.035	.000	.639
DEVICE	18.073	2	9.037	1.607	.201	.004
TEXT	5.604	2	2.802	.498	.608	.001
DEVICE * TEXT	27.248	4	6.812	1.211	.304	.006
Error	4284.671	762	5.623			
Total	12012.723	771				
Corrected Total	4337.129	770				

a. R Squared = .012 (Adjusted R Squared = .002)

Results for analysis of variance between mobile device and text segmentation on germane cognitive load (CLMGCL)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(8, 762) = 1.142$, $p = .333$ and therefore, the assumptions for ANOVA were tenable for this analysis. The two-way factorial ANOVA found no significant main effect of mobile device on germane cognitive load (CLMGCL), $F(8, 762) = .249$, $p = .780$, $\omega^2 = .48$. There was also non-significant main effect of text segmentation on CLMGCL, $F(8, 762) = 1.105$, $p = .332$, $\omega^2 = 0$. Finally, there were no significant interaction effects between mobile device and text segmentation on CLMGCL, $F(8, 762) = .533$, $p = .711$, $\omega^2 = .59$. This indicated that the mobile device and text segmentation used did not affect the germane load of the digital material (Table 4.31). Therefore, the null hypothesis was retained and no post hoc testing was required.

Table 4.31

Summary of ANOVA between Mobile Device and Text Segmentation on CLMGCL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	26.432a	8	3.304	.622	.759	.006
Intercept	18498.486	1	18498.486	3484.559	.000	.821
DEVICE	2.644	2	1.322	.249	.780	.001
TEXT	11.729	2	5.865	1.105	.332	.003
DEVICE * TEXT	11.321	4	2.830	.533	.711	.003
Error	4045.231	762	5.309			
Total	22886.938	771				
Corrected Total	4071.663	770				

a. R Squared = .006 (Adjusted R Squared = -.004)

Results for RQ3c

To answer RQ3a, a two-way factorial ANOVA was conducted to determine if there was an interaction between mobile device and text segmentation on user perception. The user perception scale (UPS) had three subscales: Perceived ease of use (PEU). Perceived use (PU), use intentions (UI), and perceived satisfaction (PS), therefore, four separate ANOVAs were performed. The sample participants (N=762) were randomly split into the three mobile device groups (N_{LT} = 289, N_{SML} = 231, and N_{SMP} = 241/242[4]) and three text segmentation groups (N_{TS1} = 256/257, N_{TS2} = 269, N_{TS3} = 236).

[4] Although there were a total of 771 participants, 9 were missing data for the PEU subscale, 10 were missing data for the PU subscale, 10 were missing data for the UI subscale, and 9 were missing data from the PS subscale. As these were all the same participants, it can be speculated that for whatever reason, communication with the database was discontinued at this point.

Results for analysis of variance between mobile device and text segmentation on perceived ease of use (PEU)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(8, 753) = .931$, $p = .490$ and therefore, the assumptions for ANOVA were tenable for this analysis. The two-way factorial ANOVA (Table 4.32) found a significant main effect of mobile device on perceived ease of use (PEU), $F(8, 753) = 10.489$, $p = .000$, $\omega^2 = .85$. Accordingly, the mobile device used had a significant main effect on participant perceived ease of use of the learning technology. The estimated omega squared ($\omega^2 = .85$) indicated that approximately 8.5% of the total variation in device on PEU was attributable to difference between mobile devices (Kirk, 1996). Tukey's HSD revealed that participants in the sample perceived laptops to be easier to use than either smartphone landscape or smartphone portrait (both *p*s = .000). There was no significant difference in perceived ease of use between the smartphone landscape and smartphone portrait groups, $p = .996$.

Table 4.32

Summary of ANOVA between Mobile Device and Text Segmentation on PEU

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	36.173a	8	4.522	3.933	.000	.040
Intercept	8769.402	1	8769.402	7628.198	.000	.910
DEVICE	24.116	2	12.058	10.489	.000	.027
TEXT	8.030	2	4.015	3.492	.031	.009
DEVICE * TEXT	2.689	4	.672	.585	.674	.003
Error	865.651	753	1.150			
Total	9896.434	762				
Corrected Total	901.825	761				

a. R Squared = .040 (Adjusted R Squared = .030)

There was also a significant main effect of text segmentation on PEU, $F(8, 753) = .3.492$, $p = .031$, $\omega^2 = .22$. Accordingly, the mobile device used had a significant main effect on participant perceived ease of use of the learning technology. The estimated omega squared ($\omega^2 = .22$) indicated that approximately 2.2% of the total variation in device on PEU was attributable to difference between mobile devices (Kirk, 1996). Tukey's HSD revealed that participants in the sample perceived medium text segments (TS2) to be easier to use than either continuous text (TS1) or small text segments (TS2) (both *p*s < .05). There was no significant difference in perceived ease of use between the continuous text (TS1) or small text segments (TS2) groups, $p = .997$.

However, there were no significant interaction effects between mobile device and text segmentation on PEU, $F(8, 753) = .585$, $p = .674$, $\omega^2 = 0$. This indicated that the mobile device and text segmentation used did not affect participant perceived ease of use of the learning technology (Figure. 4.15). Therefore, the null hypothesis was retained.

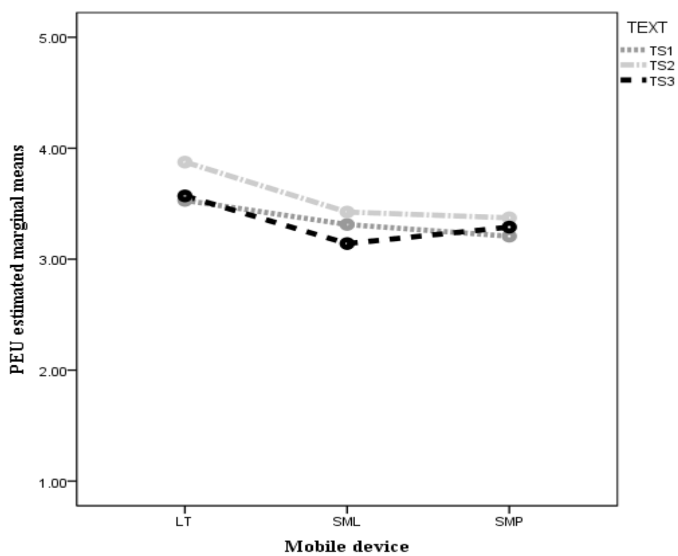


Figure 4.15. Interactions between mobile device and text segmentation on perceived ease of use.

Results for analysis of variance between mobile device and text segmentation on perceived use (PU)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(8, 752) = 1.962$, $p = .05$ and therefore, the assumptions for ANOVA were tenable for this analysis. The two-way factorial ANOVA (Table 4.33) found a significant main effect of mobile device on perceived use (PU), $F(8, 752) = 9.181$, $p = .000$, $\omega^2 = 1.13$. Accordingly, the mobile device used had a significant main effect on participant perceived use of the learning technology. The estimated omega squared ($\omega^2 = 1.13$) indicated that approximately 10% of the total variation in device on PU was attributable to difference between mobile devices (Kirk, 1996). Tukey's HSD revealed that participants in the sample perceived laptops to be more useful than either smartphone landscape or smartphone portrait (both *p*s = .001). There was no significant difference in perceived use between the smartphone landscape and smartphone portrait groups, $p = .993$.

Table 4.33

Summary of ANOVA between Mobile Device and Text Segmentation on PU

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	32.446[a]	8	4.056	2.840	.004	.029
Intercept	7640.566	1	7640.566	5349.442	.000	.877
DEVICE	26.227	2	13.113	9.181	.000	.024
TEXT	3.930	2	1.965	1.376	.253	.004
DEVICE * TEXT	1.871	4	.468	.328	.860	.002
Error	1074.076	752	1.428			
Total	8949.804	761				
Corrected Total	1106.522	760				

a. R Squared = .029 (Adjusted R Squared = .019)

There was also non-significant main effect of text segmentation on PU, $F(8, 752) = 1.376$, $p = .253$, $\omega^2 = .22$. There were no significant interaction effects between mobile device and text segmentation on PU, $F(8, 752) = .328$, $p = .860$, $\omega^2 = 0$. This indicated that the mobile device and text segmentation used did not affect participant perceived use of the learning technology (Figure 4.16). Therefore, the null hypothesis was retained.

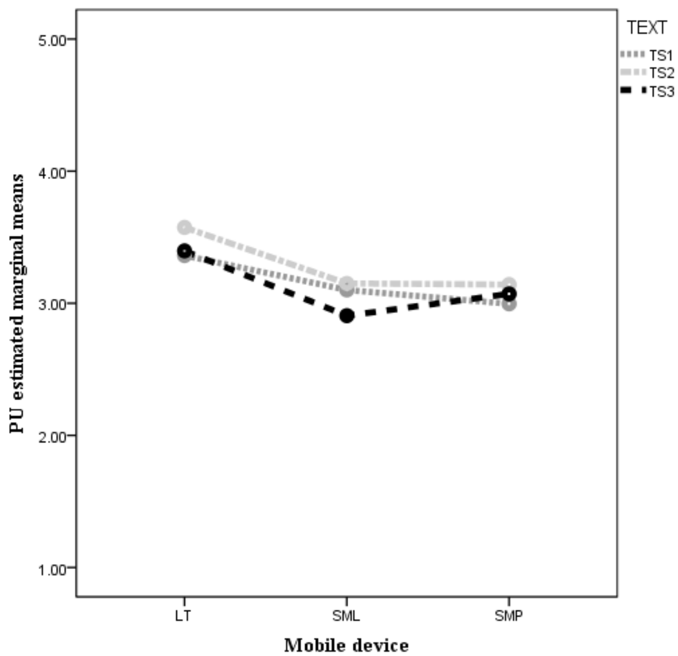


Figure 4.16. Interactions between mobile device and text segmentation on perceived use.

Results for analysis of variance between mobile device and text segmentation on use intentions (UI)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(8, 752) = 1.339$, $p = .221$ and therefore, the assumptions for ANOVA were tenable for this analysis. The two-way factorial ANOVA (Table 4.34) found a significant main effect of mobile device on use intentions (UI), $F(8, 752) = 31.093$, $p = .000$, $\omega^2 = 1.03$. Accordingly, the mobile device used had a significant main effect on participant intentions to use the learning technology. The estimated omega squared (ω^2 = 1.03) indicated that approximately 10% of the total variation in device on UI was attributable to difference between mobile devices (Kirk, 1996). Tukey's HSD revealed that participants in the sample had higher use intentions for laptops than either smartphone landscape or smartphone portrait (both *p*s = .000). There was no significant difference in use intentions between the smartphone landscape and smartphone portrait groups, *p* = .987.

Table 4.34

Summary of ANOVA between Mobile Device and Text Segmentation on UI

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	105.697a	8	13.212	8.353	.000	.082
Intercept	7069.905	1	7069.905	4469.986	.000	.856
DEVICE	98.355	2	49.177	31.093	.000	.076
TEXT	4.944	2	2.472	1.563	.210	.004
DEVICE * TEXT	2.015	4	.504	.318	.866	.002
Error	1189.393	752	1.582			
Total	8632.500	761				
Corrected Total	1295.090	760				

a. R Squared = .082 (Adjusted R Squared = .072)

There was also non-significant main effect of text segmentation on UI, $F(8, 752) = 1.563$, $p = .210$, $\omega^2 = .02$. There were no significant interaction effects between mobile device and text segmentation on UI, $F(8, 752) = .318$, $p = .866$, $\omega^2 = 0$. This indicated that the mobile device and text segmentation used did not affect participant intention to use the learning technology (Figure 4.17). Therefore, the null hypothesis was retained.

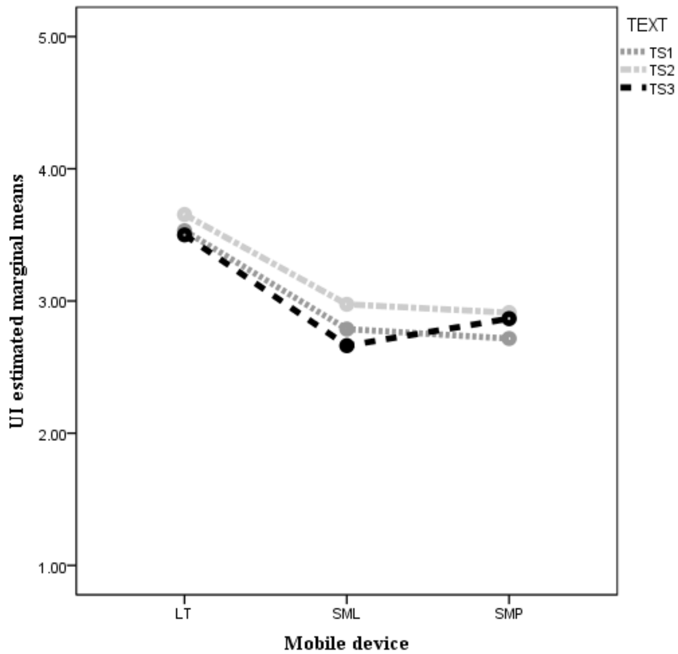


Figure 4.17. Interactions between mobile device and text segmentation on use intentions.

Results for analysis of variance between mobile device and text segmentation on perceived satisfaction (PS)

Levene's test revealed that the homogeneity of variance assumption of ANOVA was met, and the variance of each group was roughly equal, $F(8, 753) = .971$, $p = .457$ and therefore, the assumptions for ANOVA were tenable for this analysis. The two-way factorial ANOVA (Table 4.35) found a significant main effect of mobile device on perceived satisfaction (PS), $F(8, 753) = 15.077$, $p = .000$, $\omega^2 = 1.13$. Accordingly, the mobile device used had a significant main effect on participant perceived satisfaction with the learning technology. The estimated omega squared ($\omega^2 = 1.04$) indicated that approximately 10% of the total variation in device on PS was attributable to difference between mobile devices (Kirk, 1996). Tukey's HSD revealed that participants in the sample perceived more satisfaction with laptops than either smartphone landscape or smartphone portrait (both *p*s = .000). There was no significant difference in perceived satisfaction between the smartphone landscape and smartphone portrait groups, $p = .996$.

Table 4.35

Summary of ANOVA between Mobile Device and Text Segmentation on PS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	47.521a	8	5.940	4.383	.000	.044
Intercept	7186.081	1	7186.081	5302.829	.000	.876
DEVICE	40.863	2	20.432	15.077	.000	.039
TEXT	3.687	2	1.844	1.360	.257	.004
DEVICE * TEXT	2.823	4	.706	.521	.721	.003
Error	1020.421	753	1.355			
Total	8457.875	762				
Corrected Total	1067.942	761				

a. R Squared = .044 (Adjusted R Squared = .034)

There was also non-significant main effect of text segmentation on PS, $F(8, 753) = 1.360$, $p = .257$, $\omega^2 = .03$. There were no significant interaction effects between mobile device and text segmentation on PS, $F(8, 753) = .521$, $p = .721$, $\omega^2 = 0$. This indicated that the mobile device and text segmentation used did not affect participant perceived satisfaction with the learning technology (Figure 4.18). Therefore, the null hypothesis was retained.

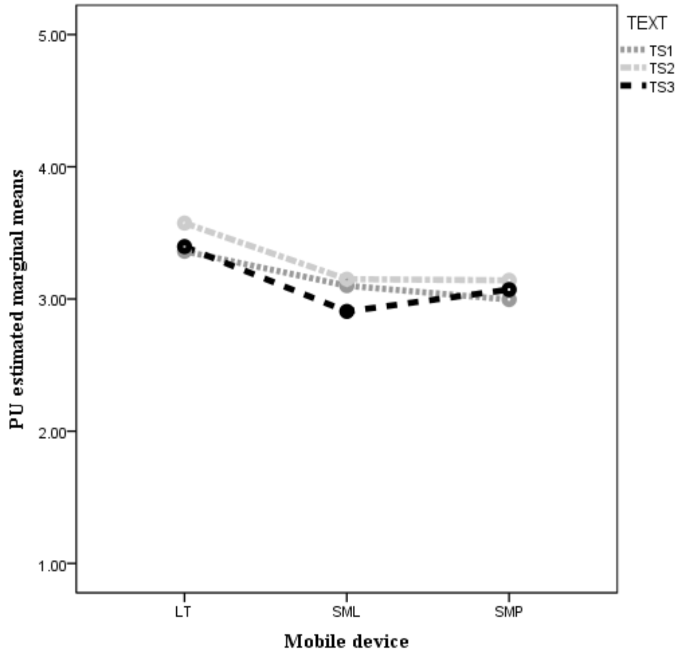


Figure 4.18. Interactions between mobile device and text segmentation on perceived satisfaction.

SUMMARY

A total of 771 students participated in this study. A large majority of the participants owned both laptops and smartphones. In general, the data pertaining to mobile device experience suggested that sample group as a whole had significant experience using mobile devices, but had a somewhat neutral attitude towards mobile learning.

There were two independent variables in this study: mobile device and text segmentation. The independent variable mobile device had three groups, namely laptop (LT), smartphone landscape (SML), and smartphone portrait (SMP). The independent variable text segmentation had three groups, namely continuous text (TS1), medium text segments (TS2), and small text segments (TS3).

There were three main dependent variables. The first was the learning outcomes (LO) 15 item test gauged to measure digital content recall. The second dependent variable, the cognitive load measurement (CLM), had three subscales that measured intrinsic cognitive load (CLMICL), extraneous cognitive load (CLMECL), germane cognitive load (CLMGCL). The reliability findings for the CLM indicated that all three subscales had high intrinsic reliability and were therefore good measures of cognitive load. The third dependent variable, the user perception survey (UPS), had four subscales that measured perceived ease of use (PEU), perceived use (PU), use intentions (UI), and perceived satisfaction (PS) of the learning technology. The reliability findings for the UPS suggested all four subscales had high intrinsic reliability and were therefore good measures of user perception.

The results for research question one (RQ1) found significant main effects of mobile device on all four UPS subscales: perception of ease (PEU), perceived use (PU), use intentions (UI), and perceived satisfaction (PS). Post hoc testing revealed that in all four cases, laptops had significantly higher means than either smartphone landscape or smartphone portrait, while there was not a significant difference between smartphone landscape and smartphone portrait. No significant effects of mobile device were found on learning outcomes (LO), intrinsic cognitive load (CLMICL), extraneous cognitive load (CLMECL), or the germane cognitive load (CLMGCL).

The results for research question two (RQ2) only found a significant main effect of text segmentation on perceived ease of use (PEU). Post hoc testing indicated that medium text segments had higher means than continuous text or small text segments. No significant effects of text segmentation were found on learning outcomes (LO), intrinsic cognitive load (CLMICL), extraneous cognitive load (CLMECL), the germane cognitive load (CLMGCL), perceived use (PU), use intentions (UI), or perceived satisfaction (PS).

The results for research question three (RQ3) found no significant interaction effects between mobile device and text segmentation on any of the dependent variables. The implications of these results will be presented in Chapter Five, along with the limitations of the study, suggestions for future research, and concluding remarks.

Chapter 5: Discussion

This research applied a quantitative methodology to make three main comparisons about mobile device screen displays and text segmentation, the results of which will help fill gaps in the current body of literature on mobile learning, specifically instructional design principles for smartphones. This study first compared large and small screen mobile displays for learning, namely laptops and smartphones, using device specific design approaches, rather than a one-design fits all approach. This comparison included examining distinctions in screen orientation for mobile learning, namely landscape and portrait orientation for learning from smartphones. The second comparison highlighted possible differences in learning from three distinctive text segmentation lengths, namely continuous text, medium text segments, and small text segments. The final comparison looked at possible interaction between mobile device screen display size and orientation and text segmentation.

Learning outcomes, cognitive load, and user perception were measured to assist in these comparisons. Learning outcomes measured whether or not participants could recall the content following each treatment. However, learning recall offers only one point of reference for determining if a particular treatment was successfully designed and/or was advantageously delivered given the display size and orientation (Churchill & Hedberg, 2008; D. Kim & Kim, 2012; Molina et al., 2014). Measuring for cognitive load added perspective on participant experiences learning with each treatment by demonstrating whether students were cognitively overloaded, under loaded, or remained successfully in the ZPD (Schnotz & Bannert, 2003; Schnotz & Kürschner, 2007). Positive user perception has been demonstrated by the literature as a viable piece of total mobile learning success (Hwang et al., 2011; Sanchez & Goolsbee, 2010; Seraj & Wong, 2014; Terras & Ramsay, 2012; Traxler, 2005; Valk et al., 2010; Y.-S. Wang et al., 2009; Yau &

Joy, 2010). It is thus important that the treatments not only produced positive learning outcomes and minimized cognitive load, but also were viewed positively by the participants.

This final chapter interprets the research findings of each research question group, and then follows each with implications for instructional design of mobile learning. Next, recommendation for future research that lends itself to continuing this study is provided. Finally, the limitations of this study are presented.

INTERPRETATION AND IMPLICATIONS OF FINDINGS

The demographic data helped define the context of the study in terms of the participants and possible generalizations that can be made from the outcomes of this particular sample group. A majority of the participants were 18 and 19 years old, and in this regard, have probably grown up with mobile devices. As such, the participants were generally well experienced with mobile devices, both laptops and smartphones. This is supported by the findings of the mobile device experience (MDE) survey. Additionally, a majority of the participants had grade point averages of B or higher, suggesting that they were relatively high academic achievers. It is important to note, therefore, that the context and demographics of this particular situation and sample group should be factored in when compared with sample groups of different demographics. This point is addressed in detail in the future research section below, but it is important to keep in mind as the findings are discussed.

Sanchez and Goolsbee (2010) noted the prevalence of smartphones among both professionals and students, consequently raising expectations for smartphone integration into school, work, and life. This is supported by national statistics that found 78% of students have regular access to a mobile device (ICEF Monitor, 2014). It has also been found that while the laptop is presently the most owned mobile device at 85%, smartphone ownership continues to increase as today's high school students become tomorrow's collegiates (Reidel, Chris, 2014). Interestingly, the demographics from this study suggest that these numbers are significantly higher in the sample than suggested. In fact, while nearly 90% of participants owned laptops, 97% owned smartphones.

The mobile device experience (MDE) survey gauged participant experience and expertise with mobile devices (Molina et al., 2014). With a mean score of 4.27 out of 5, the participants considered themselves nearly expert in the use of mobile devices (specifically smartphones). While they felt more than comfortable using their mobile devices generally, they were slightly less accustomed to using mobile devices in educational contexts. However, while students did think that mobile devices were useful in educational contexts and for studying, there remained a propensity towards using desk top and printed materials for study. There is some discrepancy as to whether all participants had the same definition of mobile devices, and this may have influenced the responses. Generally speaking, however, the group was well adept at and comfortable with interacting with both laptops and smartphones.

Mobile display size and orientation comparison (RQ1)

To address the gap in literature concerning mobile device displays when the learning design was tailored specifically to the device, this study compared mobile display screen size and orientation of a digitally delivered chemistry text lesson. It used learning outcomes (RQ1a), cognitive load (RQ1b) and user perception (RQ1c) to compare treatments. Learning outcome and cognitive load were found unaffected by mobile screen display size and orientation, while user perception was higher for laptops than for smartphones, regardless of orientation.

Specific to learning outcomes, cognitive load, and user perception

The study revealed that learning outcomes were not affected by the mobile screen display size or orientation (RQ1a). This challenges the findings of numerous studies that learning is reduced when content is delivered on a small display (Churchill & Hedberg, 2008; Jones, Buchanan, & Thimbleby, 2003; Vogt, Schaffner, Ribar, & Chavez, 2010). Churchill and Hedberg (2008) in their qualitative study with educational professionals found that small screens were a key detriment to learning from handheld devices. This further challenges the findings that compared to laptop displays, smartphones screens do not provide a comparable learning experience and are therefore harder to learn from (Heo, 2003; D. Kim & Kim, 2012; Luong & McLaughlin, 2009; Molina et al., 2014). Kim and Kim's (2012) study including one hundred and thirty-five Korean middle school students for example, found that large screens were more effective than small screens for learning English vocabulary. In their study with twenty-six higher education computer science students, Molina et al. (2014) compared large, medium, and small mobile device screens for learning and also found that participants both learned better from and preferred larger screens to medium and small screens.

These results of this study further dispute previous research findings that landscape orientation is better for learning than portrait orientation when small screen displays are used for delivery (Churchill, 2011; Churchill & Hedberg, 2008; Sanchez & Branaghan, 2011; Sanchez & Goolsbee, 2010). In their study with thirty-four higher education psychology students, Sanchez and Branaghan (2011) found that landscape orientation eliminated a reasoning deficit when compared to portrait orientation.

The study additionally revealed that the variations in screen display size and orientation did not affect the working memory differently (RQ1b). This was true for intrinsic cognitive load (CLMICL), meaning what is required to know the element itself

(Sweller, Merrienboer, & Paas, 1998) or how two elements interact (Paas, Renkl, & Sweller, 2004), as well as for extraneous cognitive load (CLMECL), which occurs when the learning design includes material and activities that are outside of, or 'extra' to what is to be learned (Chandler & Sweller, 1991; Paas et al., 2004; Sweller, 1988). The results found similarly that germane cognitive load (CLMGCL), which fosters active schema construction processes and is beneficial to learning (Hollender et al., 2010; F. G. W. C. Paas & Merriënboer, 1994), did not vary based on display size and orientation.

These results counter the findings of Ng and Nicholas (2009) and Wang and Shen (2012) which both asserted that overload occurred when participants accessed full content on a small screen. They also contradict the results of Molina et al. (2014), who found in their comparison of PCs, tablets, and smartphones with twenty-six higher education students that given the same content students experienced less cognitive overload from PCs before tablets, and both PCs and tablets, before smartphones.

Unlike the findings of RQ1a and RQ1b from this research question group, this study found that user perception was affected by the screen display size of the device used (RQ1c). This was true for all four subscales of user perception, including perceived ease of use (PEU), perceived use (PU), use intentions (UI), and perceived satisfaction (PS). Additional results indicated that participants in the sample felt laptop screens were more acceptable for accessing the digital chemistry text than smartphone screens, though only by a small margin. Screen orientation however, did not seem to have an effect on user perception.

According to the Technology Acceptance Model (TAM), this means that overall user acceptance of the specific technological tool for the task at hand was lower for smartphones in this particular instance than for the larger-screened laptops (Davis, 1985, 1989; Davis et al., 1989; Legris et al., 2003; Venkatesh et al., 2003). This supports the findings of Crescente and Lee (2011), Churchill and Hedberg (2008), and Pea and Madonado (2006), all of which found that small screen displays seemed to impede user acceptance of mobile learning. However, this specific finding contradicts that of Sung and Mayer (2013) who found in their study with eighty-nine college psychology students that student enjoyment of smaller screens increased motivation to learn. This is not to say that participants who used smartphones did not like them. In fact, the average score for all UPS subscales were closer to strongly agree on the five item scale than to strongly disagree. Rather, it suggests that under these treatment and research conditions, laptops were perceived with slightly higher regard in terms of usefulness for learning and satisfaction.

Implications for instructional design

From a design perspective, these findings add detail to some blurry aspects of the mobile learning research picture, including the impact of dedicated mobile applications on learning, the differences in screen display orientation on learning, the extraneous load added by the device itself, and the influence of user perception on learning.

This study specifically looked at the screen display size comparisons when the learning design was customized to the device, verses retro-fitted from a larger display. Current research suggests that larger screens are better for learning (Kim & Kim, 2012; Molina et al., 2014; Reeves et al., 1999), without expounding on appropriate design except to say to design for eLearning and convert to mobile learning (M. Wang & Shen, 2012). Creating dedicated smartphone applications, tailored to the device did seem to equalize the learning between groups, such that no group significantly outperformed another group. This lends evidence to the notion that instructional design must consider the device(s) used for delivery.

In terms of screen display orientation, this study indicated that the orientation of the screen has less of an impact than suggested in the literature (Churchill, 2011; Churchill & Hedberg, 2008). While there remain questions as to why this mattered less than suggested, there nevertheless seemed to be little distinction between landscape and portrait orientation in terms of learning outcomes, cognitive load, and user perception.

With regard to reducing cognitive overload, eliminating extraneous content unnecessarily added by the design is among the first recommendations (Ayres & Paas, 2012; Brunken et al., 2003; Chandler & Sweller, 1991; Mayer, 2009; Mayer & Fiorella, 2014; Sweller et al., 2011). In terms of the cognitive load effects specific to small screen mobile devices, Liu, et al. (2013) asserted that extraneous load exists in part just by interacting with the smartphone itself.

Findlater and McGrenere (2008) noted that the limited display size of small screen mobiles force designers to split content onto multiple screens. In this way, the split attention effect can be a form of extraneous cognitive load, when it is caused by the design and presentation of instruction (Liu et al., 2013; Paas et al., 2004). According to Sweller, et al., split attention is a common design flaw (Kalyuga, Chandler, & Sweller, 1999; Sweller, 2002; Sweller et al., 1998). In fact, several studies about small screen mobile devices have reproduced split attention effect, mainly because the small display breaches the spatial and temporal contiguity of the learning content (Austin, 2009; Keefe et al., 2012; Kim & Kim, 2012; Liu et al., 2013, 2012; Luong & McLaughlin, 2009; Maniar et al., 2008; Molina et al., 2014).

However, in the present study, participants reported only low levels of extraneous load, suggesting that designing a simple, dedicated, and learner-controlled user interface seemed to eliminate unnecessary cognitive load. This may explain why students remained in the zone of proximal development despite slightly elevated intrinsic load ratings

(Hassanabadi et al., 2011; Mayer & Chandler, 2001; Schmidt-Weigand et al., 2010; Schüler et al., 2013; Spanjers et al., 2012; Sung & Mayer, 2013; Tabbers, 2002).

Finally, user perspective on both the use of mobile devices for learning and the engagement and enjoyment of the learning applications are paramount for determining the success of mobile learning (Seraj & Wong, 2014). If learning satisfies with the learner, it will positively influence their success with mobile learning. Iqbal and Qureshi (2012) called this perceived usefulness. If learning is about the learner, then design of mobile learning should be user-focused, (Hwang, Shi, & Chu, 2011; Sharples et al., 2007; Valk et al., 2010). In fact, the general consensus of the literature on the matter is that negative user perception of a mobile learning component impedes its success in education (Park, 2011; Pea & Maldonado, 2006).

While positive user perception of mobile learning is in fact critical for overall success, the results of this study indicated that it is not necessarily linked to increased or decreased learning outcomes. In other words, no matter the mobile device, learning occurred even when individual participants registered lower user perception scores, suggesting that instruction design of mobile learning requires approaching design and implementation from multiple directions for success.

Text segmentation comparison (RQ2)

To address the gap in literature regarding text segmentation characteristics for various screen displays, this study compared three segmentation variations of a digitally delivered chemistry text lesson, namely continuous text, medium text segments, and small text segments. The study sought to determine which was most beneficial for reading comprehension when low prior-knowledge learners accessed high intrinsic cognitive load text via laptop and smartphone. Learning outcomes (RQ2a), cognitive load

(RQ2b), and user perception (RQ2c) were used to compare treatments. The results for RQ2 revealed that learning outcomes and cognitive load were unaffected by text segmentation. Of the four user perception subscales, only perceived ease of use (PEU) was affected by the variations in text segmentation. The other three UPS subscales were unaffected by text segmentation treatments.

Specific to learning outcomes, cognitive load, and user perception

The results indicated that learning outcomes were not affected by text segmentation (RQ2a). These results supported previous findings that text seemed to produce the most cued and free recalled details (Furnham, Gunter, & Green, 1985). Learning outcomes may have been relatively similar between text treatments because the design of the chemistry lesson allowed for the readers to implement reading comprehension strategies (Byrne & Curtis, 2000; Furnham, 2001; Furnham et al., 1990), which include pausing (Hassanabadi et al., 2011), rereading (Hyönä and Nurminen, 2006; Schmidt-Weigand et al., 2010), and learner-paced processing (Mayer, 2003; Spanjers et al., 2012).

However, the results challenge the notion that segmentation is only beneficial if the content is cut into ***meaningful*** chunks (Ayres & Paas, 2012; Mayer, 2003; Mayer & Chandler, 2001; Mayer & Moreno, 2002; Paas et al., 2003; Spanjers et al., 2012; Wong et al., 2012), which Spanjers et al. (2012) explain help foster understanding by eliminating the need for learners to create their own meaningful segments of information.

These findings that there were no significant differences in learning outcomes by text segmentation treatment conflict with some studies on the multimedia and modality effects which suggest that reading continuous text produces higher cognitive load and therefore prevents recall (Mayer, 1999; Schüler et al., 2011).

The study additionally revealed that the variance in text segmentation did not impact the working memory differently (RQ2b). This result challenges previous studies which found meaningful pieces of content caused less cognitive overload than continuous text (Ayres & Paas, 2012; Mayer, 2003; Mayer & Chandler, 2001; Mayer & Moreno, 2002; Paas et al., 2003; Spanjers et al., 2012; Wong et al., 2012). Accordingly, performance was observed to be best when the content segments were pre-determined (Hassanabadi et al., 2011; Spanjers et al., 2010), as opposed to self-segmented by the students. Moreno (2007) for example, showed participants shown segmented content outperformed participants who were shown continuous content on transfer tests.

While these findings do counter those of numerous studies, there may be an explanation for this discrepancy, in that the learner-controlled nature of the treatments allowed the participants to control the pace of learning, thus minimizing extraneous load and enhancing the capabilities of the working memory to process information (Liu, Lin, Tsai, & Paas, 2012; Mayer, 2003; Spanjers et al., 2012; Tabbers, 2002). When text is written, a reader can skip extraneous passages that are either not relevant or are too difficult to understand and concentrate on the more important parts of the text (Schüler et al., 2013, 2011). Additionally, it is important to note here that the context of this study and participant sample may account for some of those differences given device familiarity and academic achievements of the participants. However, the extent of such a determinant cannot be fully known under the current conditions of the study.

Surprisingly, even though the small text segments were segmented using a two-three sentence rule and not “meaningful” chunking, causing content to be cut mid explanation, this appeared not to cause the cognitive overload resulting from split attention effect. Split attention effect occurs when a learner must integrate multiple sources of information in order to understand it, such that the individual pieces of information cannot be understood in isolation (Ayres & Sweller, 2005; Hollender et al., 2010; Kalyuga et al., 1999; Mayer & Fiorella, 2014; Sweller et al., 1998). The process of holding information in working memory, while simultaneously attempting to integrate it with other information is cognitively demanding (Cierniak et al., 2009; Kalyuga et al., 1999; Mayer & Moreno, 1998). The results of this study challenge previous studies which found split attention effect was especially true for low prior knowledge learners or novices who are viewing high intrinsic cognitive load material (Ayres & Sweller, 2005; Chandler & Sweller, 1991; Florax & Ploetzner, 2010), which is the exact relationship of the participants to the learning content of this study. In other words, the participants in this study had not examined the material in question, which the faculty assured was of high intrinsic load, making those students novices to some degree.

As pertains to user perspective, only perceived ease of use (PEU) was affected by text segmentation (RQ2c). Participants with the medium text treatments gave higher ratings for PEU than did participants with continuous and small text segment treatments. There were no differences between text segmentation treatments by perceived use (PU), use intentions (UI), and perceived satisfaction (PS).

Implications for instructional design

In terms of instructional design, the RQ2 results spark an interesting conversation pertaining to reading comprehension and the segmentation effect, as they inform the active segmenting of content by instructional designers. Segmentation of text provides learner-controlled (Hassanabadi et al., 2011; Sung & Mayer; 2013), or automatic pauses (Mayer & Chandler, 2001), which break up the transience of dynamic text (Spanjers et al., 2012). Pauses allow the readers to catch up (Mayer, 2003), reread for better understanding (Byrne & Curtis, 2000; Furnham et al., 1990, 1988; Hyönä & Nurminen, 2006; Kozma, 1991; Schmidt-Weigand et al., 2010; Schüler et al., 2011), and process the new information before moving on (Spanjers et al., 2010). Implementing text comprehension strategies (Furnham et al., 1990) allows readers to read at their own pace (Schüler et al., 2011). In this study, participants may have used these strategies no matter the treatment, which may account for the lack of significance differences between said treatments.

However, the segmentation effect (Mayer & Moreno, 2002, 2003) of the Cognitive Load Theory, specifically states that "segments" are learning pieces that have been divided into meaningful content chunks (Ayres & Paas, 2012; Mayer & Chandler, 2001; Wong et al., 2012). Pre-segmented content provides cues or signals to learners about boundaries of meaning (Moreno, 2007) which reduce cognitive load by removing that task from the working memory process. This in turn helps learners integrate information from the recent past to improve predictions about the near future (Kurby & Zacks, 2008), leading to an increase in what can be learned (Spanjers et al., 2010, 2012). Segmentation of text specifically was found to improve text comprehension (Ayres & Paas, 2012; Florax & Ploetzner, 2010), as segments inform learners how to create meaning units of the material (Florax & Ploetzner, 2010).

In this study, it can be said that all three treatments were technically segmented. They were cut into chunks based on screen real estate (continuous text), as well as by the meaningful beginning and end of content (medium text segments), and finally by a sentence limiting rule (small text segments). No treatment outperformed the other when measured for learning outcomes and cognitive load. In this way, the findings contradict the idea that learning only benefits from segmentation when content is segmented into meaningful pieces, for although the various segmentation treatments seemed to generally benefit from segmentation, they did not fully meet the criteria for segmentation defined by previous studies.

Interactions between mobile device and text segmentation (RQ3)

The final set of research questions looked for possible interactions between mobile screen display size and orientation and text segmentation on learning outcomes (RQ3a), cognitive load (RQ3b) and user perception (RQ3c). Results indicated no interaction effects between mobile device screen display size and orientation and text segmentation. In other words, there was no statistical association between screen size/orientation and text segmentation on learning outcomes, cognitive load, or user perception. This is not to say that individual participant results were not a result of both the device and the text treatment. Rather, this indicates that there was so little variance in the treatment means that an affect was not found.

FUTURE RESEARCH

This study laid the empirical foundation for numerous future studies that could help identify and explore learning design principles for mobile devices in authentic ways.

Mobile smartphone applications

Given the low occurrence of dedicated mobile application development for the empirical study of mobile learning, future research will need to begin analyzing how such specifically designed applications influence learning and learner motivation. A majority of earlier studies did not design dedicated smartphone applications that allow for maximum control over screen real estate and content interactions. Perhaps limited by capacity, budget, or time, several studies used simulated small screen displays instead of real mobile devices (Kim & Kim, 2012; Luong & McLaughlin, 2009). While still valuable in terms of findings, such studies lack an authentic mobile/smartphone experience, which could potentially influence the results.

Some studies did use mobile devices, but offered few details as to the thought process behind the design (Heo, 2003; Keefe et al., 2012; Liu et al., 2013, 2012; Reeves, et al., 1999; Sung & Mayer, 2013). Others created mobile web applications (Molina et al., 2014) (as opposed to dedicated mobile applications), in which the screen display was decreased and manipulation of the content was limited by the web browsers (Churchill, 2011). Though some studies examined the effectiveness of specific dedicated mobile applications (Liu et al., 2013; Seraj & Wong, 2014), they offered little in the way of generalizable and actionable design principles. Additionally, it appeared that many of the studies comparing large and small screen displays retrofitted the design of the large screen for the small one (Churchill & Hedberg, 2008; Molina et al., 2014). Some even recommended that this process was ideal for smartphone learning, i.e., design for eLearning, then fit for mobile (Ahmadi & Kong, 2012; Churchill, 2011; Wang & Shen, 2012). This does not take into account, however, the differences in touchscreen, size, interaction capabilities, and user expectations. Smartphones offer a completely different ergonomic experience than a desktop PC or laptop (Maniar et al., 2008; Seraj & Wong, 2014). There are differences even in the way human eyes are capable of viewing the screens (Seraj & Wong, 2014).

This study created two dedicated smartphone applications, recorded the design and development process, and specifically compared these smartphone applications to one another and to a web version of the application. The results already contradicted earlier studies. Future research that would build upon this must include the creation and testing of dedicated applications, both in terms of design process and implantation. The results of such studies will help further identify repeatable and generalizable design principles for mobile learning.

Dedicated smartphone applications verses mobile web applications

Another interesting possibility for future research would, in a similar vein as this study, compare dedicated smartphone applications with web applications accessed via smartphones instead of laptops. This way, all treatments would be accessed via smartphone, allowing the researcher to compare dedicated smartphone applications with mobile web applications accessed from the same screen size. This would help identify any differences between dedicated and mobile web apps that may influence design choices for smartphone learning.

Text segmentation criteria

Given the results in this study, there seems more still to learn about text segmentation principles for small screen mobile devices. RQ2 identified that medium text was perceived as easier to use in this circumstance, but there is no way to determine why this is under the current study. Text comprehension research suggests that in instances like this one, where the text is long and has high intrinsic cognitive load, text is superior to audio/visual and/or audio (Fournier, 2013; Kalyuga, 2000; Kintsch, 1994; Mannes & Kintsch, 1987; Schüler et al., 2013; Schüler et al., 2012), however there is little beyond that to inform design choices for small screens. Though studies on the reverse modality effect questioned the superiority of dual-modal presentation for learning, there remains a question about how to craft a single-mode presentation of materials through the lens of Cognitive Load Theory (CLT) and the Cognitive Theory of Multimedia Learning (CTML), in other words, how to craft such presentations in ways that minimize cognitive overload and promote schema construction and automation. Kintsch (1994) and

McNamara et al. (1996) distinguished that elaborately descriptive passages work best for novices, while simple passages, with limited descriptions work better for experts. Outside of this recommendation, there is little offered in the way of how to design appropriate text-only passages, much less in terms of constructing this type of learning for a small screen mobile display. Eitle et al. (2013) even admitted that their study did not aim to find the "optimal way to present text and pictures with regard to learning success" (p. 60). Hassanabadi et al., (2011) noted that future research should examine the critical role of segmentation length, pointing out that length of segments is different than how much is on screen. Segmentation is an important design implication for mobile learning (smartphones specifically) because the limitations of the screen displays may require different or extra criteria for proper segmentation. This study identified that medium-sized segments may be preferred in mobile settings, but there is still much to learn.

Dual- and multi-modal instruction

Sung and Mayer (2013) suggest that cognitive design principles work across devices and this has been supported by other recent studies (Ayres & Paas, 2012; Sweller et al., 2011; Wong et al., 2012). However, these principles are generally applied to the design as a whole. They do not advise on how to design efficient individual elements. In the case of single modal instruction (i.e. pictures only, text only), there are limits to applying them (Reimann, 2003). This study used the segmentation effect and reading comprehension strategies to dissect chemistry text into large, medium, and small pieces to determine the best text length for web and mobile applications.

While split attention effect is more straightforwardly mitigated because it is easier to identify and the design recommendations for avoiding it are somewhat specific, even for small screen mobile displays, the modality effect adds a layer of design complexity.

Several studies (Ginns, 2005; Hassanabadi et al., 2011; Kalyuga et al., 2000; Reimann, 2003; Savoji et al., 2011; Schmidt-Weigand et al., 2010) mention the relationship between prior-knowledge and the occurrence or disappearance of cognitive load effects given this range of novice to expert. In cases where the material has high intrinsic cognitive load and the learners are novices, Mayer (2003, 2005, 2009) recommends a dual-modal approach. In some cases, however, the material does not lend itself to images, and/or is more complex than can be communicated through audio/visual presentation.

Meanwhile, smartphone users have certain expectations for interacting with their smartphones. Future research might build upon this study by exploring ways to combine text segmentation with audio, visual, and interactive elements in ways that maintain proper levels of cognitive load, while also increasing learning and user perception. Such specific design principles would be extraordinarily useful.

About laptops

The literature is clear that positive user acceptance and perspective of any mobile learning platform is crucial for its success (Mostakhdemin-Hosseini, 2009-1; Terras & Ramsey, 2012; Bhaskar et al., 2010). This study found that for this specific activity, laptops were slightly more accepted by participants than smartphones. Future studies that explored exactly why this is might help smartphone application designers improve learning design to equalize this difference.

Application within various contexts

The context of this study was very specific in that it was conducted in a higher education chemistry course, in which students were close to the same age, had regular access to and extensive experience with mobile devices and online content, and were academically high achieving students. Conducting this study under different circumstances and with a different participant group may affect the results. Future research, therefore, might conduct a similar study with different age groups. A middle school group, for example, may produce different results given that they have never known a time without smartphones. While a group of older participants may result in completely different findings given they may not operate smartphones with the same level of expertise as the participants in this study.

Future research might consider conducting this study outside of the formal education setting, maybe in an office setting or an informal learning setting. For example, conducting a similar study inside a large company may reveal quite different findings if work content was delivered in ways similar to this study.

Future research might conduct the similar studies using different content to determine if mobile device and text segmentation would unveil similar findings in various content areas. A history text, for example, may be received differently than a chemistry text when presented in this way. Such studies would be important in better understanding if design principles are really universal, or if instead, they are better practiced in only limited educational contexts.

Expanding learning outcomes

Finally, this study looked at immediate recall of the material, called learning outcomes for the purposes of this study. However, simply measuring immediate recall offers only one small piece of understanding the depth of learning in this scenario. Future research that conducts similar studies might consider examining postponed recall, retention over time, and transfer of knowledge.

LIMITATIONS OF THIS STUDY

This research had known technology, design, execution, and measurement limitations. From a technology perspective, this study did not include all of the possible comparisons. A full comparison would have included treatments that accessed the web application using a smartphone through the mobile web, as well as, a laptop treatment that was downloaded to the laptop like a software program and accessed outside of the web browser. Making this comparison in a balanced way would have required both web and dedicated treatments be created for all devices, which would have increased the number of participants required and extended the workload beyond the boundaries of practicality considering time and budget. The comparison between web and dedicated applications is an important one that should be examined in the future.

A second limitation (both a technology and design condition) of this study was that navigation and input of the learning module differed between the laptops, which used both mouse/click navigation and touchscreens, and smartphones, which had touchscreens. Touchscreen technology offers a unique experience to the user. There are numerous studies on touchscreen technology (see Brasel & Gips, 2014; Fong-Gong Wu, 2011a, 2011b; Shamus P. Smith, 2012; Sunghyuk Kwon, 2010). While this is an interesting facet of mobile technology to research, the touchscreen interaction was not a focus here. To mitigate this limitation, the applications were designed with minimal navigation; however it is not known what affect device input and navigation had on learning outcomes, cognitive load, or user perception.

A third limitation of this study appertained to the lack of control over the mobile devices of the participants, which spanned consumer brands, operating systems, and size variations. While these differences may have had no effect on the results, there was no way to either (a) control for all variables, or (b) assign weight to possible associations on the results. Without providing a thousand devices, this may always be a limitation of this type of study.

A fourth limitation of this study was time span. This study was completed within a single class period (from the student's perspective). Therefore, some of the self-reported answers may have been influenced (in positive and negative ways) by the brevity of the study. Learning outcomes, cognitive load, and user perception may change if the participants accessed material in similar ways all semester long, or over the course of several weeks. In this way, this particular study provides only a snapshot of a moment of learning, rather than a long-term learning experience.

A final limitation concerned the learning outcomes test. The current study only measured immediate recall given the parameters of the data collection environment and limited access to the participants in that setting. However, measuring for transfer and retention over time might reveal the long-term learning potential of such text and device treatments. This is an area where future research would mostly likely unveil more specific learning design guidelines. It would additionally, allow for the creation of empirically validated instruments and pre- and post-tests.

SUMMARY

There is much yet to add to our understanding of mobile learning design, specific to smartphones. This research verified the proliferation of smartphones in the fabric of higher education and the expertise with which students utilize the devices. While smartphones are abundant among higher education campuses, they are not yet utilized at length in the classrooms. In part, this is true because there is a decided lack of customized, dedicated applications for use in higher education classrooms.

Designing effective learning applications for smartphones requires accurate design principles. Such principles can only be authenticated under circumstances similar to those with which mobile device users are accustomed. In this way, the look, feel, and interaction of the applications under study must replicate those applications preferred by the users. Three dedicated applications were designed for this study and the results challenged findings from previous studies that did not use dedicated applications, demonstrating the importance of authentic delivery.

This study used learning outcomes, cognitive load, and user perception to help gauge the effects of mobile device display size and orientation, as well as text segmentation on learning outcomes, cognitive load, and user perception. The findings suggested that when learning is designed for the device, the gap between learning from smartphones and laptops is diminished, although user perception may still vary. Empirical exploration of the pros and cons of mobile learning design principles will require measuring learning applications in multiple ways, so a more complete picture can be drawn.

Finally given the required cost and development time, it would be ideal if researchers could work together and build on or improve dedicated applications such that researchers are not required to start from scratch with every query. This would save time and money, as well as allow for expanding research.

Appendix

APPENDIX A: DEMOGRAPHIC AND MOBILE LEARNING PROFILE (DMLP)

DMLP = 16 total items

Social demographic items (SD) – 3 items *(single selection)*	
SD1	Gender: Male, Female
SD2	Race: Caucasian, Black, Hispanic, Asian, Other
SD3	Age: Under 18, 18, 19, 20, 21, 22, 23, 24, 25, Over 25
SD4	What was your GPA in Chemistry 301 (please round to the nearest GPA)? 1.00, 1.25, 1.50, 1.75, 2.00, 2.25, 2.50, 2.75, 3.00, 3.25, 3.50, 3.75, 4.00

Mobile device experience, ownership, and expertise (MDE) – 4 items *(For items MDE2-4: 5 pt. Likert scale where 1 is "no experience" and 5 is "well experienced")*	
MDE1	I own the following mobile devices: (select all that apply) Laptop, tablet, smartphone, mp3/iPod, smartwatch
MDE2	Experience in the use of mobile devices.
MDE3	Experience in the use of a smartphone device.
MDE4	Experience in the use of mobile learning tools.

Attitude towards mobile learning (AML) – 6 items *(5 pt. Likert scale where 1 is "no experience" and 5 is "well experienced")*	
AML1	I think it's useful to use mobile devices and educational contexts.
AML2	I think it's useful to use mobile devices to study.
AML3	I think it's useful to use smartphones and tablets in educational contexts.
AML4	I think it's useful to use smartphones and tablets to study.
AML5	I prefer to use a desktop computer or laptop to study.
AML6	To study, I prefer to print the material.

APPENDIX B: LEARNING OUTCOMES: PROTONATION RECALL (LO)

Post-test on protonation (LO) – 15 items *(single selection)*	
LO1 Answer: C	An acid that is protonated: A. Has lost all of its acidic protons B. Is an uncommon form of an acid used in biologic research C. Has its acidic proton(s) "on" D. Is a term used only for polyprotic acids
LO2 Answer: D	Understanding how pH affects the protonation states of compounds is important in biochemical research and in particular pharmaceutical development because: A. The pH of biological systems is not buffered. B. The body takes up compounds the same regardless of charge. C. Blood tends to be much more acidic than stomach acid. D. The solubility of compounds changes dramatically as their protonation states change.
LO3 Answer: A	For a conjugate acid/base pair, the conjugate acid is the ______ form and the conjugate base is the ______ form? A. protonated; deprotonated B. deprotonated; protonated
LO4 Answer: B	When the pH of a solution equals the value of the pKa of an acid, what can we say about the concentrations of the protonated form of the acid, HA, and its deprotonated form A-? A. $[HA] > [A^-]$ B. $[HA] = [A^-]$ C. $[HA] < [A^-]$
LO5 Answer: A	When the pH of a solution is greater than the pK_a of the acid, what is true of the ratio of the protonated, HA, to the deprontated, A^-, form of the acid $^{[HA]}/_{[A-]}$? A. $^{[HA]}/_{[A-]} < 1$ B. $^{[HA]}/_{[A-]} = 1$ C. $^{[HA]}/_{[A-]} > 1$ D. $^{[HA]}/_{[A-]} = ½$

LO6 Answer: D

Which of the following would be the protonated form of the base methyl amine, CH_3NH_2?

A. $CH_3NH_4^+$
B. CH_3NH^-
C. $CH_3NH_2^+$
D. $CH_3NH_3^+$

LO7 Answer: A

The pKa of formic acid is 3.75. In a solution with pH = 2.52, which will have the highest concentration?

A. Formic acid, HCOOH
B. The formate ion, $HCOO^-$
C. They will be equal

LO8 Answer: B

A polyprotic acid has:

A. An unknown amount of protonation states
B. Multiple acidic protons
C. At least two amine functional groups

LO9 Answer: D

A polyprotic acid has two K_a values. How many protonation states does this acid have?

A. Zero
B. One
C. Two
D. Three

LO10 Answer: B

There exists some polyprotic acid, H_2A, with the following pK_a values:

$pK_{a1} = 1.92$
$pK_{a2} = 7.18$

Would this acid be fully protonated, fully deprotonated or somewhere in-between at pH 10?

A. Fully Protonated
B. Fully Deprotonated
C. Somewhere in-between

LO11 Answer: B

Phosphoric acid, H_3PO_4, has three acidic protons with the following pK_a values and equilibrium reactions:

$H_3PO_4\,(aq) + H_2O\,(l) \leftrightarrow H_2PO_4^-\,(aq) + H_3O^+\,(aq) \quad pK_{a1} = 2.15$
$H_2PO_4^-\,(aq) + H_2O\,(l) \leftrightarrow HPO_4^{2-}\,(aq) + H_3O^+\,(aq) \quad pK_{a2} = 7.2$
$HPO_4^{2-}\,(aq) + H_2O\,(l) \leftrightarrow PO_4^{3-}\,(aq) + H_3O^+\,(aq) \quad pK_{a3} = 12.35$

At which pH would we observe equal concentrations of $H_2PO_4^-$ and HPO_4^{2-} in solution?

A. 2.15
B. 7.20
C. 12.35
D. 14.00

LO12 Answer: B

A certain drug must be deprotonated to properly bind at its active site and therefore perform its desired function. A doctor should carefully consider: If the drug is deprotonated when given to the patient because it will remain this way in the body.

A. How the drug is administered (IV versus orally) because the pH of the body differs in different parts of the body
B. How to neutralize the drug before entering the body to minimize the damage to the human systems.

LO13 Answer: C

A particular drug is more readily absorbed when it is uncharged. This drug is a weak base and remains uncharged only when deprotonated. It has a pK_a of 6.4 at its active site.

Will this drug be better absorbed in the stomach (pH = 2) or in the small intestine (pH = 7.5)?

A. The stomach because the the pH is high enough to deprotonate the drug.
B. The stomach because the the pH is low enough to deprotonate the drug.
C. The small intestine because the the pH is high enough to deprotonate the drug.
D. The small intestine because the the pH is low enough to deprotonate the drug.

LO14 Answer: C

A new medication has a pK_a of 7.40. In which bodily system will the medication be about equally protonated and deprotonated?

A. pH values of all biological systems vary too greatly to say
B. The stomach; pH between 2 and 3
C. The blood; pH between 7.35 and 7.45
D. The large intestine; pH between 5.5 and 7

LO15 Hemoglobin, a blood protein, changes protonation state based on the pH of its environment. The pH of venous blood is slightly lower the pH of arterial blood. You will find a greater concentration of protonated hemoglobin in which type of blood?

Answer: C

A. Venous blood because its lower pH results in a higher degree of protonation.
B. Arterial blood because its lower pH results in a higher degree of protonation.
C. Venous blood because its higher pH results in a higher degree of protonation.
D. Arterial blood because its higher pH results in a higher degree of protonation.

APPENDIX C: COGNITIVE LOAD MEASUREMENT (CLM)

This is what full sentence looks like. I am tired of formatting this shit and hope the rest of it goes quickly!

Cognitive load measurement (CLM) – 10 items *(10 pt. rating scale)* INSTRUCTIONS: All of the following questions refer to the mobile learning activity that just finished. Please respond to each question on the following scale (0 means *not at all the case* and 10 means *completely the case*). 0,1,2,3,4,5,6,7,8,9,10		
Intrinsic cognitive load (ICL)	CLM1	The topics covered in the activity were very complex.
	CLM2	The activity covered chemistry formulas that I perceived as very complex.
	CLM3	The activity covered concepts and definitions that I perceive as very complex.
Extraneous cognitive load (ECL)	CLM4	The instructions and/or explanations during the activity were very unclear.
	CLM5	The instructions and/or explanations were, in terms of learning, very unclear.
	CLM6	The instruction and/or explanations were full of unclear language.
Germane cognitive load (GCL)	CLM7	The activity really enhanced my understanding of the topics covered.
	CLM8	The activity really enhanced my knowledge and understanding of protonation state.
	CLM9	The activity really enhanced my understanding of the chemistry formulas covered.
	CLM10	The activity really enhanced my understanding of the concepts and definitions.

APPENDIX D: USER PERCEPTION SURVEY (UPS)

This is what full sentence looks like. I am tired of formatting this shit and hope the rest of it goes quickly!

Technology Acceptance Method (TAM) – 8 items *(5 pt. Likert scale where 1 is "strongly disagree" and 5 is "strongly agree")*	
PEU1	Studying learning materials using this device is easy for me.
PEU2	My interaction with this device has been flexible, direct, and fluid.
PEU3	Overall, I believe that this learning environment is easy to use.
PU1	I think that the use of this type of device could help me in my learning tasks.
PU2	Using this device enables me to accomplish study tasks more quickly.
PU3	Overall, I find that using this device is a useful studying tool.
UI1	I intend to use this device for studying in the future.
UI2	I would recommend the use of this device for study.

Perceived Satisfaction (PS) – 4 items *(5 pt. Likert scale where 1 is "strongly disagree" and 5 is "strongly agree")*	
PS1	I am satisfied with accessing learning contents using this device.
PS2	I am satisfied with the interaction with this device for studying.
PS3	I think that using this device for learning could be motivating.
PS4	I like using this device for studying.

APPENDIX E: MOBILE DEVELOPMENT DOCUMENTS AND INFORMATION

The mobile applications for this study were created from scratch. I created the architecture and design of the application, as well as created all graphics included. The content was provided by the chemistry department and was taken from their online course material. The text, however, was retrofitted to meet the device display and text segmentation parameters of this study.

The programming was completed by three different coders, an iOS programmer from Austin, and Android programmer from San Francisco, and a web and database programmer from Salt Lake City. These programmers were interviewed and hired to complete the project for a total cost of $3,000.

The planning, architecture, and graphics development occurred over the course of four months (from November through February). The coding, quality assurance (QA), and beta testing occurred following my dissertation proposal on January 31, 2015, and ran the length of February and through the first week of March. This was an unusually tight turn-around and as such, I had as much prepared ahead of time (documents, graphics, etc.) as possible.

The project was not without its challenges. In addition to managing the schedules of three programmers in three different states, it was difficult to ensure that all three applications looked alike. This required a significant bit of back and forth, as well as several hours of beta testing and QA.

The database collected an enormous amount of data and had to be created specifically for this project. All three applications fed into the same database, which produced a comma delimited file with two hundred and eight columns of information. To ensure that each column was properly functioning also required detailed testing.

The following is the development document that was created for the various developers. The document was directly copied, and as such does not follow the standard APA formatting. I decided to include it to demonstrate how robust the planning and communication was for the applications development.

LAPTOPS ONLY – Dark Gray highlight
SMARTPHONES ONLY – Light Gray highlight

SMARTPHONE Icon
For smartphones only, the screen icon:

Icon: Asset file(s):
research-101-icon.png

Visual Screen Details (bkgd color, font, etc.)
Unless a graphic is provided all backgrounds should be gray (R242, G242, B242).
Answer selections should fill in circles with RGB Blue.
INSTUCTIONS, CLASS SELECTION, and AGREEMENT: Black, Arial, Size (see samples)
Question Items Font: Black, Times New Roman, Size (see samples)

Loading screen – (smartphone apps ONLY)

Loading screen: Asset file(s):
research-101-loadingscreen.png

Screen 1: Home screen - Welcome Message

Welcome to the Research 101 [Web, iPhone, Android] Application.

This application is specifically for use for Angela Marie Karam's dissertation research, through the University of Texas at Austin, College of Education, Department of Curriculum and Instruction and the College of Natural Sciences, Department of Chemistry, entitled "A comparison of the effects of mobile device display size and orientation, and text segmentation on learning, cognitive load, and user perception in a higher education chemistry course."
© 2015 All material is copy righted and intellectual property owned by Angela Marie Karam.

Screen 1: Asset file(s):
research-101-homescreen-start.png
research-101-homescreen-startselect.png

Screen 2: Participation Agreement

Consent to Participate in Research

Identification of Investigator and Purpose of Study

You are invited to participate in a research study, entitled "A comparison of the affects of mobile device display size and orientation, and text segmentation on learning, cognitive load, and user perception in a higher education chemistry course." The study is being conducted by Angela Karam, PhD Candidate, Department of Curriculum and Instruction, College of Education, The University of Texas at Austin, available at angmkaram@gmail.com.

The purpose of this research study is to examine how mobile device screen display size and orientation and text segmentation affect learning, cognitive load, and user perception.

Your participation in the study will contribute to a better understanding of instructional design principles to improve learning, balance cognitive load, and enhance user perception of learning from display specific mobile devices. You are free to contact the investigator at the above email address to discuss the study. You must be at least 18 years old to participate.

If you agree to participate:
The learning module will take approximately 50 minutes of your time.
You will complete an activity about protonation state**.**
You will be compensated for your participation by receiving in-class credit for the day of the study.

Risks/Benefits/Confidentiality of Data

There are no known risks. There will be no costs for participating, nor will you benefit from participating. Your name and personal information will not be collected. You will instead be assigned a random user ID. A limited number of research team members will have access to the data during data collection.

Participation or Withdrawal

Your participation in this study is voluntary. You may decline to answer any question and you have the right to withdraw from participation at any time. Withdrawal will not affect your relationship with The University of Texas in anyway. If you do not want to participate either simply stop participating or close the browser window.

This study will be finished today and we will not contact you in any way in the future.

Contacts

If you have any questions about the study, contact the researcher Angela Karam via email at angmkaram@gmail.com**.** This study has been reviewed by The University of Texas at Austin Institutional Review Board and the study number is **[STUDY NUMBER].**

Questions about your rights as a research participant.
If you have questions about your rights or are dissatisfied at any time with any part of this study, you can contact, anonymously if you wish, the Institutional Review Board by phone at (512) 471-8871 or email at orsc@uts.cc.utexas.edu.

If you agree to participate, click the AGREE button below; otherwise, please exit the learning module now.

Thank you.

Agree		Will Not Participate

Data spreadsheet:
Column D

Column name	AGREE
Column returns	0 = Agree 1 = Will not participate

Backend: Device Determination

LAPTOPS: Automatically returns "laptop"
SMARTPHONES: What device are they using?

Data spreadsheet:
Column F

Column name	MOBILE
Column returns (alpha)	Laptop iPhone 5 S4 S5, etc.

Backend: Participant ID Assignment
Assigns Numeric ID Based on order of "agree"

iPhones ID#s: 1001-1999
Andriod ID #s: 2001-2999
Laptops ID #s: 3001-3999

Data spreadsheet:
Column C

Column name	PID
Column returns	1001 1002 1003 1004, etc

Backend: Device and Treatment Assignment

Independent variable groups: Devices (3) and Text segmentation (3)
Treatments: Combination of device and text segmentation (9)

Text Segmentation

Device Treatments		TS1	TS2	TS3
	LT	T1a	T2d	T3g
	SML	T1b	T2e	T3h
	SMP	T1c	T2f	T3j

How assignments are made

LAPTOP: Examples of random treatment assignment for laptops (3 total treatments):
Laptop 1 clicks agree and is assigned T1a (continuous text passage).
Laptop 2 clicks agree and is assigned T2d (medium segments).
Laptop 3 clicks agree and is assigned T3g (short segments).
Laptop 4 clicks agree and is assigned T1a (continuous text passage).
Laptop 5 clicks agree and is assigned T2d (medium segments).
Laptop 6 clicks agree and is assigned T3g (short segments), etc.

SMARTPHONE: Examples of random treatment assignment for smartphones (6 total treatments):
Smartphone 1 clicks agree and is assigned T1b (landscape, continuous text passage).
Smartphone 2 clicks agree and is assigned T1c (portrait, continuous text passage).
Smartphone 3 clicks agree and is assigned T2e (landscape, medium segments).
Smartphone 4 clicks agree and is assigned T2f (portrait, medium segments).
Smartphone 5 clicks agree and is assigned T3h (landscape, short segments).
Smartphone 6 clicks agree and is assigned T3j (portrait, short segments).
Smartphone 7 clicks agree and is assigned T1b (landscape, continuous text passage).
Smartphone 8 clicks agree and is assigned T1c (portrait, continuous text passage).
Smartphone 9 clicks agree and is assigned T2e (landscape, medium segments).
Smartphone 10 clicks agree and is assigned T2f (portrait, medium segments).
Smartphone 11 clicks agree and is assigned T3h (landscape, short segments).
Smartphone 12 clicks agree and is assigned T3j (portrait, short segments), etc.

Data spreadsheet:
Column G

Column name	DEVICE
Column returns	1 = LT = laptop 2 = SML = smartphone landscape 3 = SMP = smartphone portrait

Data spreadsheet:
Column H

Column name	TEXT
Column returns	1 = TS1 = continuous text 2 = TS2 = medium segments 3 = TS3 = short segments

Data spreadsheet:
Column I

Column name	TRTMT	LOGIC #: *ColG + ColH is DEVICE+TEXT = TRTMT*
Column returns	1 2 3 4 5 6 7 8 9	Laptops (will always assign 1,4,7): 1: 1+1 is LT+TS1 = T1a 4: 1+2 is LT+TS2 = T2d 7: 1+3 is LT+TS3 = T3g Smartphones (will always assign 2,3,5,6,8,9): 2: 2+1 is SML+TS1 = T1b 3: 3+1 is SMP+TS1 = T1c 5: 2+2 is SML+TS2 = T2e 6: 3+2 is SMP+TS2 = T2f 8: 2+3 is SML+TS3 = T3h 9: 3+3 is SMP+TS3 = T3j

Screen 3: Class Selection

Class#	Day	Time	Prof
50140	MWF	10:00-11:00	MCCORD
50145	MWF	11:00-12:00	MCCORD
50203	MWF	1:00-2:00	BIBERDORF
50150	TTH	9:30-11:00	VANDEN BOUT
50155	TTH	11:00-12:30	SPARKS
50160	TTH	12:30-2:00	SPARKS

NOTE: Students will see class number, day/time, and prof so they know to pick the correct class.
However, Class# is the only item that will go into the data spreadsheet.

Data spreadsheet:
Column B

Column name	CLASS_ID

Column returns	50140 50145 50203 50150 50155 50160

Screen 3a (LAPTOP ONLY):

Are you using a touchscreen laptop?

Yes	No

NOTE for SMARTPHONE: Should automatically put a "1" in Column E

Data spreadsheet:
Column E

Column name	INPUT
Column returns	0 = mouse 1 = touchscreen

Section 1 Instructions/Assets
LAPTOP:
Read the following carefully:

The Research 101 UTCOE application has three main sections:
Section 1: Pre-lesson survey
Section 2: Protonation state learning material
Section 3: Post-lesson test and survey

Once you begin, you must complete the full activity. DO NOT leave the application until you are finished or your responses will not be saved.

You must answer every question to complete the study.

Once you leave each section, you will not be able to return to it.

If you have any questions, please raise your hand and a facilitator will come to you.

When you are ready to begin, click/tap the START button below.

START Section 1

SMARTPHONES:

Use images provided.

Section 1: Asset file(s):
Section 1 Instructions start.png
Section 1 Instructions start_selected.png
Section 1: Pre-lesson Survey Questions
Demographic and mobile learning profile (DMLP) **14 total items**
Questions will appear as one survey to participants with no breaks in between question sections.

Social demographic items (SD) – 4 items *(single selection)*	
Code	Item text/copy and possible answers
SD1	1. Select your gender. Male, Female
SD2	2. Select your race. White, black, Hispanic, Asian, American Indian, Native Hawaiian/Pacific Islander, Other
SD3	3. Select your age. Under 18, 18, 19, 20, 21, 22, 23, 24, 25, Over 25
SD4	4. What was your GPA in Chemistry 301? (please round to the nearest half) 1.00, 1.50, 2.00, 2.50, 3.00, 3.50, 4.00

Data spreadsheet:
Column J

Column name	SD1
Column returns	0=male 1=female

Data spreadsheet:
Column K

Column name	SD2
Column returns	1=white 2=black 3=hispanic 4=asian 5=american indian 6=native hawaiian/pacfic islander 7=other

Data spreadsheet:
Column L

Column name	SD3
Column returns	17=younger than 18 18 19 20 21 22 23 24 25 26=older than 25

Data spreadsheet:
Column M

Column name	SD4
Column returns	1.0 1.5 2.0 2.5 3.0 3.5 4.0

Mobile device experience, ownership, and expertise (MDE) – 4 items *(For MDE2-4: 5 pt. Likert scale where 1 is "no experience" and 5 is "well experienced")*	
MDE1	5. I own the following mobile devices: (select all that apply) Laptop, tablet, smartphone, mp3/iPod, smartwatch

MDE2	6. Experience in the use of mobile devices.
MDE3	7. Experience in the use of a smartphone device.
MDE4	8. Experience in the use of mobile learning tools.

Data spreadsheet:
Column N

Column name	MDE1	LOGIC
Column returns	1=laptop 2=tablet 3=eReader 4=smartphone 5=iPod 6=smartwatch	Should list in numerical order each number selected. EX: If they selected laptop, tablet, and smartphone, it would list the number 124 1 for laptop, 2 for tablet, 4 for smartphone

Data spreadsheet:
Column O-Q

Column name	MDE2-MDE4
Column returns	1 *no experience* 2 3 4 5 *well experienced*

Data spreadsheet:
Column R

Column name	MDEAVG	LOGIC
Column returns	#.###	Will average totals of MDE2-MDE4. (MDE2+MDE3+MDE4)/3 EX: (2+3+5)/3 =3.667

Attitude towards mobile learning (AML) – 6 items *(5 pt. Likert scale where 1 is "strongly disagree" and 5 is "strongly agree") 1,2,3,4,5*	
AML1	9. I think it's useful to use mobile devices in educational contexts.
AML2	10. I think it's useful to use mobile devices to study.
AML3	11. I think it's useful to use smartphones and tablets in educational contexts.

AML4	12. I think it’s useful to use smartphones and tablets to study.
AML5	13. I prefer to use a desktop computer or laptop to study.
AML6	14. To study, I prefer to print the material.

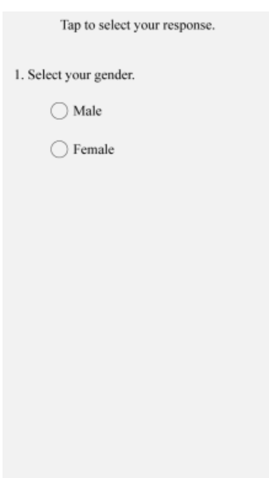
Data spreadsheet:
Column S-X

Column name	AML1-AML6
Column returns	1 *strongly disagree* 2 3 4 5 *strongly agree*

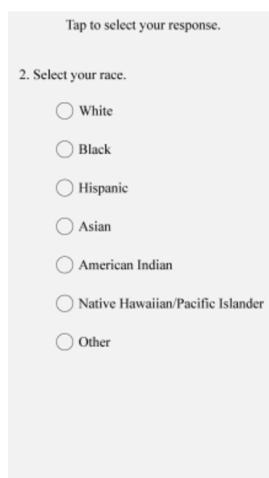
Data spreadsheet:
Column Y

Column name	AMLAVG	LOGIC
Column returns	#.###	Will average totals of AML1-AML6. (AML1+AML2+AML3+AML4+AML5+AML6)/6 EX: (1+4+2+3+5+4)/6 =3.16

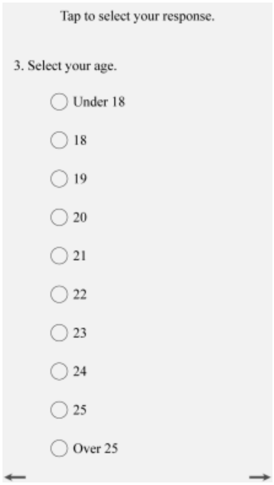
Section 1: Pre-lesson Survey Look and Feel
Samples of each type of question on screen below.



gender sample

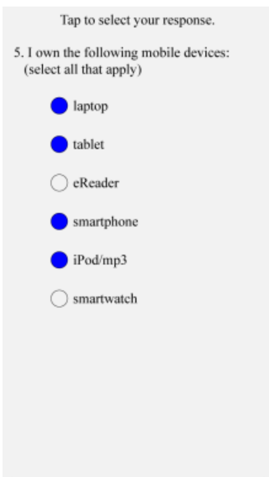


race sample



age sample

GPA sample



MDE 1 sample

MDE 2-4 sample

AML 1-6 sample

Missed Questions

If a question is not answered, the participant will be notified and given the question number they missed. This goes for all survey and test items in the module.

Section 2 Instructions/Assets
LAPTOP: **When they have completed the first section**

You have completed the Section 1.

Remember! Once you leave Section 1, you will not be able to return to it.

In the following Section 2, you will be presented with chemistry material on Protonation State.

Read through the material carefully.

Take your time.

You can revisit pages, as needed.

A short test on the material and survey will follow this activity.

When you are ready to begin Section 2, click/tap START.

START Section 2

SMARTPHONES:

Use images provided.

Section 2 Instructions: Asset file(s):
Section 2 Instructions start.png
Section 2 Instructions start_selected.png

Section 2: Treatment options

The assigned treatment will load here. Screens will vary based on treatment, but screen numbers per text segmentation are the same across the board. (NOTE: only continuous text differs per device/orientation)

Total screens/graphics per treatment group

Text Segmentation

Device Treatments		**TS1 Continuous Text**	**TS2 Medium Segments**	**TS3 Small Segments**
	LT	T1a (4 screens)	T2d (14 screens)	T3g (37 screens)
	SML	T1b (9 screens)	T2e (14 screens)	T3h (37 screens)
	SMP	T1c (8 screens)	T2f (14 screens)	T3j (37 screens)

Data spreadsheet:
Column

<table>
<tr><td colspan="2">LOGIC:(cumulative, so if they go to screen 2 and come back, it should add the times on screen 1 for total time on screen 1.</td><td colspan="2">EX: Say they visit screen 1 for :30 seconds then move to screen 2 for :20 seconds, then come back to screen 1 for another :45 seconds, it would compute like this:
TS11T = 1:15 added (0:30+0:45)
TS11V = 2
TS12T = 0:20
TS12V = 1</td></tr>
<tr><td>TS_T</td><td>Column</td><td>TS_V</td><td>Column</td></tr>
<tr><td>TS1_1T
Treatment screen time
TS1 = continuous text
1=first screen of text
T=total time on screen</td><td>#</td><td>TS1_1V
Treatment screen time
TS1 = continuous text
1=first screen of text
V=total times visiting screen</td><td>#</td></tr>
<tr><td colspan="4">TS1 Continuous Text Treatments
Laptop (4 screens) will only use TS1_1T,V through TS1_4T,V
Smartphone landscape (9 screens) TS1_1T,V through TS1_9T,V
Smartphone portrait (8 screens) TS1_1T,V through TS1_8T,V
Leave additional columns blank.</td></tr>
<tr><td>TS1_1T</td><td>Z</td><td>TS1_1V</td><td>AA</td></tr>
</table>

TS1_2T	AB	TS1_2V	AC
TS1_3T	AD	TS1_3V	AE
TS1_4T	AF	TS1_4V	AG
TS1_5T	AH	TS1_5V	AI
TS1_6T	AJ	TS1_6V	AK
TS1_7T	AL	TS1_7V	AM
TS1_8T	AN	TS1_8V	AO
TS1_9T	AP	TS1_9V	AQ
TS2 Medium Segmented Text Treatments			
TS2_1T	AR	TS2_1V	AS
TS2_2T	AT	TS2_2V	AU
TS2_3T	AV	TS2_3V	AW
TS2_4T	AX	TS2_4V	AY
TS2_5T	AZ	TS2_5V	BA
TS2_6T	BB	TS2_6V	BC
TS2_7T	BD	TS2_7V	BE
TS2_8T	BF	TS2_8V	BG
TS2_9T	BH	TS2_9V	BI
TS2_10T	BJ	TS2_10V	BK
TS2_11T	BL	TS2_11V	BM
TS2_12T	BN	TS2_12V	BO
TS2_13T	BP	TS2_13V	BQ
TS2_14T	BR	TS2_14V	BS
TS3 Small Segmented Text Treatments			
TS3_1T	BT	TS3_1V	BU
TS3_2T	BV	TS3_2V	BW
TS3_3T	BX	TS3_3V	BY
TS3_4T	BZ	TS3_4V	CA
TS3_5T	CB	TS3_5V	CC
TS3_6T	CD	TS3_6V	CE
TS3_7T	CF	TS3_7V	CG
TS3_8T	CH	TS3_8V	CI
TS3_9T	CJ	TS3_9V	CK
TS3_10T	CL	TS3_10V	CM
TS3_11T	CN	TS3_11V	CO

TS3_12T	CP	TS3_12V	CQ
TS3_13T	CR	TS3_13V	CS
TS3_14T	CT	TS3_14V	CU
TS3_15T	CV	TS3_15V	CW
TS3_16T	CX	TS3_16V	CY
TS3_17T	CZ	TS3_17V	DA
TS3_18T	DB	TS3_18V	DC
TS3_19T	DD	TS3_19V	DE
TS3_20T	DF	TS3_20V	DG
TS3_21T	DH	TS3_21V	DI
TS3_22T	DJ	TS3_22V	DK
TS3_23T	DL	TS3_23V	DM
TS3_24T	DN	TS3_24V	DO
TS3_25T	DP	TS3_25V	DQ
TS3_26T	DR	TS3_26V	DS
TS3_27T	DT	TS3_27V	DU
TS3_28T	DV	TS3_28V	DW
TS3_29T	DX	TS3_29V	DY
TS3_30T	DZ	TS3_30V	EA
TS3_31T	EB	TS3_31V	EC
TS3_32T	ED	TS3_32V	EE
TS3_33T	EF	TS3_33V	EG
TS3_34T	EH	TS3_34V	EI
TS3_35T	EJ	TS3_35V	EK
TS3_36T	EL	TS3_36V	EM
TS3_37T	EN	TS3_37V	EO

Data spreadsheet:
Column EP

Column name	TRMTOT	LOGIC
Column returns	##.##	Will add all time from all text screens. So, if the treatment has five screens, it will add the totals from all five screens. EX: TS11T+TS12T+TS13T+TS14T+TS15T=TRMTOT

Section 3 Instructions/Assets
LAPTOP: **WHEN THEY COMPLETE THE TEXT TREATMENT**

You have completed Section 2.

Remember! Once you leave Section 2, you will not be able to return to it.

In the following Section 3, you will take a short test on Protonation State, followed by survey questions.

Please answer all questions.

If you do not know an answer, please take your best educated guess.

When you are ready to begin Section 3, click/tap START.

START

SMARTPHONES:

Use images provided.

Section 3: Asset file(s):
Section 3 Instructions start.png
Section 3 Instructions start_selected.png

Section 3: Post-Lesson Test and Survey

Learning outcomes: Protonation state recall (LO) Total **15 total items**

Post-test on protonation (LO) – 15 items *(single selection)*	
LO1 Answer:	An acid that is protonated: Has lost all of its acidic protons

C	Is an uncommon form of an acid used in biologic research Has its acidic proton(s) "on" Is a term used only for polyprotic acids
LO2 Answer: D	Understanding how pH affects the protonation states of compounds is important in biochemical research and in particular pharmaceutical development because: A. The pH of biological systems is not buffered. B. The body takes up compounds the same regardless of charge. C. Blood tends to be much more acidic than stomach acid. D. The solubility of compounds changes dramatically as their protonation states change.
LO3 Answer: A	For a conjugate acid/base pair, the conjugate acid is the ______ form and the conjugate base is the ______ form? protonated; deprotonated deprotonated; protonated
LO4 Answer: B	When the pH of a solution equals the value of the pKa of an acid, what can we say about the concentrations of the protonated form of the acid, HA, and its deprotonated form A-? $[HA] > [A^-]$ $[HA] = [A^-]$ $[HA] < [A^-]$
LO5 Answer: A	When the pH of a solution is greater than the pK_a of the acid, what is true of the ratio of the protonated, HA, to the deprontated, A^-, form of the acid ${}^{[HA]}/_{[A-]}$? ${}^{[HA]}/_{[A-]} < 1$ ${}^{[HA]}/_{[A-]} = 1$ ${}^{[HA]}/_{[A-]} > 1$ ${}^{[HA]}/_{[A-]} = ½$
LO6 Answer: D	Which of the following would be the protonated form of the base methyl amine, CH_3NH_2? $CH_3NH_4^+$ CH_3NH^- $CH_3NH_2^+$ $CH_3NH_3^+$
LO7 Answer: A	The pKa of formic acid is 3.75. In a solution with pH = 2.52, which will have the highest concentration? Formic acid, HCOOH The formate ion, $HCOO^-$ They will be equal
LO8 Answer: B	A polyprotic acid has: An unknown amount of protonation states Multiple acidic protons At least two amine functional groups

LO9 Answer: D	A polyprotic acid has two K_a values. How many protonation states does this acid have? Zero One Two Three
LO10 Answer: B	There exists some polyprotic acid, H_2A, with the following pK_a values: $pK_{a1} = 1.92$ $pK_{a2} = 7.18$ Would this acid be fully protonated, fully deprotonated or somewhere in-between at pH 10? Fully Protonated Fully Deprotonated Somewhere in-between
LO11 Answer: B	Phosphoric acid, H_3PO_4 , has three acidic protons with the following pK_a values and equilibrium reactions: $H_3PO_4\,(aq) + H_2O\,(l) \leftrightarrow H_2PO_4^-\,(aq) + H_3O^+\,(aq)$ $pK_{a1} = 2.15$ $H_2PO_4^-\,(aq) + H_2O\,(l) \leftrightarrow HPO_4^{2-}\,(aq) + H_3O^+\,(aq)$ $pK_{a2} = 7.2$ $HPO_4^{2-}\,(aq) + H_2O\,(l) \leftrightarrow PO_4^{3-}\,(aq) + H_3O^+\,(aq)$ $pK_{a3} = 12.35$ At which pH would we observe equal concentrations of $H_2PO_4^-$ and HPO_4^{2-} in solution? 2.15 7.20 12.35 14.00
LO12 Answer: B	A certain drug must be deprotonated to properly bind at its active site and therefore perform its desired function. A doctor should carefully consider: If the drug is deprotonated when given to the patient because it will remain this way in the body. How the drug is administered (IV versus orally) because the pH of the body differs in different parts of the body How to neutralize the drug before entering the body to minimize the damage to the human systems.
LO13 Answer: C	A particular drug is more readily absorbed when it is uncharged. This drug is a weak base and remains uncharged only when deprotonated. It has a pK_a of 6.4 at its active site. Will this drug be better absorbed in the stomach (pH = 2) or in the small intestine (pH = 7.5)? The stomach because the the pH is high enough to deprotonate the drug.

	The stomach because the the pH is low enough to deprotonate the drug. The small intestine because the the pH is high enough to deprotonate the drug. The small intestine because the the pH is low enough to deprotonate the drug.
LO14 Answer: C	A new medication has a pK_a of 7.40. In which bodily system will the medication be about equally protonated and deprotonated? pH values of all biological systems vary too greatly to say The stomach; pH between 2 and 3 The blood; pH between 7.35 and 7.45 The large intestine; pH between 5.5 and 7
LO15 Answer: C	Hemoglobin, a blood protein, changes protonation state based on the pH of its environment. The pH of venous blood is slightly lower the pH of arterial blood. You will find a greater concentration of protonated hemoglobin in which type of blood? Venous blood because its lower pH results in a higher degree of protonation. Arterial blood because its lower pH results in a higher degree of protonation. Venous blood because its higher pH results in a higher degree of protonation. Arterial blood because its higher pH results in a higher degree of protonation.

Data spreadsheet:

Column name	LO1-LO20	LOGIC
Column returns	A B C D E	LO1-LO20 Should list which item they selected as the answer. A,B,C,D, or E
Column name	LO1P-LO20P	LOGIC
Column returns	5=correct 0=incorrect	All LO items are multiple choice

LO#	Column	LO#P	Column
LO1	EQ	LO1P	ER
LO2	ES	LO2P	ET
LO3	EU	LO3P	EV
LO4	EW	LO4P	EX
LO5	EY	LO5P	EZ
LO6	FA	LO6P	FB
LO7	FC	LO7P	FD

LO8	FE	LO8P	FF
LO9	FG	LO9P	FH
LO10	FI	LO10P	FJ
LO11	FK	LO11P	FL
LO12	FM	LO12P	FN
LO13	FO	LO13P	FP
LO14	FQ	LO14P	FR
LO15	FS	LO15P	FT

Data spreadsheet:
Column FU

Column name	LOPER	LOGIC
Column returns	100 93.33 86.67 80 73.33 67.67 60 53.33 46.67 40 33.37 26.67 20 13.33 6.67 0	Total out of 15 correct: Total correct = times 5 = percentage 15 correct = 75 = 100% 14 correct = 70 = 93.33% 13 correct = 65 = 86.67% 12 correct = 60 = 80% 11 correct = 55 = 73.33% 10 correct = 50 = 66.67% 9 correct = 45 = 60% 8 correct = 40 = 53.33% 7 correct = 35 = 46.67% 6 correct = 30 = 40% 5 correct = 25 = 33.33% 4 correct = 20 = 26.67% 3 correct = 15 = 20% 2 correct = 10 = 13.33% 1 correct = 5 = 6.67% 0 correct = 0 = 0

Cognitive load measurement (CLM) **10 total items**

Cognitive load measurement (CLM) – 10 items *(10 pt. rating scale)* INSTRUCTIONS: All of the following questions refer to the mobile learning activity that just finished. Please respond to each question on the following scale (0 means *not at all the case* and 10 means *completely the case*). 0,1,2,3,4,5,6,7,8,9,10	
CLM1	1. The topics covered in the activity were very complex.
CLM2	2. The activity covered chemistry formulas that I perceived as very complex.
CLM3	3. The activity covered concepts and definitions that I perceive as very

	complex.
CLM4	4. The instructions and/or explanations during the activity were very unclear.
CLM5	5. The instructions and/or explanations were, in terms of learning, very unclear.
CLM6	6. The instruction and/or explanations were full of unclear language.
CLM7	7. The activity really enhanced my understanding of the topics covered.
CLM8	8. The activity really enhanced my knowledge and understanding of protonation state.
CLM9	9. The activity really enhanced my understanding of the chemistry formulas covered.
CLM10	10. The activity really enhanced my understanding of the concepts and definitions.

CLM1-CLM3
Data spreadsheet:
Column FV-FX

Column name	CLM1-CLM3	LOGIC
Column returns	0 *not at all the case* 1 2 3 4 5 6 7 8 9 10 *completely the case*	0-10 single select 0=not at all 1-9 are just numbers, no words 10=completely the case

Data spreadsheet:
Column FY

Column name	CLMICL	LOGIC
Column returns	#.###	Will average rankings from CLM1-CLM3 to find intrinsic cognitive load (ICL) rate. (CLM1+CLM2+CLM3)/3 EXS: (9+5+4)/3=6

		(7+3+9)/3=6.333 (9+8+9)/3=8.667 (1+3+4)/3=2.667

Data spreadsheet:
Column FZ-GB

Column name	CLM4-CLM6	LOGIC
Column returns	0 *not at all the case* 1 2 3 4 5 6 7 8 9 10 *completely the case*	0-10 single select 0=not at all 1-9 are just numbers, no words 10=completely the case

Data spreadsheet:
Column GC

Column name	CLMECL	LOGIC
Column returns	#.###	CLM4-CLM6 to find extraneous cognitive load (ECL) rate. (CLM4+CLM5+CLM6)/3 EXS: (9+5+4)/3=6 (7+3+9)/3=6.333 (9+8+9)/3=8.667 (1+3+4)/3=2.667

Data spreadsheet:
Column GD-GG

Column name	CLM7-CLM10	LOGIC
Column returns	0 *not at all the case* 1 2	0-10 single select 0=not at all 1-9 are just numbers, no words

	3 4 5 6 7 8 9 10 *completely the case*	10=completely the case

Data spreadsheet:
Column GH

Column name	CLMGCL	LOGIC
Column returns	#.###	CLMGCL Will average rankings from CLM7-CLM10to find germane cognitive load (GCL) rate. (CLM7+CLM8+CLM9+CLM10)/4 EXS: (9+5+4+4)/4=5.5 (7+3+9+6)/4=6.25 (9+8+9+8)/4=8.5 (1+3+4+4)/4=3

User perception survey (UPS) **12 total items**

Technology Acceptance Method (TAM) – 8 items *(5 pt. Likert scale where 1 is "strongly disagree" and 5 is "strongly agree") 1,2,3,4,5*	
PEU1	11. Studying learning materials using this device is easy for me.
PEU2	12. My interaction with this device has been flexible, direct, and fluid.
PEU3	13. Overall, I believe that this learning environment is easy to use.
PU1	14. I think that the use of this type of device could help me in my learning tasks.
PU2	15. Using this device enables me to accomplish study tasks more quickly.
PU3	16. Overall, I find that using this device is a useful studying tool.
UI1	17. I intend to use this device for studying in the future.
UI2	18. I would recommend the use of this device for study.

Data spreadsheet:
Column GI-GK

Column	PEU1-PEU3

name	
Column returns	1 *strongly disagree* 2 3 4 5 *strongly agree*

Data spreadsheet:
Column GL

Column name	PEUAVG	LOGIC
Column returns	#.###	Will average totals of PEU1-PEU3. (PEU1+PEU2+PEU3)/3 EX: (1+4+2)/3 =3.16

Data spreadsheet:
Column GM-GO

Column name	PU1-PU3
Column returns	1 *strongly disagree* 2 3 4 5 *strongly agree*

Data spreadsheet:
Column GP

Column name	PUAVG	LOGIC
Column returns	#.###	Will average totals of PU1-PU3. (PU1+PU2+PU3)/3 EX: (1+4+2)/3 =3.16

Data spreadsheet:
Column GQ, GR

Column name	UI1-UI2

Column returns	1 *strongly disagree* 2 3 4 5 *strongly agree*

Data spreadsheet:
Column GS

Column name	UIAVG	LOGIC
Column returns	#.###	Will average totals of UI1-UI2. (UI1+UI2)/2 EX: (1+4)/2 =2.5

Perceived Satisfaction (PS) – 4 items *(5 pt. Likert scale where 1 is "strongly disagree" and 5 is "strongly agree")*	
PS1	19. I am satisfied with accessing learning contents using this device.
PS2	20. I am satisfied with the interaction with this device for studying.
PS3	21. I think that using this device for learning could be motivating.
PS4	22. I like using this device for studying.

Data spreadsheet:
Column GT-GW

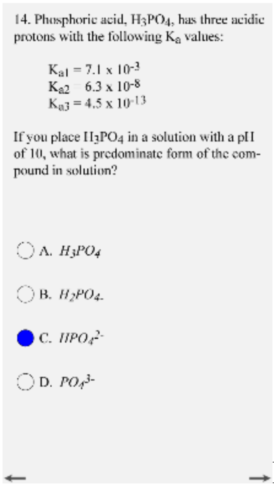
Column name	PS1-PS4
Column returns	1 *strongly disagree* 2 3 4 5 *strongly agree*

Data spreadsheet:
Column GX

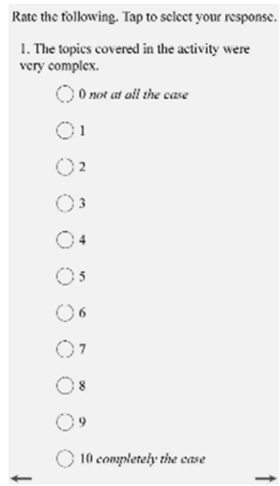
Column name	PSAVG	LOGIC
Column returns	#.###	average of PS 1-5 (PS1+PS2+PS3+PS4)/4

Section 3: Post-lesson Test/Survey Look and Feel

Samples of each type of question on screen below (see graphics folder ***question samples*** for full images).



LO sample



CLM sample

PEU, PU, UI, PS sample

Missed Questions

If a question is not answered, the participant will be notified and given the question number they missed. This goes for all survey and test items in the module.

Final Instructions/Complete

LAPTOP:

WHEN THEY COMPLETE THE TEST AND SURVEY

You have completed the Section 3.

Remember! Once you leave Section 3, you will not be able to return to it.

You have completed all three sections of this study. To complete the study, click/tap COMPLETE below.

Thank you for participating in this research study.

COMPLETE

SMARTPHONES:

Use images provided.

Screen Complete: Asset file(s):
LAST SCREEN_Completion screen.png
LAST SCREEN_Completion screen_selected.png

Data spreadsheet:

Column GY

Column name	TIME	LOGIC
Column returns	##.##	TOTAL TIME DURING APP Clock starts after IRB agreement and ends when module completes.

Data spreadsheet:

Column GZ

Column name	COMPLETE	LOGIC
Column returns	0=completed 1=not completed	This will register once they complete all items in the application. If they never click the button to exit the app, they automatically are assigned a “1” for not completed.

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