Practice Makes Perfect? When Does Massed Learning Improve Product Usage Proficiency?

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Previous research has shown that spacing of information (over time) leads to better learning of product information. We develop a theoretical framework to describe how massed or spaced learning schedules interact with different learning styles to influence product usage proficiency. The core finding is that with experiential learning, proficiency in a product usage task is better under massed conditions, whereas with verbal learning, spacing works better. This effect is demonstrated for usage proficiency assessed via speed as well as quality of use. Further, massed learning also results in better usage proficiency on transfer tasks, for both experiential and verbal learning. We also find that massed learning in experiential learning conditions leads not only to better usage proficiency but also to positive perceptions of the product. Overall, the pattern of results is consistent with a conceptual mapping account, with massed experiences leading to a superior mental model of usage and thus to better usage proficiency.

When repetitions of an advertisement are spaced rather than massed, memory for ad information is superior. This is known as the spacing effect (e.g., Appleton-Knapp, Bjork, and Wickens 2005; Janiszewski, Noel, and Sawyer 2003) and has been shown to be a robust phenomenon. However, most studies examining this effect focus on memory-related outcomes. Yet, in many consumption situations, consumers may be attempting to learn to perform specific tasks with products, wherein usage proficiency may be a more relevant goal.

Consider, for example, a consumer learning to use the Nintendo Wii system. She may look through the on-screen instructions a few times to understand and learn the sequence of steps to follow in order to play a game. While playing the game, this knowledge is useful but may not completely map onto learning how to handle the remote or manipulate the Nunchuk controller. Thus, while she possesses descriptive knowledge of how to perform a specific task using a product feature, she may not have attained a level of proficiency in using it.

This is an important issue for firms that introduce products designed to perform various tasks. For example, professionals have access to increasing levels of functionality and sophistication when it comes to handheld devices such as smart phones (e.g., Blackberry, iPhone). Many features of these phones require users to learn to accomplish a task by pressing a sequence of buttons. Learning to use the product feature proficiently likely involves a series of attempts over time. If consumers do not attain a level of proficiency in using the product's features, then their enjoyment, derived utility, and continued use may be detrimentally affected.

In fact, enhanced task proficiency has been shown to lead to a variety of positive outcomes (Chan and Storey 1996), including feelings of self-efficacy (Bandura 1986). In marketing, product usage proficiency leads to increased consumption (Rogers 1996; Shih and Venkatesh 2004) and greater postpurchase satisfaction (e.g., Thompson, Hamilton, and Rust 2005), which in turn affects repeat-purchase intentions (Gupta, McLaughlin, and Gómez 2007) and positive word of mouth (Wangenheim and Bayón 2007). However, extant research comparing massed versus spaced learning has generally not considered usage proficiency as a learning outcome. This is the focus that we adopt in our research.

Individuals become proficient from "massed" learning or, over time, via "spaced" learning. For instance, a new Wii

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user may play a game repeatedly during one intense gaming session and thus attain proficiency, or this proficiency may be reached via multiple play episodes over an extended period of time. For such products, it is often within the firm's control to facilitate massed trials. For example, a Best Buy salesperson may ask a teen trying Rock Band for the first time to play around with its features. An AT&T rep may encourage a potential customer to program five friends' contact information into a new cell phone. Such intense back-to-back use of specific features can also be facilitated during events that accompany many new product launches. Alternatively, a consumer may find herself undertaking usage under back-to-back or spaced conditions depending on the amount of free time available. Hence, from both a consumer and a marketer perspective, knowing whether massed versus spaced learning leads to greater usage proficiency is a relevant goal.

An additional factor to be considered in this context is how individuals learn. In some situations, individuals acquire usage skills experientially via hands-on practice, whereas in other situations they rely primarily on verbal information in the form of oral or written instructions (e.g., Thompson et al. 2005). Yet neither verbal learning nor experiential learning research has systematically examined the impact of spaced versus massed learning on skill-based task performance. In general, verbal learning research has assessed the influence of spaced versus massed learning on memory (Janiszewski et al. 2003), whereas experiential learning research has focused on the impact of spaced versus massed learning on relatively simple tasks or motor movements (Donovan and Radosevich 1999).

By integrating theoretical accounts of the key drivers of different learning styles (verbal vs. experiential) and learning schedules (spaced vs. massed), the current research advances a framework regarding usage proficiency for common product usage contexts. Two important theoretical insights can be gained from this endeavor. First, it is not clear whether the spacing effect is contingent on verbal learning. In other words, can we find evidence for a massing effect under experiential learning conditions? Second, we explicate the mechanism underlying usage proficiency originating from different types of learning. To this end, we develop a conceptual mapping account outlining how procedural learning leads to product usage proficiency. The following section briefly reviews verbal and experiential learning research.

LEARNING PARADIGMS

Individuals may learn to use skill-based products (Burson 2007) via at least two primary methods. The first method can be characterized as learning from oral or written instructions. The second method is experiential learning, which arises from doing. These two forms of learning have been suggested to "account for a significant proportion of human learning in formal and informal contexts" (Nokes and Ohlsson 2005, 770).

Verbal Learning. Verbal learning (i.e., learning stemming from oral or written commands) is a top-down, instruction-based process (Nokes and Ohlsson 2005; Taatgen et al. 2008). This type of learning generates declarative information that is descriptive in nature and that must then be integrated and applied to a focal task. For example, an individual may read the steps required to use a handheld product; however, the individual must still apply that knowledge by performing the step-by-step procedure in order to actually use the product.

It is also likely that the individual is exposed to the information multiple times. Multiple exposures to the same information can be spaced over time or massed together. Research has shown that spaced (vs. massed) exposures lead to better memory retention of verbal information (e.g., Dempster 1996; Ebbinghaus 1885). In marketing, the "spacing effect" has been illustrated in the form of greater recognition and retention for spaced versus massed messages (Appleton-Knapp et al. 2005; Janiszewski et al. 2003; Singh et al. 1994). However, virtually all verbal learning research in this area has focused on memory (e.g., Janiszewski et al. 2003) and not on its application to product usage.

Experiential Learning. Experiential learning is a bottom-up, construction-based process (Nokes and Ohlsson 2005; Taatgen et al. 2008). This type of learning generates both declarative and procedural knowledge about a particular task. Procedural knowledge is action-based (Anderson 1999). It involves knowing *how* to perform a task as opposed to merely knowing *what* needs to be done (Squire, Knowlton, and Musen 1993).

Skill-learning research has also shown a performance advantage for spaced learning (Lee and Magill 1983). However, most of the research highlighting this pattern has been conducted on simple tasks (Donovan and Radosevich 1999), such as key presses on a standard keyboard or simple arm movements. Recent reviews of the motor-learning literature hint that theory from research on simple tasks may not generalize to more complex real world tasks (Wulf and Shea 2002). Next, we advance a conceptual framework for making predictions regarding product usage performance across different learning styles and learning trials.

USAGE PROFICIENCY: A CONCEPTUAL MAPPING ACCOUNT

The process of developing procedural knowledge for a skill-based task (Ackerman 1990; Anderson 1999) has been shown to occur in the following three stages: (*a*) "We are presented with a description of a way to perform a task," (*b*) "We practice it, perhaps haltingly at first but our proficiency improves with continued practice and it benefits from feedback," and (*c*) "We reach the point at which our ability to perform the task is automatic, we no longer have to think about it" (Nickols 2000, 19). Stage one in the proceduralization process is declarative in nature, involves learning task steps, and relies on verbal learning. In contrast, stages two and three are procedural in nature, involve the performance of task steps, rely on experiential learning (Anderson 1999), and could eventually become automatic.

Consider a product usage situation, in which consumers use a feature of the product to perform a specific task. When individuals attempt to acquire product usage proficiency through experiential learning (stage 2 of the process described above), they develop tacit or informal production rules (Anderson and Fincham 1994). Informal production rules are action-based and emerge via hands-on practice or through trial and error (Anderson and Fincham 1994). These rules are relational in nature and include combining two or more subtasks in a certain way (Kadijevich and Haapasalo 2001) or establishing concrete linkages or associations between them (Neves and Anderson 1981). For instance, kneading the dough is an important step in baking. This step usually involves a particular order of actions for high-quality dough to result. While Betty Crocker verbalizes aspects of dough kneading on the product package, the procedural knowledge itself is embedded in the action-based production rules that an individual develops.

Over repetitions, such informal production rules develop into a fluent routine of physical steps and correlate with the formation of a mental model (Norman 2002) of the product and its usage. Contexts that enhance discovery and learning of these rules and linkages positively influence understanding and conceptual accretion (e.g., Tirre 1991). Fluency with individual components of a usage task has been shown to result in superior conceptual accretion and higher-order learning (e.g., Fisk, Oransky, and Skedsvold 1988). In turn, greater conceptual accretion results in better proficiency (Francis and Gallard 2005).

One measure of proficiency is fluency, or the ease with which an item is processed (Yang, Gallo, and Beilock 2009, 1359), often measured as "time on task" or "speed of completion" (Vance et al. 1989; Yang et al. 2009), while another is the quality of performance (e.g., Vance et al. 1989). In situations where learning-to-use is vital in deriving product benefits, understanding how proficiency develops under varying learning conditions is important. Going forward, we apply the conceptual mapping account developed above to make predictions on how learning schedules and styles interact to affect usage proficiency.

Informal production rules and knowledge about relational linkages do not exist in written form and need to be discovered via actual use. With experiential learning, massed practice affords the opportunity to use real-time feedback during usage to make connections between subtasks as well as any needed adjustments. Hence, back-to-back or massed practice is likely necessary to maximize conceptual accretion and enhance fluency in task performance. A good example of this is learning a piano piece: we practice the same sequence multiple times in succession so as to learn the key combinations to press (subtask), as well as the timing between these combinations (relational linkages). Similarly, while learning to use touch phones like the iPhone or the Blackberry Storm, we often need to use a new application multiple times in succession to get a feel for how the sequence of steps work together. Hence, our conceptual mapping account predicts that proficiency at a skill-based task should be better when experiential learning is massed (vs. spaced).

In contrast, when individuals read the description, instructions, or written schema for performing a task with a product feature (stage 1 in the knowledge proceduralization process), they engage in verbal learning. This type of learning requires that individuals review and mentally rehearse (Appleton-Knapp et al. 2005; Janiszewski et al. 2003) the necessary task sequence. Since they do not engage in physical usage during this phase, informal production rules and relational linkages between component subtasks have not yet been established; thus, proficiency is likely to depend on how well the written instructions have been learned. Past research from the verbal learning domain has consistently shown that spaced (vs. massed) presentation of written material leads to better memory (e.g., Appleton-Knapp et al. 2005; Noel 2006). Since usage proficiency in this context depends on memory for the instructions, spaced (vs. massed) learning schedules should lead to better proficiency (i.e., shorter completion times). Combining the above:

H1: With experiential learning, a massed (vs. spaced) schedule will lead to better usage proficiency for a focal task.

H2: With verbal learning, a spaced (vs. massed) schedule will lead to better usage proficiency for a focal task.

EXPERIMENT 1: USAGE PROFICIENCY FOR FOCAL TASK

The following experiments test our predictions. In experiment 1, we test hypotheses 1 and 2 for a focal task, using a measure of usage proficiency relying on completion time. In experiment 2, we extend the experiential learning results to a transfer task. In experiment 3, we use a different measure of usage proficiency based on quality of task performance and also use process measures to test the structural model. Finally, in experiment 4, we test the robustness of the structural model and also show how learning schedules lead to positive consumer responses on downstream variables.

Overview of Experimental Paradigm

A laboratory experiment was conducted using a new digital music software product called MediaCoder that is used for electronic audio recording, file modification, and organization of digital music. Such products are highly relevant to the participant group; similar products have been used in recent experimental research within marketing (e.g., Thompson et al. 2005). To reduce the possibility of demand effects, a cover story disguised the experiment as a product assessment study. Participants saw a product overview describing it as a beta version of an upcoming product needing user testing. Included were details on the software's purpose, its features, and ways in which music files could be modified and managed using it. The focal usage task consisted of performing a set of operations on a sample music file (importing it, specifying modification options, modifying the file, and saving it). These operations result in a change in file format that uses less space on the computer without adversely affecting the quality of the music. The above-described task was embedded within the overall experiment. An advantage of specifying this usage task is that performance of the task would lead to uniform quality in the output across subjects, with between-subject differences in proficiency reflected by the time taken to complete the task (e.g., Vance et al. 1989).

Design and Procedure

The experiment consisted of a 2 (learning style: verbal vs. experiential) × 2 (learning schedule: massed vs. spaced) between-subjects full-factorial design administered to participants individually via the MediaLab computer interface. Fifty-eight undergraduate students completed the study in exchange for course credit and were randomly assigned to the four conditions. All participants were first shown written, step-by-step instructions on how to use the software product to complete the task. Instructions were then removed for the experiential learning condition, wherein participants were given three practice trials. They were told to complete the earlier described tasks on sample music files using the software product. In contrast, participants in the verbal learning condition were not provided with any practice trials but reviewed the instructions for completing the software task three more times. Participants in the massed learning condition experienced their trials (instructions) in succession, while those in the spaced condition did so between filler tasks (see fig. 1).

All filler tasks (questions relating to participants' favorite restaurants and movies) used in the spaced learning condition were also administered to participants in the massed learning condition in order to equalize the overall time spent across schedules. Precautions were taken, as noted in the literature, for controlling for primacy and recency effects (e.g., Appleton-Knapp et al. 2005). In order to reduce primacy effects, the filler tasks were administered to the massed group before they undertook their learning trials. In order to minimize recency effects, a common unrelated distractor task was administered to all participants after the learning trials. After the learning trials and distractor task, all participants were tested on their ability to use the product to complete the task as quickly as possible. We controlled for quality and accuracy of performance by configuring the task in a way that task completion would lead to predictable and uniform quality in the final sample file.

Since we used an open-source software program, which is accessible to the general public, information was then collected regarding participants' prior exposure to or experience with the software, product category relevance, gender, and age. Covariate analyses revealed no differences across groups; hence, these variables were excluded from additional analyses.

Dependent Measure

Completion time for the focal task using the software product formed the dependent measure since this is a commonly used metric in the study of task performance. Numerous studies in psychology (e.g., Vance et al. 1989), human factors (see Hornbæk [2006] for a review), and medicine (e.g., Summers et al. 1999), as well as recent research on skill-based products within marketing, have used completion times as a measure of learning (e.g., Murray and Häubl 2007; Thompson et al. 2005). Also, since the product usage and context were expected to be moderately complex, we tested for differential accuracy in task performance across conditions (i.e., whether individuals correctly completed the component tasks). An examination of the final test files indicated that all participants completed the task correctly; thus, differences in proficiency could be explained by differences in completion time.

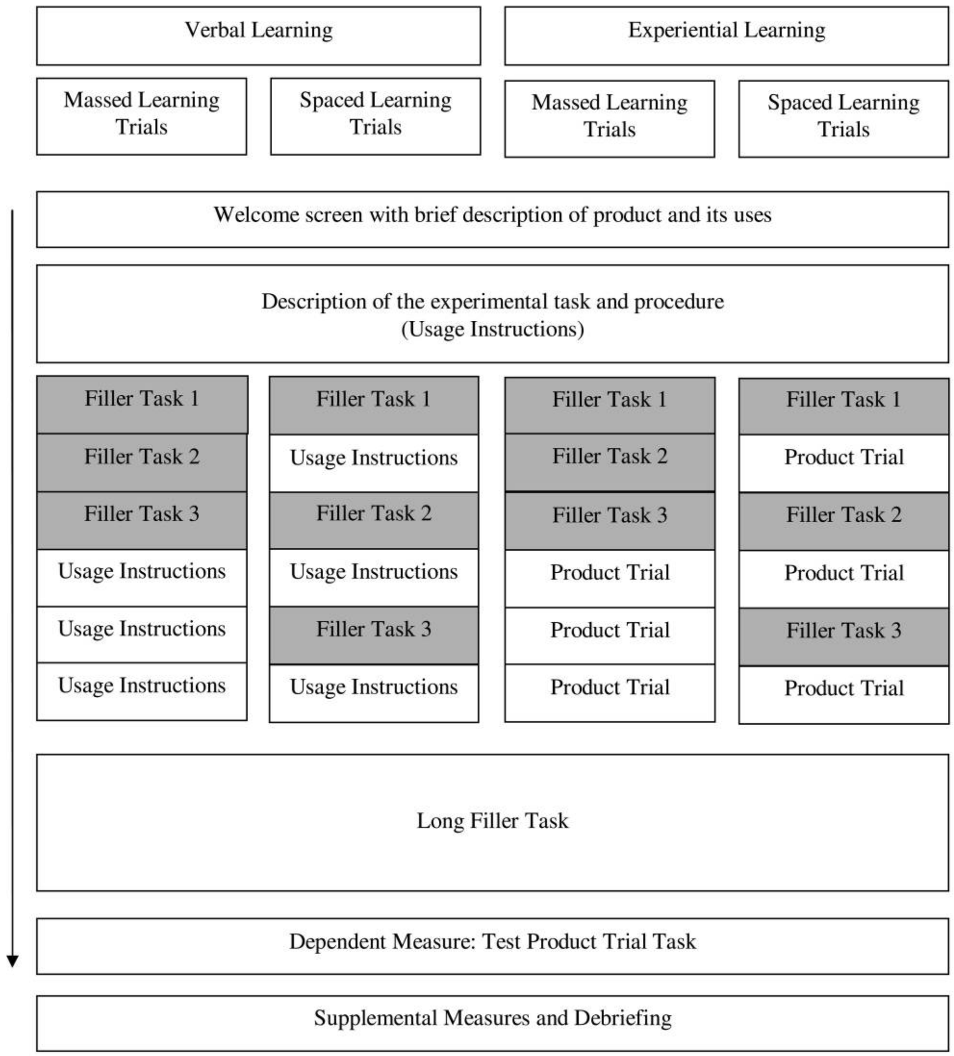
Results

In order to ascertain that the product was moderately complex, we collected participants' complexity ratings of the product after using it. A three-item scale with 1 and 7 as endpoints was used for this purpose (using the software is complicated/simple, is confusing/clear, takes a lot of effort/little effort; $\alpha = .94$). Results show that perceived complexity of the product was not significantly different from the midpoint of the scale ($M_{complexity} = 4.03$; $p > .87$).

We estimated a linear model with task completion times as the dependent variable and the two experimental manipulations as fixed factors. This was followed by planned contrasts (one-tailed, due to a priori specification of the direction of effect) to test hypotheses 1 and 2. The overall model ($F(3, 54) = 13.5$, $p < .001$) and the main effect of learning style was significant, with faster completion times for experiential compared to verbal learning ($M_{exp} = 41.1$ seconds, $M_{verb} = 85.9$ seconds; $t = 3.27$, $p < .002$). The main effect of learning schedule was not significant ($M_{space} = 56.3$ seconds, $M_{mass} = 58.8$ seconds; $t = 1.08$, $p > .25$). Importantly, the two-way interaction of learning style and schedule was significant ($t = 2.56$, $p < .02$). Planned contrasts revealed that for the verbal learning group, the spaced schedule led to faster test performance than the massed schedule did ($M_{verb\_space} = 76.9$ seconds, $M_{verb\_mass} = 97.8$ seconds; $t = 2.03$, $p < .03$), while for the experiential learning group, the massed schedule led to faster test performance than the spaced schedule did ($M_{exp\_mass} = 35.3$ seconds, $M_{exp\_space} = 45.1$ seconds; $t = 2.04$, $p < .03$). Hence, both hypotheses 1 and 2 were supported (see fig. 2).

FIGURE 1

BASIC EXPERIMENTAL PROCEDURE



Discussion

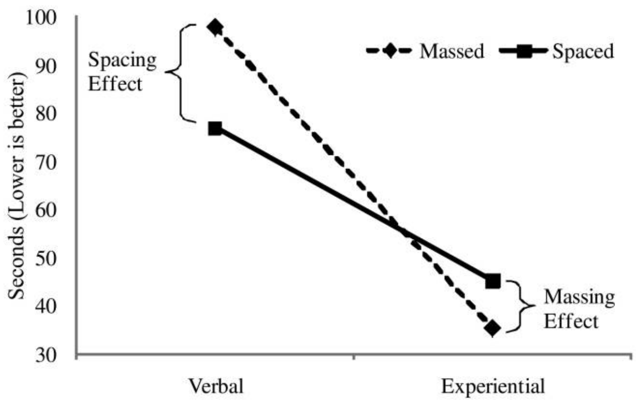
Results from experiment 1 provide initial evidence of the superiority of a massed learning schedule in terms of faster completion when usage learning is experiential—a "massing" effect—while the reverse occurs when learning is verbal, consistent with the spacing effect. Further, we develop a new theoretical account—conceptual mapping—to make predictions underlying this phenomenon. In later studies, we build on the findings from experiment 1 and the theoretical account to further explicate the process and relate it to downstream variables.

A possible alternative explanation for the experiential group findings from experiment 1 could be that multiple modalities are involved for this group given that they also received exposure to instructions once (prior to the schedule manipulation). To rule this out, we conducted an additional study focusing on the experiential group ($n = 87$) with the same overall procedure but with initial instructions shown via video. We find that the superiority of the massed schedule was robust ($M_{\text{video\_mass}} = 40.7$ seconds, $M_{\text{video\_space}} = 65.6$ seconds; $t = 3.05$, $p < .003$), thereby ruling out the alternative explanation that multiple modalities in learning may have contributed to the benefits for the massed experiential (vis-à-vis the spaced experiential) group.

Experiment 1 provides nascent evidence on the substantive issue of how usage proficiency evolves in moderately complex products under different learning styles. Skill-learning research has predominantly focused on two ends of the complexity spectrum. Research paradigms rely on either extremely simple motor tasks (e.g., key presses, ball

FIGURE 2

EXPERIMENT 1: TASK COMPLETION TIME



NOTE.—All mean completion times are significantly different at $p < .05$ or better.

throws, single or two degrees of freedom arm movements) with little or no cognitive or declarative component (e.g., Simon and Bjork 2001) or extremely complex and ambiguous tasks, such as the Tower of Toronto, Space Fortress, or Air Traffic Control tasks that often involve high-level cognitive skills and/or complex motor movements (e.g., Shebilske et al. 1999). Theories from either end of the spectrum do not generalize well to moderately complex usage (Wulf and Shea 2002), which is where many modern consumer products are situated—cell phones, do-it-yourself hobby kits, video games, computer interfaces, and various self-service technologies (Meuter et al. 2005). Understanding how consumers gain usage proficiency in these contexts, therefore, has wide-ranging implications for learning theory and product design. Initial evidence from experiment 1 suggests that the two predominant learning paths to proficiency are contingent on how the initial trials are spaced.

Conceptual mapping theory also extends current verbal learning theories, such as encoding variability and study-phase retrieval (e.g., Appleton-Knapp et al. 2005; Janiszewski et al. 2003; Noel 2006), by (*a*) integrating verbal and experiential learning in moderately complex domains where one style may not naturally be preferred over the other and (*b*) outlining conditions when massed learning schedules benefit performance. In experiment 1, massed learning leads to better *focal task* usage proficiency with experiential learning. If the conceptual mapping account is valid, then the superiority of massed learning should also hold for other related tasks. Experiment 2 examines the effect of learning trials (massed vs. spaced) on skill-based *transfer task* usage proficiency when learning is experiential.

EXPERIMENT 2: TRANSFER OF LEARNING

Experiment 2 focuses on usage proficiency on a transfer task when learning is experiential. A transfer task is one that is related to but different from the task initially attempted during learning trials. In addition to the theoretical insights generated from the study of transfer of learning in this domain, this research offers practical implications for how different learning schedules may influence subsequent usage in cases where a product has multiple functionalities. For instance, individuals may try out different modes of image capture in a digital camera during their first interaction with the product (say, in a store) but over time may use features that are different than the one initially learned (e.g., various resolution settings, timer setup). How well consumers are able to perform these related but previously unlearned tasks may have a strong bearing on how much the product is eventually used and, in turn, how easily or quickly it diffuses through the marketplace (Shih and Venkatesh 2004).

As described earlier, experiential learning is primarily a bottom-up process in which individuals rely on developing informal production rules (Anderson and Fincham 1994; Taatgen et al. 2008) that are action-based and relational in nature (Kadijevich and Haapasalo 2001; Neves and Anderson 1981). Bottom-up (or construction-based) processing, which underlies experiential learning, leads to greater performance flexibility (Taatgen et al. 2008), which in turn correlates with better transfer task performance (Carnahan and Lee 1989). Hence, for experiential learning, we expect that the schedule (e.g., spaced or massed) that leads to superior focal task performance will also result in superior transfer task performance. The conceptual mapping account predicts that with experiential learning, a massed (vs. spaced) learning schedule should benefit task performance (as shown in experiment 1). This is due to the learning of informal production rules and relational linkages between component subtasks (e.g., Anderson and Fincham 1994), which is less likely with a spaced learning schedule due to the breaks between trials. This component-level fluency leads to superior conceptual accretion and higher-order learning (Fisk et al. 1988), which translates into better proficiency (Francis and Gallard 2005). Importantly, conceptual mapping has also been shown to foster better generic task strategies and problem-solving heuristics, which are acquired as part of the developmental process (Tirre 1991). Thus,

H3: With experiential learning, a massed (vs. spaced) schedule will lead to better usage proficiency for a transfer task.

Design, Procedure, and Dependent Variables

Experiment 2 used a single-factor (learning schedule: massed vs. spaced) design. Learning style was fixed at experiential. Fifty-six undergraduate students completed the study in exchange for course credit. To account for product-specific idiosyncrasies, a different product and task was used in this experiment. The product used in this study was Audacity, an open-source audio-modification software. This software product provides tools to enable changes to digital music. The focal task (on which participants learned to use the product) required participants to use Audacity to change the baseline volume of a music file, while the transfer task (the dependent measure) involved introducing a fading-off period toward the end of the music. The transfer task required participants to use different menu options within the same overall menu structure. Both tasks thus required the use of the same primary menu but differed in terms of the submenu used to complete the task. The tasks also involved the same number of steps.

The cover story, the learning schedule manipulation, and the filler tasks were all similar to those used in experiment 1. After the learning trials involving the focal task and a common filler task, participants were asked to complete the transfer task. Transfer task completion time was measured unobtrusively and formed our dependent measure to test hypothesis 3. Verbal recall measures and thought protocols were then collected and coded for evidence of conceptual accretion. Two independent coders rated each protocol on a 9-point scale (1 = low conceptual accretion; 9 = high conceptual accretion). Protocols that reflected either a logical grouping of product features used for the tasks (i.e., either by menu or by functionality) or a useful mental model of the features and connections between them were coded as being higher in conceptual accretion. In contrast, protocols that remained at the subtask or specific step level (e.g., "click option A, then click option B") without any accompanying broader and/or deeper description of the product and its usage context were coded as being lower in conceptual accretion. Intercoder reliability, measured using Krippendorff's α, was .86 for the conceptual accretion score (all disagreements were resolved by discussion). For example, a participant rated low in accretion wrote, "1. Open the file. 2. Using the selection tool 3. Effects > Amplify > 10.0 > Allow Clipping > OK." In contrast, a participant rated high in conceptual accretion wrote, "Import the music file (Project → Import) and select the entire music by clicking and dragging the mouse across. Then you perform amplification (under Effects menu → Amplify). You set the threshold value to 10 and put a checkmark in the 'clip recording' to allow clipping and then say ok."

The same covariates from experiment 1 were also collected. Only significant covariates are reported in our analyses. Results from the measure of complexity ($\alpha = .92$) indicate that the software was rated as moderately complex and was not significantly different from the midpoint of the scale ($M_{\text{complexity}} = 4.06$, $p > .73$).

Results and Discussion

Transfer Task Usage Proficiency. We estimated a single-factor model with completion time as the dependent variable and learning schedule as the independent variable. In support of hypothesis 3 we observed a significant main effect for the schedule factor ($F(1, 54) = 5.32, p < .025$). Specifically, participants in the massed learning condition completed the transfer task significantly faster than those in the spaced learning condition ($M_{\text{space}} = 84.9$ seconds, $M_{\text{mass}} = 67.4$ seconds).

Conceptual Mapping. A similar model was estimated with participants' accretion scores as the dependent variable and learning schedule as the predictor variable. Raw free recall (number of individual product features mentioned) and prior knowledge of the product were included as covariates. The coefficient for the schedule factor was significant, with conceptual accretion scores of the massed learners significantly higher than those of spaced learners ($M_{\text{mass}} = 6.73$, $M_{\text{space}} = 6.09$; $t = 1.92$, $p < .03$). This pattern indicates that massed learning leads to not only better usage proficiency but also better conceptual understanding of the task.

The conceptual mapping account predicts that in experiential learning contexts, massed learning leads to greater task proficiency; but in verbal learning contexts, spaced learning leads to greater proficiency (experiment 1). Experiment 2 extends this account to transfer performance in the case of experiential learning. Specifically, since back-to-back or massed practice facilitates the learning of component tasks and relational links between subtasks, the user is able to obtain procedural knowledge that is more general and flexible in application, thereby enabling superior learning and performance transfer (Taatgen et al. 2008; Tirre 1991). Generally speaking, the massed schedule allows for some degree of conceptual mapping to occur such that subtasks can be logically connected and a coherent mental model (e.g., Day and Nedungadi 1994; Norman 2002) of product usage can be developed. This is reflected by the greater conceptual accretion observed in participants' thought protocols.

The above set of findings raises the question of how verbal learning contexts affect conceptual accretion and how learning schedules in such environments affect proficiency for transfer tasks. Specifically, will transfer task performance following verbal learning reflect a pattern similar to that shown for experiential learning in experiment 2? Alternatively, will a dissociative pattern emerge for the two learning styles, as was the case for a focal product usage task in experiment 1? Experiment 3 is designed to investigate this question. Further, in keeping with the multidimensional nature of proficiency, we broaden our experimental paradigm to develop objective measures relating to the quality of performance (instead of the fluency at performing a task). We also recruit new measures to capture the richness of individuals' conceptual accretion and employ them to test for causal relationships.

EXPERIMENT 3: USAGE PROFICIENCY AND CONCEPTUAL MAPPING

Proficiency is a multidimensional construct (e.g., Vance et al. 1989), and this research focuses on one dimension—speed, or time to completion—in experiments 1 and 2 in order to tap fluency with usage. We now address a second dimension—quality of performance—in experiments

3 and 4. Quality of task performance, that is, how well a product is used, is particularly important in the consumer context since it plays a central role in determining users' perceptions of the product (e.g., Norman 2002). For instance, the phenomenal success of the iPhone and the Wii may be traced to how well consumers were able to use these products.

We now develop our expectations on how learning schedules interact with learning styles to influence performance on a transfer task. Usage proficiency depends on learning component tasks as well as learning how they fit together. In contrast to experiential learning—which is primarily a hands-on, bottom-up process that leads to greater performance flexibility (Taatgen et al. 2008), which in turn leads to better transfer task performance (Carnahan and Lee 1989)—verbal learning is primarily a top-down process (Taatgen et al. 2008) in which individuals rely on memory for instructions. Memory for the focal task steps learned during initial review of instructions should serve as the basis for subsequent product usage. When usage is the same as that reviewed in instructions, better verbal memory for the subtask steps should facilitate performance. Prior knowledge is unlikely to be a source of interference in this case, and hence performance should be better, a pattern we see in experiment 1 for spaced (vs. massed) learning.

However, when usage involves a slightly different set of component subtasks and connections—a transfer task—better memory for the focal task's components may serve as a source of interference for the transfer task. Such memory-based interference has been shown to occur in both individual (Burke and Srull 1988) and group (Lindsey and Krishnan 2007) verbal learning domains. Further, it is especially prevalent when contexts are related, as in competitive (Kent and Allen 1994) or contextual interference (Kumar and Krishnan 2004). Specifically, interference should inhibit (*a*) the performance of the component subtasks that make up the transfer task and (*b*) the learning of interconnections between subtasks, which is procedurally derived while performing the task.

Hence, for verbal learning we expect that the schedule (e.g., spaced or massed) that leads to superior focal task performance will actually result in inferior transfer task performance. Spaced learning conditions correspond to such a context. With verbal learning, spacing of learning episodes leads to better memory (Appleton-Knapp et al. 2005; Janiszewski et al. 2003)—in this case, memory for focal task instructions. This, in turn, should lead to interference with performing the transfer task, with the consequence that transfer task performance should be worse (compared to when initial learning is massed). Conversely, massed learning of instructions should result in less interference from the focal task steps (due to poor memory for focal task instructions), without detrimentally affecting general background knowledge about the product. Hence, due to the availability of general usage-related information and minimal interference from prior knowledge, undertaking the transfer task following massed (vs. spaced) verbal learning episodes more readily allows for the discovery of new, transfer task–related linkages and application of informal production rules during actual product use. As mentioned previously, this component-level fluency manifests in superior conceptual accretion and higher-order learning (Fisk et al. 1988) and correlates with better proficiency (Francis and Gallard 2005). Stated formally,

> **H4:** With verbal learning, massed (vs. spaced) schedule will lead to better usage proficiency on a transfer task.

Note that this is in contrast to the pattern of effects for experiential learning. This is because verbal and experiential learning groups have different drivers of proficiency; hence, the pattern of learning schedule (e.g., spaced vs. massed) effects is different for focal versus transfer tasks.

Conceptual Mapping. The superiority of massed trials for experiential learning found in experiments 1 and 2 should be replicated in experiment 3. The conceptual mapping account suggests that conditions that facilitate learning both component subtasks and relational linkages lead to the development of a more coherent mental model. When learning is experiential, a massed schedule affords the opportunity to use real-time feedback during usage to make connections between subtasks, as well as any needed adjustments, thereby maximizing conceptual accretion (experiment 1 and 2). Thus, participants' concept maps (e.g., Novak 2002) should be more comprehensive, accurate, and better organized for the massed learners when learning is experiential.

When learning is verbal, participants are engaged in reviewing instructions for the focal task. Consistent with the spacing effect, verbal recall should be worse for the massed group. For this massed group, lower recall of focal task instructions reduces interference and encourages the formation of flexible, transferable knowledge. In turn, concept maps are likely to reflect more generalized knowledge about the product or usage context. Hence, we should expect better conceptual accretion for individuals engaged in massed learning across both experiential and verbal learning contexts, even though the spacing effect for raw recall should remain robust for the verbal learning group. We aim to add to our initial evidence in support of the conceptual mapping account by recruiting different measures of conceptual accretion. Given the objective nature of the conceptual accretion measure, we use it to test for mediation between learning schedule and usage proficiency. Specifically, we test the structural account of conceptual accretion mediating the effect of learning schedule on usage proficiency. Experiment 3 thus tests the substantive phenomenon (the superiority of massed learning) and the theoretical account (conceptual mapping) using new measures for each construct.

Design, Procedure, and Dependent Variables

Experiment 3 used a 2 (learning style: verbal vs. experiential) × 2 (learning schedule: massed vs. spaced) between-subjects full-factorial design with usage proficiency on a transfer task as the dependent measure. One hundred and five undergraduate students completed the study in exchange for course credit. We developed a new test task for the software used in experiment 2 (Audacity) and constructed objective measures derived out of this task. Specifically, we constructed the task such that each participant produced a unique file whose quality could then be analyzed using the Audacity software. The transfer task entailed converting a music file into a mobile phone ringtone. In essence, this task involved trimming the music file to a suitable length (20 seconds) and boosting the lower (bass) frequencies of the music so that it sounds better on the smaller speakers usually found on cell phones. After these steps, the participant was asked to save the output file and proceed to the next section of the study. This output file was subsequently analyzed for (*a*) deviation from the length of the ringtone specified in the instructions and (*b*) amplitude of base frequencies in the ringtone. Each participant's performance on these two dimensions was determined from their output file by an independent judge using the analysis features provided in the Audacity software.

The cover story, learning schedule, learning style manipulations, and filler tasks were all similar to earlier experiments. After the learning trials and a common filler task, participants were asked to complete the transfer task. Covariates, verbal recall measures, and thought protocols were then collected. The new method in measuring conceptual accretion applied the concept mapping procedure developed by Novak and colleagues (e.g., Novak 2002; Novak and Cañas 2004). Participants were asked to draw a boxes-and-arrows diagram of their understanding of how the software is used to perform the experimental audio-related task (Novak 2002). Individual concept maps were then coded on a 9-point scale (1 = low; 9 = high) by two independent coders for correctness (reliability = .85), comprehensiveness (reliability = .88), and organization (reliability = .88; Besterfield-Sacre et al. 2004). A summated score was constructed from these items to form the measure of overall concept map quality (Cronbach's $\alpha = .96$). Prior history, personal relevance, focused attention, motivation, and trait measures of technological anxiety were also measured as covariates and were reported if significant.

Results and Discussion

Usage Proficiency. Since the deviations from optimum ringtone length followed a Poisson distribution—most deviations close to zero seconds and a few deviations extending to almost 70 seconds—we conducted a Poisson regression with amount of deviation (error length) as our dependent measure. Learning style and schedule served as the independent variables, with age and prior history as covariates. We observed significant main effects for learning schedule ($z = 10.9$, $p < .001$) and style ($z = 13.2$, $p < .001$). Importantly, a significant two-way interaction ($z = 7.52$, $p < .001$) qualified these effects. Planned contrasts revealed that the average error length was significantly lower for the massed group, both when learning was experiential ($M_{mass\_exp} = 4.1$ seconds vs. $M_{space\_exp} = 14.9$ seconds; $z = 10.9$, $p < .001$) as well as verbal ($M_{mass\_verb} = 18.9$ seconds vs. $M_{space\_verb} = 22.2$ seconds; $z = 3.71$, $p < .003$). This difference was greater for the experiential (vs. verbal) group as seen by the significant two-way interaction.

We also estimated a linear model with the two experimental manipulations as factors and the amplitude of bass frequencies in the ringtone as the dependent measure. The coefficient for the main effect of learning schedule was positive and significant ($t = 2.7$, $p < .01$), while the coefficients for learning style and the two-way interaction were not statistically significant ($p > .15$). Consistent with earlier findings on transfer task performance, planned contrasts showed that both in the experiential ($M_{mass\_exp} = -48.6$ decibels vs. $M_{space\_exp} = -55.3$ decibels; $t = 2.71$, $p < .01$) and verbal learning groups ($M_{mass\_verb} = -55.9$ decibels vs. $M_{space\_verb} = -60.1$ decibels; $t = 1.67$, $p < .05$), massed learners evidenced significantly higher baseline volumes for bass (low) frequencies (as required by the task) than the spaced group. Further, a follow-up contrast between the massed experiential learning group and the other groups indicated that individuals undergoing massed experiential learning exhibited significantly better performance than the other three groups ($t = 3.64$, $p < .001$). Overall, the pattern of effects is consistent with our predictions, although some of the effects did not reach significance. Across both measures we find support for hypothesis 4 (i.e., with verbal learning, massed trials lead to better performance on transfer tasks).

Conceptual Mapping. We expected conceptual accretion to be consistently better for massed learning across both learning styles. We subjected the concept map ratings to a two-way linear model with learning schedule and learning style as factors and prior history as a covariate. Our analyses revealed a main effect for schedule in the direction expected ($M_{mass} = 16.7$, $M_{space} = 13.6$; $t = 2.36$, $p < .02$). Further, planned contrasts indicated that massed learning resulted in better conceptual accretion for both the experiential ($M_{mass\_exp} = 17$ vs. $M_{space\_exp} = 14.3$; $t = 2.29$, $p < .03$) and verbal learning groups ($M_{mass\_verb} = 16.4$ vs. $M_{space\_verb} = 12.8$; $t = 1.96$, $p < .03$). As expected, neither the main effect nor the interaction effect for learning style significantly affected the quality of conceptual accretion ($p > .15$).

Verbal Recall. Recall scores for task instructions were subjected to a two-factor linear model with learning schedule and learning style as factors. The main effects for the factors were not significant, but the two-way interaction was significant at the $p = .07$ level. Follow-up contrasts indicated that with verbal learning the pattern of recall was consistent with the spacing effect observed in extant literature ($M_{space\_verb} = 41.8$ words, $M_{mass\_verb} = 35.4$ words; $t = 2.15$, $p < .03$). As expected with experiential learning, mean verbal recall did not differ by the learning schedule ($M_{space\_exp} = 32.6$ words, $M_{mass\_exp} = 33.2$ words; $t = .44$, $p > .5$).

As the pattern of results show above, although the spacing effect for verbal recall remains a robust phenomenon, when it comes to product usage proficiency (transfer task) and conceptual accretion, a massed schedule appears to be more beneficial. For both experiential and verbal learning contexts, transferable usage knowledge—evidenced by usage proficiency—is enhanced with massed learning. This is indicated by the reduced error length and the relatively higher level of bass frequencies in the ringtone music for the massed learners. This pattern of better performance was also accompanied by better conceptual accretion for the massed group.

Mediation Analyses. The goal of our mediation analysis is to test the effect of learning schedule on usage proficiency via conceptual accretion. We followed the paradigm originally described by Baron and Kenny (1986), but since we had two different measures of performance, each with a different underlying distribution, we used the nonparametric bootstrapping procedure developed by Imai et al. (2010) for causal mediation analysis. This procedure is consistent with recent calls within consumer research to broaden the paradigm for mediation testing (Zhao, Lynch, and Chen 2010). Also, the package developed by Imai and colleagues for use under the *R* statistical environment is flexible for use on different types of models and distributions. Our analyses revealed that for both dependent measures, the overall mediation effect was significant. Point estimates for the mediation effect for the deviation measure (1.08) as well as the amplitude measure (5.28) was significant; 95% confidence intervals for both estimates did not include zero. Also, for both sets of mediation analyses, we found that the direct paths from learning schedule to proficiency were also significant (0.56 for deviation and 6.26 for amplitude; both 95% confidence intervals outside zero), indicating support for a partially mediated model of effects.

Experiments 1 and 2 offered evidence regarding the superiority of massed experiential learning in usage proficiency and advance a theory that broadly explains how consumers attain proficiency while learning to use products. Experiment 3 tests the robustness of (*a*) the massing effect by using a broader conceptualization of usage proficiency and (*b*) the conceptual mapping account by using a different measure of conceptual accretion. Experiment 4 builds on these results for conceptual mapping by adding measures of product perceptions. The latter is especially relevant given that individuals' product-related perceptions have been shown to ultimately influence future purchase behavior (e.g., Wood and Moreau 2006).

EXPERIMENT 4: USAGE PROFICIENCY AND PRODUCT PERCEPTIONS

In most consumer contexts, how well a product is used also correlates with how consumers evaluate the product and, thus, with its success. Notable examples of a good usage experience correlating with commercial success include consumer products such as the iPhone or Wii, Web sites such as Google, software such as Microsoft Office, and even professional-grade products such as the Nikon series of digital SLR (single-lens reflex) cameras. Thus, an initial trial with products not only guides what consumers learn but also may affect consumers' perceptions (e.g., Wood and Moreau 2006). It is important, therefore, to understand how the learning process influences attitudes toward the product.

Since how well consumers use a product is positively correlated with perceptions (e.g., Norman 2002), it follows that the learning schedule that leads to greater proficiency should correlate with positive attitudes. Massed experiential learning corresponds to such a pattern; thus, we expect that consumers' attitudes and willingness to pay will be greater for massed (vs. spaced) experiential learners.

Design, Procedure, and Dependent Variables

In experiment 4, we focus on experiential learning, with learning schedule (massed vs. spaced) manipulated across groups. Fifty-eight undergraduate students completed the study in exchange for course credit. The cover story, learning schedule manipulation, and filler tasks were all similar to earlier experiments. After the learning trials and a common filler task, participants were asked to complete the transfer task, after which covariates, verbal recall measures, and thought protocols were collected. The transfer task involved creating a participant-specific output file (a ringtone), which was subsequently analyzed for quality of performance using the protocol developed in experiment 3.

Since product adoption is a function of actual proficiency as well as consumers' perceptions of the product's usability (Wood and Moreau 2006), we collected measures for overall attitude toward the product (7-point scale anchored at useless/useful, bad/good, undesirable/desirable, and unfavorable/favorable; $\alpha = .96$) and willingness to pay, in order to test the impact of different experiential learning schedules on consumers' impressions. We also collected concept maps from each participant during the experiment (e.g., Novak 2002; Novak and Cañas 2004). Individual concept maps were coded by two independent coders for correctness (reliability = .85), comprehensiveness (reliability = .83), and organization (reliability = .80), following the procedure used earlier (Besterfield-Sacre et al. 2004). A summated score was then constructed from these items to form a subjective measure of overall concept map quality ($\alpha = .95$).

In addition, we also adapted two concept map–related measures from the education literature for new product usage. These adapted measures afford a deeper exploration of the conceptual mapping account. First, we noted the number of (*a*) independent concepts, (*b*) relationships between concepts, and (*c*) cross-links between different concept groups for each map. These were normalized and averaged to form an objective measure of concept map quality. Second, to obtain a tertiary measure of how evolved an individual's knowledge is, we adapted Novak and Cañas's (2004) definition of "string" versus "mesh" maps. A string map shows jumps from one concept to another with no other higher-order relationships explicated and reflects a rote form of knowledge. In contrast, a mesh map is rich in concepts and meaningful linkages between relatively distant concepts. We coded each concept map as either being close to a string (1) or mesh (9) map and used the average of two independent coders' ratings (reliability = .81) as an exploratory quality-of-mental-representation measure.

Thus, the dependent variables in our analyses consisted of (*a*) the two objective quality-of-performance measures of usage proficiency (error length of the ringtone and volume of bass frequencies), (*b*) consumer attitudes to the product and willingness to pay, and (*c*) the three measures of conceptual accretion described above. The same covariates as in experiment 3 were collected and reported if significant.

Results and Discussion

Usage Proficiency. Similar to experiment 3, we conducted a Poisson regression with amount of deviation (error length) as the dependent measure, learning schedule as the independent variable, and prior history, product relevance, and focused attention as covariates. The coefficient for the schedule factor was significant ($z = 2.29$, $p < .02$) and in the direction hypothesized. On average, the massed group exhibited significantly less deviation from the optimum length compared to the spaced group ($M_{\text{mass}} = 14.1$ seconds vs. $M_{\text{space}} = 16.7$ seconds). One-way ANOVAs on the amplitude of bass frequencies also revealed a main effect in the direction hypothesized. The massed group demonstrated significantly higher baseline volumes for bass (low) frequencies (as required by the task) than the spaced group did ($M_{\text{mass}} = -52.4$ decibels vs. $M_{\text{space}} = -59.4$ decibels), indicating better usage performance.

Product Perceptions. A regression model with product attitude as the dependent variable, learning schedule as the independent variable, and attention, relevance, and prior history as covariates revealed a significant effect for the schedule factor in the hypothesized direction. Massed learners exhibited better product attitudes compared to spaced learners ($M_{\text{mass}} = 17.2$ vs. $M_{\text{space}} = 15.6$; $\beta = 3.12$, $p < .04$). Similarly, willingness to pay was also greater for the massed learning group compared to the spaced schedule group ($M_{\text{mass}} = \$24.6$ vs. $M_{\text{space}} = \$18.3$; $\beta = 7.3$, $p < .04$), providing additional support for the efficacy of massed learning schedules in improving not only usage proficiency but also product-related perceptions.

Conceptual Mapping. The objective (scores) and subjective (ratings) concept map measures were each regressed on the learning schedule factor. A significant effect in the direction hypothesized provides support for the conceptual mapping account. Specifically, we find that massed learning leads to better quality in participants' concept maps on both the subjective ($M_{\text{mass}} = 23.4$ vs. $M_{\text{space}} = 19$; $\beta = 1.53$, $p < .033$) and objective ($M_{\text{mass}} = 20.1$ vs. $M_{\text{space}} = 17.6$; $\beta = 2.23$, $p < .03$) measures, as compared to spaced learning. Further, a regression on our tertiary quality-of-mental-representation measure suggests that individuals in the massed learning condition exhibited richer, more well-connected maps ($M_{\text{mass}} = 9.2$ vs. $M_{\text{space}} = 7.5$; $\beta = .6$, $p < .02$), compared to individuals in the spaced learning condition. The coefficients for attention and prior history were positive and significant ($p < .05$) in these analyses. As in experiment 3, this pattern indicates that massed learning leads to better conceptual accretion.

Mediation Analyses. Following the procedure from experiment 3, we used the Imai et al. (2010) algorithm to estimate mediation models with schedule as the predictor, conceptual accretion as mediator, and performance as the criterion variable. We used an average of the subjective and objective conceptual accretion measures as our mediator variable and retained the covariates described earlier. The first model, with error length as the dependent variable, revealed partial mediation consistent with experiment 3 (point estimates were .12 for the mediated path and .05 for the direct path; 95% confidence intervals of both estimates did not include zero). The second model, with amplitude as the dependent measure, also revealed partial mediation (consistent with experiment 3 findings). Specifically, point estimates for both the direct path and the mediated path (15.18 and 6.89, respectively) were significant. The 95% confidence intervals for each of these coefficients lay outside zero, thereby supporting a partially mediated model of effects.

We also performed mediation analysis with schedule as the predictor, conceptual accretion (composite score used earlier) and performance as the mediators, and attitude as the criterion variable with the same covariates. Since performance is an endogenous variable in this analysis, we constructed a composite measure for it by normalizing and averaging across the deviation and amplitude measures. Analyses reveal that the mediation model was significant. Point estimates for the mediated path (schedule to attitude with both mediators included) and the direct path from schedule to attitude were significant (5.54 and 5.09, respectively), with 95% confidence intervals for both estimates lying outside zero.

The above analyses replicate and extend findings in experiment 3 and provide support for the theoretical model explaining the role of conceptual accretion in the development of usage proficiency under different learning schedules. Also, experiment 4 shows that learning from massed product trial leads not only to greater usage proficiency and conceptual accretion but also to positive product perceptions such as attitude and willingness to pay.

GENERAL DISCUSSION

The current research has two core contributions. First, we find evidence for a massing effect under experiential learning conditions. Second, we develop a conceptual mapping account that explicates the mechanism driving usage proficiency and highlights optimal learning conditions for experiential and verbal learning. We elaborate on these contributions below.

Substantive Implications

Across four experiments, we demonstrate that massing of learning trials can, in fact, lead to better product usage proficiency. With verbal learning, we replicate the spacing effect observed in prior research (e.g., Appleton-Knapp et al. 2005; Noel 2006), whereas with experiential learning, we find evidence in support of a massing effect (experiment 1). Further, we find that the superiority afforded by massed learning also extends to different product usage contexts (transfer tasks, experiment 2). Indeed, even in the verbal learning domain, we show that although the spacing effect manifests for focal usage tasks, the reverse is true for a transfer task, with massing leading to better usage proficiency (experiment 3). This pattern of effects is robust across different measures of task performance (experiments 3 and 4). Also, we find evidence in support of our conceptual mapping account using two different measures of conceptual accretion (experiments 2–4). Finally, when learning is experiential, we find that massed learning leads not only to greater proficiency at product use but also to positive product-related perceptions (experiment 4). Taken together, the overarching substantive contribution is the superiority of massed learning, under specific conditions.

Why are these effects important or meaningful? Our main focus in this research is usage proficiency. Enhanced usage proficiency has been shown to lead to a variety of positive consumer outcomes by way of better utility derived from products (e.g., Chan and Storey 1996), greater feelings of self-efficacy (e.g., Bandura 1986; Dahl and Moreau 2007), and greater postpurchase satisfaction (e.g., Thompson et al. 2005), which in turn may lead to stronger repurchase intentions and positive word of mouth (Gupta et al. 2007; Wangenheim and Bayón 2007). Enhanced task proficiency and transfer to different product uses has also been shown to directly contribute to faster diffusion of new products (Shih and Venkatesh 2004). Our findings speak to these important outcomes by explicating the role of two conditions that may enhance the development of usage proficiency during initial product trial. Consumers often try out new products before engaging in purchase. Phenomena such as in-store trials and marketing tactics such as free-trial offers relate to consumers' need for physical feedback from product trial. Our research highlights the opportunity marketers have for using these initial trials to help consumers acquire proficiency early in the purchase/consumption process. Encouraging back-to-back trial or practice may lead to better understanding of the product and directly help with new product adoption. From the consumer's standpoint, repeated practice with new products may provide a better understanding of novel attributes and pave the way for future, different uses, eventually resulting in greater derived benefits from complex products. In turn, utility and satisfaction from new products may be positively influenced, a pattern we find some evidence for in experiment 4.

In addition to the insights derived from the interaction of learning schedules and learning styles in product use, the substantive phenomenon of learning to use products offers a fertile ground for future research. Behaviors such as multitasking or task switching are prevalent in current, technologically saturated environments. Conceptualizing initial learning trials with these behaviors in focus offers a rich avenue for future research. Another phenomenon related to product usage is the idea of habitual usage and "lock-in" (e.g., Murray and Häubl 2007)—the notion of continued usage of an interface or Web site leading to "automatic" usage-related behaviors. Our framework suggests that back-to-back product trial may help develop usage proficiency, which, in turn, may eventually lead to automaticity.

Theoretical Implications

The substantive findings highlighted in the present research call attention to the limited degree to which theory gleaned from verbal learning domains applies to common product usage situations. For example, existing approaches largely rely on declarative memory in the form of learning *about* attributes from advertisements or product messages (e.g., Singh et al. 1994). We take into account procedural knowledge, focusing on *how to use* attributes and the interplay between declarative and procedural knowledge (Anderson 1999) to develop our conceptual mapping account. This account broadens the scope of learning research in marketing by delineating how individuals learn from product usage.

The conceptual mapping viewpoint takes into account the interrelated nature of verbal and experiential knowledge (e.g., Nokes and Ohlsson 2005), especially in product usage contexts. This theoretical account posits that product usage is determined by (*a*) learning how to perform subtasks (an action that may be completed via instructions or via experiential learning) and (*b*) learning how subtasks are interconnected and learning the transitions between subtasks (learning that is primarily experiential). This account is supported by the pattern of results we find for conceptual accretion across both measures of participants' conceptual knowledge—open-ended thought protocols as well as concept maps. In particular, greater conceptual accretion was found for participants who had the opportunity to learn subtasks via practice (massed learning groups in experiments 2–4) and, interestingly, the opportunity to generate procedural knowledge that was transferable (experiments 3 and 4). Importantly, verbal memory for the instructions did demonstrate the spacing effect (experiment 3), thereby dissociating verbal memory from conceptual accretion. This new account enriches extant cognitive theories such as encoding variability and study-phase retrieval (Appleton-Knapp et al. 2005; Janiszewski et al. 2003) in explaining the impact of learning schedules on product usage.

This article presents initial evidence highlighting the different ways in which usage proficiency may develop in common product usage contexts. Our findings bridge the gap between verbal learning paradigms, where both the learning and test criteria relate to verbal memory (e.g., Janiszewski et al. 2003) versus skill-learning research where both the learning and test criteria are primarily performance-based (e.g., Lee and Magill 1983), by looking at how verbal and experiential learning schedules translate to usage proficiency. This phenomenon has been investigated in our article in a moderately complex setting. As modern products continue to exhibit increasing levels of complexity, they often call on greater expertise. In this regard, exploring how initial learning trials and learning styles interact at different levels of complexity and expertise presents a challenging and exciting avenue for future research.

APPENDIX A

FOCAL TASK FOR STUDY 1

INSTRUCTIONS

From inside the MediaCoder software:

1. Click File → Add File
2. In the box that opens, navigate to My Documents and select the file “AAA.wma”
3. Within the MediaCoder window in the lower left quarter select the “Audio” tab
4. In this tab select the “Lame MP3” option in the Encoder setting
5. After this, click the “Start” button located on the toolbar.
6. Once you are done, close the MediaCoder window and press the “Continue” button to move on.

APPENDIX B

TRANSFER TASK FOR STUDY 3

INSTRUCTIONS

Please use Audacity to create a CELLPHONE RINGTONE from the music file “**SoLong.wav**”. To do so, you need to:

a) **Import** the file (it is located in “MyDocuments/MyMusic”) and **trim** it to about 20 seconds in length, then,
b) Modify the sound so that **lower** (**base**) frequencies are heard better. This usually helps the sound from becoming too ‘tinny’ when heard on cellphone speakers. You may use the “**equalizer**” or “**normalize**” or the “**compressor**” tool in the “**Effects**” menu for this purpose. Then,
c) Convert the stereo to a **mono** track (you may do this by either deleting one of the tracks or combining both into one)

After you’re done with these changes EXPORT the file to the DESKTOP as a new .wav file and NAME this file with your participant ID (You can do the **exporting and saving** by clicking “FILE”, then “EXPORT AS WAV” and then going to the DESKTOP and typing in your participant ID# as the filename. That is, you’re saving the exported file as “101.wav” if your ID is 101 OR “102.wav” if your ID is 102 and so on. Your participant ID# is written on the **top** of the sheet of paper provided to you by the experimenter).

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