Arun Lakshmanan & H. Shanker Krishnan

The Aha! Experience: Insight and Discontinuous Learning in Product Usage

Success of many products depends on how consumers learn to use them. This research suggests that initial product trial may lead to jumps in consumer learning. Such discontinuities in learning co-occur with the experience of insight—namely, a better conceptual understanding of how to use the product. Notably, such learning also positively affects downstream outcomes such as affect and usage intentions. Whereas exploration during initial trial facilitates insight-based learning, usage instructions seem to limit this type of learning. The implication for marketing managers is to structure initial trials in a manner conducive to exploration, thus leading to insight-driven learning and the associated positive outcomes.

Keywords: insight, discontinuous learning, skills, learning, product usage

Many consumer products entail physical usage to derive benefits. As such, how consumers interact with and learn to use these products is critical in influencing product adoption (Robertson and Gatignon 1986; Shih and Venkatesh 2004) and in defining the customer experience (Dahl and Moreau 2007; Moreau and Dahl 2005). For example, the tremendous and continuing success enjoyed by Nintendo's motion sensitive Wii game has been attributed to the active role the consumer plays in learning to use it and continued engagement in the consumption experience.

Consider a consumer who is eager to try out a new Wii game that has just hit the stores. She takes a moment to review the instructions and then begins playing. After a few trials, something clicks in her mind, and she "gets" the new interface. Almost concurrently, she begins playing considerably better. This sudden improvement in performance (viz., discontinuous learning) makes her perceive the game as fun. Note that anecdotal evidence on jumps in learning and performance are plentiful, coming from fields as diverse as animal cognition (Grether and Maslow 1937), evolutionary biology (punctuated equilibriums; Gould and Eldredge 1977), organizational learning (e.g., Sinkula 1994), and technological evolution (Sood and Tellis 2005).

The preceding example illustrates the benefit derived from the process of learning, and yet research in marketing has primarily used a cost lens to study how consumers learn to use products (e.g., Johnson, Bellman, and Lohse 2003; Murray and Häubl 2007; Wernerfelt 1985). From this latter viewpoint, learning to use a product is a cost to be overcome by the consumer and, consequently, the firm. For example, firms can provide free trials to reduce the learning cost for the consumer. Over time and repeated use, the consumer becomes habituated to (or invested in) the product, which in turn limits switching. Not surprisingly, the dominant theory representing consumer learning is the power law (Johnson, Bellman, and Lohse 2003), which depicts a steady process by which consumers learn to use products.

In contrast, discontinuous improvement in usage learning offers a benefits-based approach and has not been explored in much detail. Nor has a coherent theory been developed to explicate how discontinuous learning can manifest. This is a noteworthy omission because there are numerous examples of new products that have succeeded (or failed) as a result of active consumer learning. For example, the pervasiveness of the Wii is attributed to how intuitively consumers get up to speed on the motion-sensitive remote (Mossberg and Boehret 2006). Similarly, the phenomenal success of the iPhone is credited to how well consumers adapted to the touch-screen-enabled interaction. It is no coincidence that these product launches were followed by strong positive reactions, triggering an almost cultlike attachment to the product through numerous blogs, social networks, and customer interest groups. We believe that the positive consumer sentiment is the result of a discontinuous learning path traversed by consumers during initial trial.

Accordingly, the goal of this research is, first, to demonstrate that consumers indeed learn to use products in a discontinuous way and that this form of learning is accompanied by the experience of insight in relation to product usage. Second, we test the effect of such learning patterns on downstream measures of liking and usage intentions. Third, we explicate the antecedent role of exploration in the process. Finally, we explore how firms can encourage such types of learning.

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The research described here contributes to extant knowledge in three ways. First, we outline a different form of learning—discontinuous learning—and contrast it with the traditional power law view. Our research suggests that consumers' proficiency gain with using new products is sometimes characterized as a sudden, abrupt change rather than the commonly expected gradual improvement. Second, we draw on the creativity and human learning literatures to explicate (1) the role of insight in learning to use a product, (2) insight's relationship to discontinuous learning, and (3) its unique behavioral consequences. Our findings suggest that discontinuous learning is correlated with the experience of insight. In turn, this seems to have unique positive consequences for future usage. Third, this research is among the first in marketing to investigate the development of procedural knowledge (know-how), thereby enriching extant consumer learning literature. Prior research in consumer learning has relied largely on declarative knowledge ("know-what") such as brand–benefit associations and product/brand knowledge (Table 1). Our research is among the first to expand consumer learning into the procedural domain by studying product usage. Next, we review the literature pertaining to learning of product usage to provide the background for our research.

Learning to Use Products

Types of Knowledge

A long-standing framework describing human memory and knowledge is the declarative–procedural model originally laid out by Cohen and Squire (1980). In this framework, "declarative" refers to the learning, representation, and use of knowledge pertaining to facts and events, whereas "procedural" refers to the learning and control of sensorimotor and cognitive skills as well as in the development of routines such as habits. The declarative system has been implicated in the rapid learning of arbitrarily related information (one-shot learning) and the propositional and/or associative linking of information and concepts. From a consumer learning perspective, brand–benefit/product–benefit associations and knowledge of product attributes fall in the domain of declarative knowledge (e.g., Van Osselaer and Janiszewski 2001). In contrast, procedural knowledge is primarily related to how to do things (Squire 1986). Because how-to knowledge is largely embodied in the actual action undertaken (Anderson 1999), it may not be readily accessible to verbalization. For example, even though a person may get better at swimming through practice, he or she may not be readily able to describe that knowledge. It is usually best demonstrated when the person actually performs the actions.

Although various models of consumer learning have been advanced over time, a majority of these have been grounded in declarative paradigms. Models such as adaptive learning or human associative memory models in consumer research have explicitly referred to their declarative roots (e.g., Van Osselaer and Janiszewski 2001). Furthermore, theories on analogical transfer (e.g., Gregan-Paxton 2001) and consumer covariation judgments (Hutchinson and Alba 1997; Van Osselaer and Alba 2000) have been developed in declarative, brand-association, and attribute-inference contexts. Even models of experiential consumer learning (e.g., Hoch and Ha 1986) have been explicated principally from a declarative standpoint.

In contrast, product usage primarily relies on procedural knowledge. Notably, many consumer products require a sequence of actions to be performed, sometimes including physical manipulation, to use them. In day-to-day product usage contexts, how-to knowledge is made up of both explicit step-by-step scripts of what is to be done, as well as a proficiency embedded in the actual doing of the task. For example, how-to knowledge in using a video game joystick consists of both a step-by-step, verbally describable script of what controls need to be manipulated (declarative: akin to instructions found in a user manual) and a degree of skill in physically manipulating the joystick (procedural: embedded in actual task performance). Thus, although learning to use a product primarily calls on procedural knowledge, declarative knowledge is often closely intertwined in this process and may, in some situations, foster superior learning. Moreover, the extent to which a person's declarative knowledge is naturally engaged during usage may determine the learning pathway traversed during product trial. We next describe two possible learning paths.

Two Learning Paths

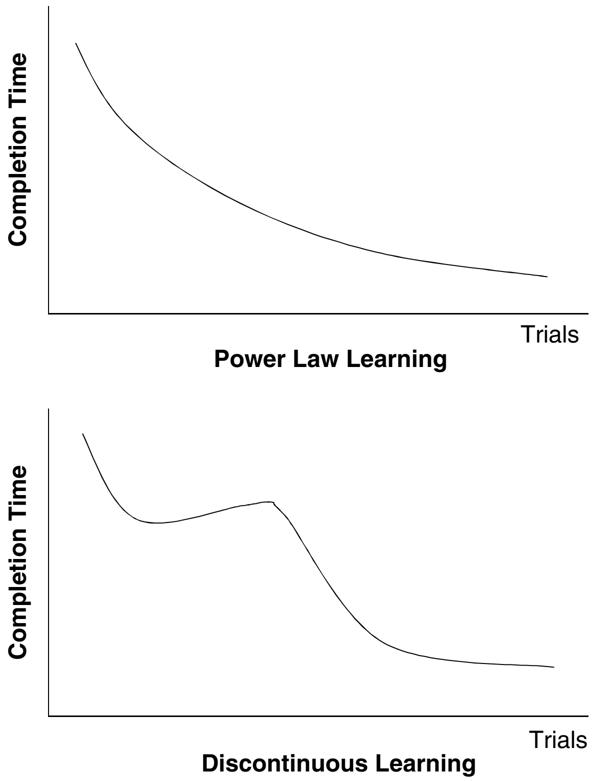
With two types of knowledge involved in usage learning, the process of learning to use products may also follow different routes depending on how learning occurs during initial product trial. For example, as a consumer uses a product repeatedly, his or her procedural knowledge—the fluency with which individual steps are performed—improves with each repetition. This improvement is typically gradual as the consumer becomes more familiar with performing the steps over time, thereby gaining *efficiency*. However, using a product also might lead to greater conceptual learning as the user explores the "usage space" and discovers optimal ways to perform a task with the product. Typically, when this happens, it also leads to the user forming an effective mental model of the product (Norman 2002). This process is similar to the formation or completion of a schema often described as a type of insight (Schilling 2005; Smith, Ward, and Finke 1995). In this connection, exploration of the product (or "playing around" with it), by helping the generation of a mental model, helps foster greater *effectiveness* in performing tasks. Thus, performance in these situations might exhibit abrupt improvements rather than a smooth, gradual change (Figure 1).

In both these routes, the consumer eventually attains proficiency in using the product. However, in the first path, proficiency is primarily attained through enhanced procedural knowledge, whereas in the latter (discontinuous) path, proficiency gains are also accompanied by enhanced conceptual (or declarative) knowledge. These paths are not necessarily orthogonal. Only the trend of performance improvement differs in each pathway, and this difference in learning paths offers unique consequences for product usage, which forms the focus of the current research (Figure 2).

Layout of Studies

We depict the layout of studies in Figure 3. In Study 1, we first provide evidence of two types of learning—power law and discontinuous learning—and theoretically link the

FIGURE 1
Trend of Completion Times



experience of insight with discontinuous learning. Study 2 highlights the unique behavioral consequences of insight. In Study 3 we experimentally manipulate a key antecedent of insight-driven learning—namely, exploration. Finally, in Study 4, we show how a commonly followed firm practice—written instructions (e.g., in manuals)—can act as a boundary condition to insight-driven learning.

Study 1: Discontinuous Learning and Insight

Consider a consumer who is learning to use a new smartphone that combines appointment books, diaries, calendars, and cameras to support communication activities. This product integrates several tasks: looking up numbers, dialing, talking, exchanging photographs, text messaging, and e-mailing. Each of these tasks further comprises specific actions, such as retrieving voice mail or sending e-mails. In turn, each action requires a set of operations, such as key presses and clicks, to perform the task (activity theory; Bødker 1989; Leont'ev 1974; Norman 2005). As users repeat these operations, they acquire proficiency.

The most well-accepted principle used to describe this empirical phenomenon is the power law of practice (Newell and Rosenbloom 1981), which states that repetition and performance (task completion times) are related by monotonically diminishing returns such that while performance improves with practice, it does so at a diminishing rate. Essentially, the theoretical argument is that when people are learning new skills, significant gains in performance occur early and are followed by gradually diminishing gains over time. This relationship has been best modeled using a power function of the following general form:

$$T = BN^{-\beta},$$

where T is the performance time (time needed to complete a task), B is the time taken in the first trial, and N is the trial number (the amount of practice). The rate at which performance changes is represented by β, the negative sign indicating that completion time decreases at the rate specified by β. Studies in the marketing field have also attested to the power law principle and its ability to explain learning effects better than a linear trend at the aggregate level (Johnson, Bellman, and Lohse 2003). Accordingly, the following hypothesis pertains to consumers' learning curves at the aggregate level, regarding product usage performance (reflected by task completion times):

H_1: In the aggregate, learning curves based on repeated use of a product are best approximated by the power law (versus a linear trend).

FIGURE 2
Antecedents and Consequences of Insight and Discontinuous Learning

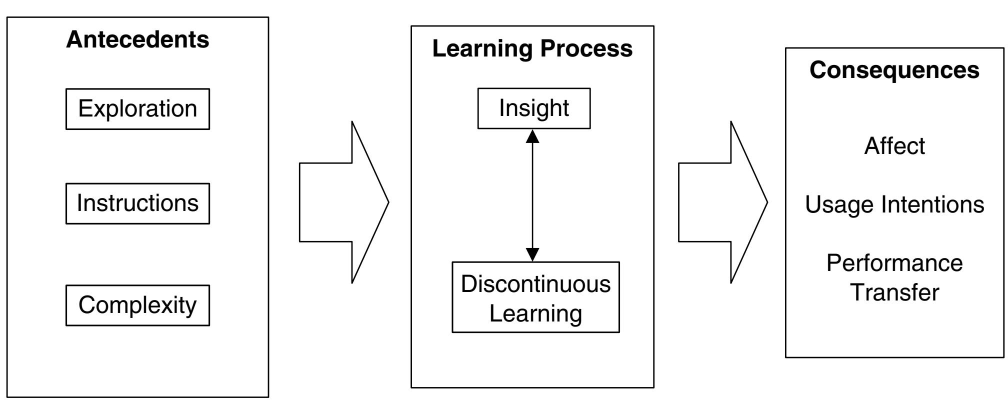


TABLE 1
Extant Consumer Learning Research

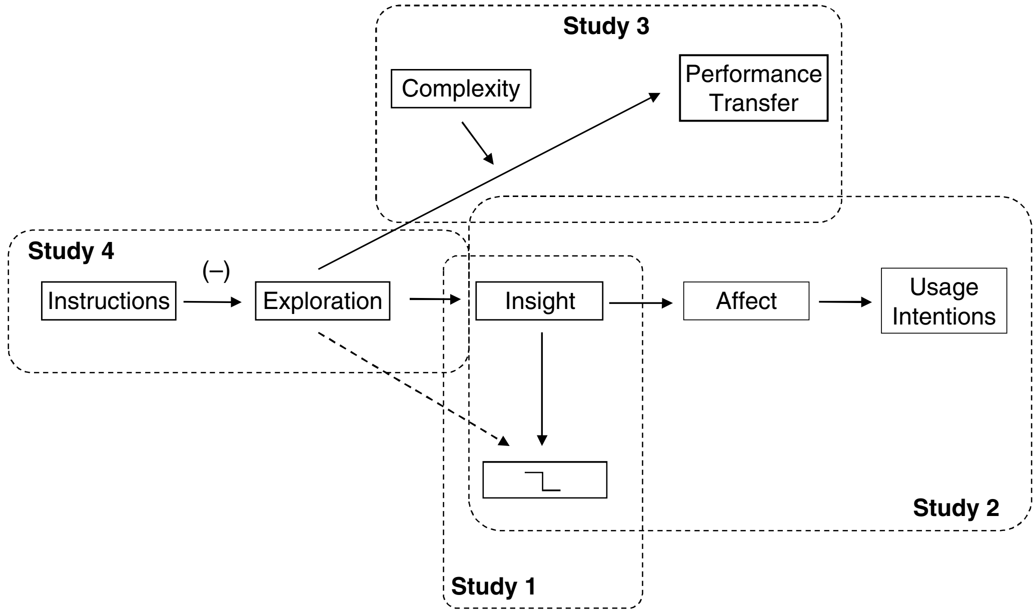
A: Declarative Knowledge	
Low Involvement/Behavioral Learning	
Nord and Peter (1980)	A Behavior Modification Perspective on Marketing
Rochschild and Giadis (1981)	Behavioral Learning Theory: Its Relevance to Marketing and Promotions
Hawkins and Hoch (1992)	Low-Involvement Learning: Memory Without Evaluation
Janiszewski and Warlop (1993)	Influence of Classical Conditioning Procedures on Subsequent Attention to the Conditioned Brand
Hawkins, Hoch, and Meyers-Levy (2001)	Low-Involvement Learning: Repetition Effects on Learning from Ads
Attribute and Associative Learning	
Johnson and Russo (1984)	Product Familiarity and Learning of New Information
Cole and Houston (1987)	Encoding and Media Effects on Consumer Learning Deficiencies in the Elderly
Burke and Srull (1988)	Competitive Interference and Consumer Memory for Advertising
Hutchinson and Alba (1991)	Ignoring Irrelevant Information: Situational Determinants of Consumer Learning
Macklin (1996)	Preschoolers' Learning of Brand Names from Visual Cues
Janiszewski and Van Osselaer (2000)	Connectionist Model of Brand-Quality Associations
Van Osselaer and Alba (2000)	Consumer Learning and Brand Equity
Mukherjee and Hoyer (2001)	The Effect of Novel Attributes on Product Evaluation
Van Osselaer and Janiszewski (2001)	Two Ways of Learning Brand Associations
Shapiro and Spence (2002)	Factors Affecting Encoding, Retrieval, and Alignment of Sensory Attributes in a Memory-Based Brand Choice Task
Law (2002)	Can Repeating a Brand Claim Lead to Memory Confusion? The Effects of Claim Similarity and Concurrent Repetition
Wood and Lynch (2002)	Prior Knowledge and Complacency in New Product Learning
Janiszewski, Noel, and Sawyer (2003)	A Meta-Analysis of the Spacing Effect in Verbal Learning
Van Osselaer and Alba (2003)	Locus of Equity and Brand Extension
Van Osselaer, Janiszewski, and Cunha (2004)	Stimulus Generalization in Two Associative Learning Processes
Eisenstein and Hutchinson (2006)	Action-Based Learning: Goals and Attention in the Acquisition of Market Knowledge
Cunha, Janiszewski, and Laran (2008)	Protection of Prior Learning in Complex Consumer Learning Environments
Cunha and Laran (2009)	Asymmetries in the Sequential Learning of Brand Associations: Implications for the Early Entrant Advantage
Griffin and Broniarczyk (2010)	The Slippery Slope: The Impact of Feature Alignability on Search and Satisfaction
Poynor and Wood (2010)	Smart Subcategories: How Assortment Formats Influence Consumer Learning and Satisfaction
Others	
Hoch and Deighton (1989)	Managing What Consumers Learn from Experience
Peracchio (1992)	How Do Young Children Learn to Be Consumers? A Script Processing Approach
Learning by Analogy	
Gregan-Paxton and Roedder-John (1997)	Consumer Learning by Analogy: A Model of Internal Knowledge Transfer
Gregan-Paxton (2001)	The Role of Abstract and Specific Knowledge in the Formation of Product Judgments: An Analogical Learning Perspective
Gregan-Paxton and Moreau (2003)	How Do Consumers Transfer Existing Knowledge? A Comparison of Analogy and Categorization Effects
Gregan-Paxton, Hoeffler, and Zhao (2005)	When Categorization Is Ambiguous: Factors That Facilitate the Use of a Multiple Category Inference Strategy
Shapiro, Spence, and Gregan-Paxton (2009)	Factors Affecting the Acquisition and Transfer of Novel Attribute Relationships to New Product Categories

TABLE 1
Continued

Author(s)	Title
A: Declarative Knowledge	
Covariation Judgments and Inferences	
Bettman, Roedder-John, and Scott (1986)	Covariation Assessment by Consumers
Roedder-John, Scott, and Bettman (1986)	Sampling Data for Covariation Assessment: The Effect of Prior Beliefs on Search Patterns
Pechmann and Ratneshwar (1992)	Consumer Covariation Judgments: Theory or Data Driven?
Broniarczyk and Alba (1994)	The Role of Consumers' Intuitions in Inference Making
Hutchinson and Alba (1997)	Heuristics and Biases in the Eye-Balling of Data: The Effects of Context on Intuitive Correlation Assessment
Experiential Learning	
Hoch and Ha (1986)	Consumer Learning: Advertising and the Ambiguity of Product Experience
Ha and Hoch (1989)	Ambiguity, Processing Strategy, and Advertising-Evidence Interactions
Huffman and Houston (1993)	Goal Oriented Experiences and the Development of Knowledge
West (1996)	Predicting Preferences: An Examination of Agent Learning
West, Brown, and Hoch (1996)	Consumption Vocabulary and Preference Formation
Warlop, Ratneshwar, and Van Osselaer (2005)	Distinctive Brand Cues and Memory for Product Consumption Experiences
Schlosser (2006)	Learning Through Virtual Product Experience: The Role of Imagery on True Versus False Memories
Latour and Latour (2010)	Bridging Aficionados' Perceptual and Conceptual Knowledge to Enhance How They Learn from Experience
Quantitative Models of Consumer Learning	
Keane and Erdem (1996)	Decision Making Under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Market
Villas-Boas (2004)	Consumer Learning, Brand Loyalty, and Competition
Bradlow, Hu, and Ho (2004)	Modeling Behavioral Regularities of Consumer Learning in Conjoint Analysis
Akcura, Gonul, and Petrova (2004)	Consumer Learning and Brand Valuation: An Application on Over-the-Counter Drugs
Lewis (2005)	Incorporating Strategic Consumer Behavior into Customer Valuation
Iyengar, Ansari, and Gupta (2007)	A Model of Consumer Learning for Service Quality and Usage
Freimer and Horsky (2008)	Try It, You Will Like It: Does Consumer Learning Lead to Competitive Price Promotions?
Narayanan and Manchanda (2009)	Heterogeneous Learning and the Targeting of Marketing Communication for New Products
Zhao, Zhao, and Helsen (2011)	Consumer Learning in a Turbulent Market Environment: Modeling Consumer Choice Dynamics After a Product Harm Crisis
B: Procedural Knowledge	
Effects of Procedural Knowledge	
Johnson, Bellman, and Lohse (2003)	Cognitive Lock-In and the Power Law of Practice
Murray and Haubl (2007)	Explaining Cognitive Lock-In: The Role of Skill-Based Habits of Use in Consumer Choice
Murray and Bellman (2011)	Productive Play Time: The Effect of Practice upon Consumer Demand for Hedonic Experiences
Expectation Versus Actual Usage (Learning from Usage)	
Moreau and Wood (2006)	From Fear to Loathing? How Emotion Influences the Evaluation and Early Use of Innovations
Burson (2007)	Consumer Product Skill Matching: The Effects of Difficulty on Relative Self-Assessment and Choice
Acquisition of Procedural Knowledge	
Lakshmanan, Lindsey, and Krishnan (2010)	Practice Makes Perfect? When Does Massed Learning Improve Product Usage Proficiency

Notes: Predominant focus of this approach is on isolating and quantifying "consumer learning" [usually of quality of the product] as a factor in purchase behavior change time. For complete bibliographic information for these sources, see the Web Appendix at http://www.marketingpower.com/jmnov11.

FIGURE 3
Conceptual Overview and Layout of Studies



Notwithstanding the popularity of the power law, a growing body of research points to its limitations in uniquely describing individual-level learning (Rickard 1997). For example, individual's gains in cognitive skills may deviate significantly from the power law (Rickard 1999). Therefore, if individual curves are analyzed separately, what other pathways can we expect? Multiple pathways are possible, such as power curves of varying parameters, exponential curves, and logarithmic curves (Estes 1956; Myung, Kim, and Pitt 2000). We hypothesize that some of them are likely to take a specific form—namely, a discontinuous learning pattern.

The form of the curve may be predicted by the way proficiency is acquired during initial product use. As described previously, one route is when repeated use of a product leads to the development of action-based production rules (Anderson 1999), in turn leading to more proficient use: Efficiency is gained through practice. This path is best illustrated by the incremental gains observed in most power law curves of learning. An alternative path entails conceptual learning as the user explores the usage space and discovers optimal ways to perform the given task. As the person uses the product, he or she forms a mental model of the product (Norman 2002), which helps with task performance: Effectiveness is gained along with enhanced conceptual understanding. In turn, increased effectiveness is more likely to lead to sudden gains in proficiency (Rickard 1999), thereby leading to discontinuous learning curves (Figure 1).

Furthermore, when the user engages in discovery-based learning, in addition to greater physical familiarity with the product, he or she is also likely to develop a better understanding of how the steps in product use and various features hang together. Among the different conceptualizations of cognitive insight in the creativity literature (Schilling 2005), the process by which a schema is completed and reorganizing of information occurs closely describes the formation of a product's mental model through usage. The subjective experience underlying this process is correlated with the experience of an "Aha!" moment (Mayer 1995; Schilling 2005; Smith, Ward, and Finke 1995). This experience is akin to that of a first-time user of the Wii Nunchuk, who, while learning to manipulate the remote, develops not only the procedural, physical skill in operating it but also gains an understanding of how the device works for him or her (an Aha! experience). In this context, consistent with prior conceptualizations of cognitive insight, we define insight as an experience in which product usage for the individual translates from a relatively unconnected set of steps into a meaningful sequence of actions. In a way, the occurrence of insight signals a change in a person's declarative knowledge (reorganizing of information into a mental model; Schilling 2005). Combining the preceding two expectations, formally, we hypothesize the following:

> H_2: At the individual level, learning curves also exhibit discontinuities in performance (completion times), in addition to power law learning.
>
> H_3: Discontinuous learning is more positively related to the occurrence of insight (vs. power law learning).

Two caveats are worth noting. First, power law and discontinuous learning curves are both possible at the individual level—each being indicative of a particular learning path. In addition, although we expect a significant proportion of discontinuous learners, we make no predictions about their relative proportion. Second, the presence of individual discontinuous curves does not contradict H_1, because all consumers do not improve at the same time; averaging discontinuous curves across each trial effectively hides its existence from aggregate-level analyses.

Overview of Experimental Protocol

We conducted a laboratory-based study using Audacity, a software product used for audio recording, mixing, file modification, and organization of digital music. Such products are highly relevant to our participant group because they involve digitally stored music; in addition, similar products have been used in recent experimental research in marketing (e.g., Thompson, Hamilton, and Rust 2005). Our broad experimental approach uses multiple product usage episodes (trials) to allow for and track participants' learning. We constructed a task (detailed in the next section) for which completion time could be measured unobtrusively. Task completion time has a rich history in prior psychology and human-factors research as a measure of proficiency (for a review, see Hornbaek 2006) and has been used in marketing to tap into user skills as well as related downstream phenomena (e.g., Huang, Lurie, and Mitra 2009; Johnson, Bellman, and Lohse 2003; Moe and Yang 2009; Murray and Häubl 2007). The experimental task was repeated within subjects, and completion time was measured for each repetition. We used the completion times for each participant to deduce the type of learning curve. We outline the details of the procedure next.

Method

One hundred fifty-three undergraduate marketing students at a large midwestern university participated in exchange for course credit. Data were collected using computers on which Audacity was preinstalled. The task (on which participants learned to use the product) required them to use Audacity to change the baseline volume of digital music files stored on the respective computers. This type of audio modification is particularly relevant to the participants because it may be eventually used to change ringtones, alarms, or chimes in a variety of digital devices. Because Audacity is an open-source software product, we also collected information on participants' prior exposure to it (less than 10% had any prior exposure). Analyses using this variable revealed no differences across groups, and we collapsed data for hypothesis testing.

At the outset of the study, a brief description of Audacity was shown to all participants, introducing it as a beta version of an upcoming product needing user testing. Included in the description were details about its purpose, various features, and different ways digital music can be modified and managed using it. After this, instructions on how to perform the usage task were shown once (Part 1 of the Web Appendix at http://www.marketingpower.com/jmnov11). Then, participants completed the specified task multiple times during the session. A set of six identical files (using different file names to avoid suspicion and tedium) were placed in a folder. Each participant completed the main experiment through MediaLab, and at the appropriate juncture, Audacity was opened to undertake the usage tasks. We ascertained correct completion using a probe question at the end of each trial. The analyses showed that all participants completed the tasks correctly.

We plotted learning curves for each participant using the completion times (measured unobtrusively using MediaLab) for each trial, and independent coders categorized these plots into two classes: discontinuous curves or power law curves (see Figure 1). Coders, blind to the conditions of the experiment, were instructed to code the graphs according to the criterion of whether they observed a gradual, smooth reduction in completion times or whether they saw a distinct, abrupt drop. If they did see a drop, they were instructed to mark the trial on which they observed the drop. Intercoder agreement was high (Krippendorff's $\alpha = .79$), and disagreements were resolved by discussion.

In addition, cognitive response protocols were collected toward the end of the session for process analysis. These were coded for the presence of words/phrases showing that the participant was able to form a deeper understanding of the product usage during learning trials. This procedure is especially common in usability research (Ericsson 2006; Van den Haak and De Jong 2003) and also has a rich history in psychology (Crutcher 1994; Ericsson and Simon 1993; Payne 1994) and consumer decision making (Beihal and Chakravarti 1982) for process tracing. Phrases were coded for evidence of a mental model of how the product was to be used and how its features fit together. Demographics and covariates were collected at the end.

Covariates

Among the variables of interest for this study, we placed particular focus on four variables that could potentially affect participants' information processing with respect to usage learning through product trial. We measured prior knowledge of the product category using six items. All items loaded onto a single factor, and the summated scale was reliable (Cronbach's $\alpha = .88$). We used a measure of anxiety with technological products (four items) adapted from prior research (Meuter et al. 2005) ($\alpha = .85$). In addition, we measured product category relevance using a three-item scale ($\alpha = .91$). Finally, after the experimental session and an unrelated filler task, we administered the need-for-cognitive-closure scale (Webster and Kruglanski 1994). We include all covariates in regression models and report them if they are significant.

Analysis and Results

To test the power law hypothesis for aggregate learning curves (H_1), we fit a model of the form given in Equation 1 to aggregate completion times. The resulting model had a good fit, and the fit was significantly better than the benchmark linear model ($R^2_{Power} = .97$, $R^2_{Linear} = .81$; $F(1, 915) = 312.12$, $p < .001$), providing direct support for H_1.

To test H_2, we performed the following steps: To cross-validate coders' categorization, we first estimated the power law model (Equation 1) on individual completion time data that were classified as power law curves:

$$CT = \alpha \times TRIAL^{-\beta}, \tag{1}$$

where CT is completion time for the usage task, α is a constant representing baseline performance at the first trial, β represents the rate parameter governing the negative change in completion times over trials, and TRIAL is the number of the learning trial. In addition, we fit the sigmoid-shaped dose-response curve used in the life sciences (Motulsky and Christopoulos 2003) to test for abrupt changes in completion times. The sigmoid curve has been used to model discontinuous changes, such as radical innovation and the impact of disruptive technologies (e.g., Sood and Tellis 2005), and thus forms an appropriate foundation for modeling the discontinuous change in individual completion times. The functional form is given by the following:

$$\text{(2)} \qquad CT = \beta + \frac{\alpha - \beta}{1 + 10^{(\text{TRIAL} - \gamma)}},$$

where α and β are the top and bottom intercepts and γ is the slope parameter, which also governs the trial number in which completion time drops abruptly. We used the Bayesian information criterion (BIC; Schwarz 1978) to assess model fit because it imposes a strong penalty for additional parameters (thereby correcting for overfitting).

Specifically, we fit both Equations 1 and 2 on each group with TRIAL as independent variable (numbered from 1 to 6) and completion time (CT) as the dependent variable. We freely estimated model parameters for the power model (α = baseline performance, β = rate) as well as the sigmoid model (α = top intercept, β = bottom intercept, and γ = slope). We retained individual-level observations throughout and fit a fully disaggregate model on each group. We used the maximum likelihood estimation with the default Gauss-Newton algorithm via the nls procedure in the R statistical environment.

In support of the coders' classification, we find that for the curves classified as power law, Equation 1 fit the data better than Equation 2. To test whether curves classified as discontinuous were indeed fit better by Equation 2, we needed to obtain sufficient degrees of freedom for each comparison while minimizing issues due to averaging across participants. To this end, we pooled individual curves into groups according to the trial in which the abrupt drop was observed. We estimated Equations 1 and 2 on each group and found that across all model comparisons, the sigmoid equation fit the data better for discontinuous curves versus the power equation (Table 2). In support of H_2, we observed that 54% of the curves were discontinuous ($\chi^2 = 495.78$, $p < .001$), a proportion significantly greater than the null hypothesis of no discontinuous change.[1]

We tested H_3 by independently assessing type of learning (power law vs. discontinuous) and presence of insight and examining the correlation between these two variables. If insight is not positively correlated with discontinuous learning, H_3 is rejected. We tested H_3 by estimating a logistic regression model with the occurrence of insight as dependent variable; learning curve type (power vs. discontinuous) as predictor; and prior knowledge, technological anxiety, product category relevance, and need for closure as covariates. In support of H_3, we observed a significant main effect for curve type (Wald $\chi^2 = 4.3$, $p < .04$) such that discontinuous curves were positively related to the experience of insight. None of the covariates were statistically significant ($p > .2$).

[1]A separate study (n = 78) independently replicated this finding with 30% of learners in that study evidencing discontinuous curves ($\chi^2 = 126.36$, $p < .001$). Model comparisons between the two learning curves for all groups were consistent with Study 1, attesting to the robustness of this empirical finding.

TABLE 2
Model Comparisons (BIC)

Curve Type	Power Model	Sigmoid Model	$d.f._{sigmoid}$
A: Study 1			
Discontinuity at Trial 2	1034.43	1027.75	99
Discontinuity at Trial 3	1873.7	1868.13	183
Discontinuity at Trial 4	814.25	807.44	81
Discontinuity at Trial 5	912.65	909.86	87
Discontinuity at Trial 6	421.4	419.66	39
Power law group	4548.65	4632.83	41
B: Study 2			
Discontinuity at Trial 2	1178.94	1133.86	105
Discontinuity at Trial 3	1812.16	1807.51	147
Discontinuity at Trial 4	1069.09	1065.14	93
Discontinuity at Trial 5	204.97	203.57	15
Discontinuity at Trial 6	177.23	177.02	15
Power law group	5277.65	5371.78	489
B: Study 4			
Discontinuity at Trial 2	167.29	165.78	15
Discontinuity at Trial 3	638.14	637.3	57
Discontinuity at Trial 4	317.18	314.56	27
Discontinuity at Trial 5	185.82	185.07	15
Discontinuity at Trial 6	32.92	32.65	3
Power law group	2933.51	2955.96	303

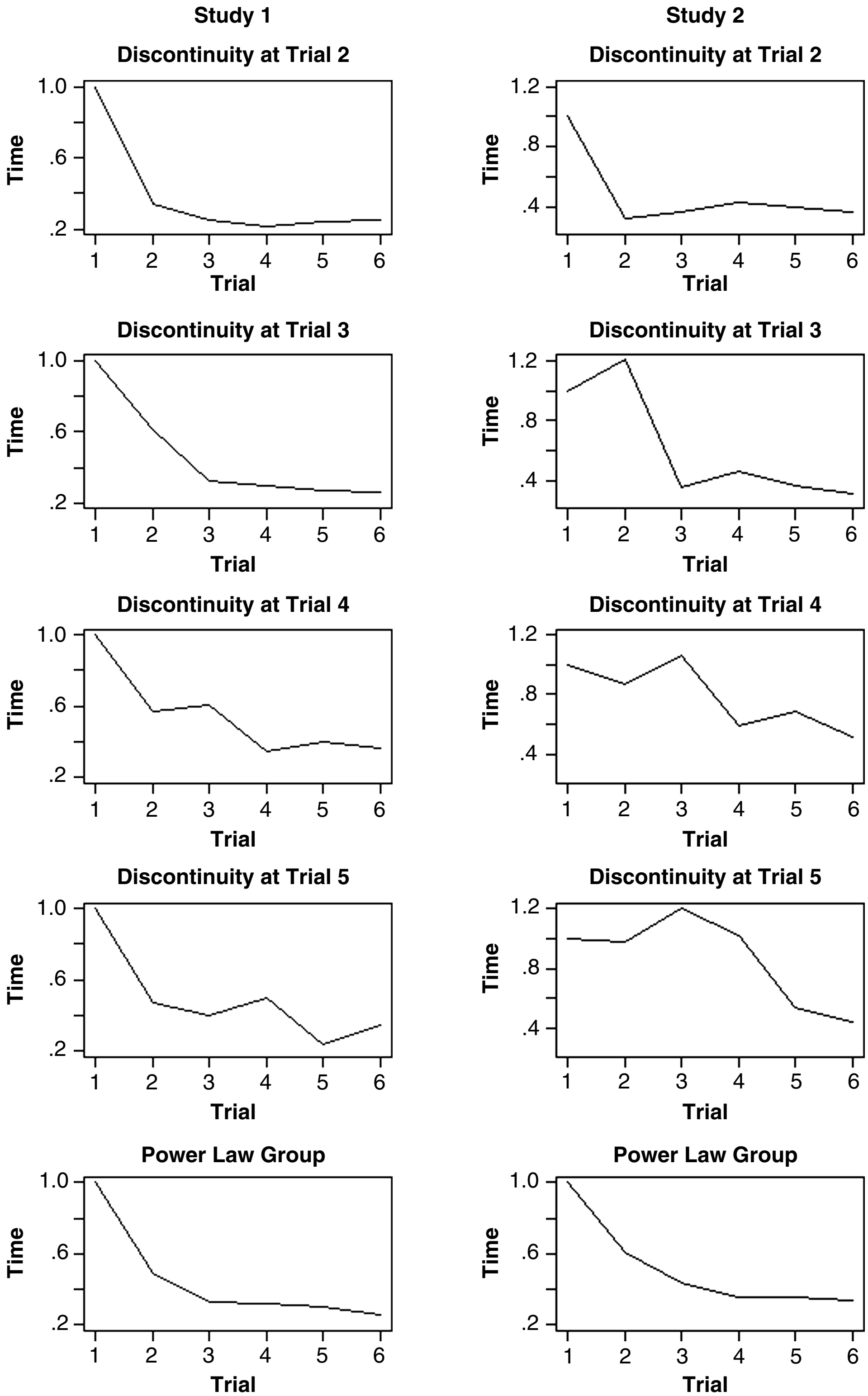
Notes: The two-parameter power models each have one greater degree of freedom than that reported for the three-parameter sigmoid models.

Discussion

The findings from this study provide evidence of a qualitatively different form of learning at the individual level. Although the power curve fit the aggregate data well and accounted for 97% of the variation in performance improvement, the fit overshadowed the existence of other forms of learning. When the same data were investigated at the individual level, we identified a significant number of learners (54% of our sample) who exhibited abrupt jumps in performance during their product usage. It is important to note that discontinuous and power law learners did not differ in terms of their eventual postlearning performance ($p > .5$). Thus, proficiency with using the product was no different between the learning paths; only the form of learning differed (for the empirical curves, see Figure 4).

Importantly, the logistic regression of the incidence of insight (culled from participant's cognitive responses) based on learning curve type (H_3) was significant, suggesting that differences in the form of learning are correlated with qualitatively different learning experiences. In particular, we find that those people who exhibited discontinuous performance gains also were more likely to form a mental model for how to use the product. This process, similar to the completion of a mental schema, should lead to the Aha! experience (cognitive insight; Schilling 2005). This

FIGURE 4
Empirical Curves



Notes: The figures reflect average completion times by group and thus are not isomorphic with individual curves.

raises the question, Why should such an experience matter? The next study examines why discontinuous learning and insight may lead to unique consumer consequences, such as affect and product perceptions.

Study 2: Positive Consequences of Insight-Driven Learning

Our expectations regarding consumer perceptions stem from two characteristics of discontinuous learning. First, discontinuous learning is defined by abrupt improvements in performance, and second, experience of insight is more likely to accompany this form of learning. This Aha! experience should be more likely to positively affect the mood of the consumer on account of the "joy of learning." In other words, users who experience insight are likely to feel good about their learning experience. Furthermore, signal detection principles suggest that, in general, incremental changes are less likely to be noticed than abrupt ones. It is reasonable to expect that consumers who have a jump in learning (à la the discontinuous curve) would be more likely to notice their own improvement versus those whose gains are more incremental (the power law trend). Conversely, consumers whose performance improvement is more in line with the power curve are (1) less likely to experience insight and (2) less likely to notice their improved performance, thereby feeling less positive in general. Therefore, combining the preceding, we hypothesize the following:

H_4: (a) Users with discontinuous (vs. power law) learning exhibit greater positive affect, and (b) the effect of discontinuous learning on affect is mediated by insight.

Extensive research has shown that positive affect generated from an experience often transfers to another (even unrelated) context and has the potential to directly affect consumer decision making (Isen 2001). Thus, affect generated through insight should also transfer to the product. In this connection, because insight also corresponds with better understanding (Norman 2002; Schilling 2005), positive affect generated through discontinuous learning is accentuated. As a result of (1) the temporal proximity of the Aha! experience with product usage and (2) the direct connection between understanding generated through insight and product usage, the positive affect should be transferred to the product. In combination with greater clarity about the product and learning-driven positive affect, a person should develop stronger perceptions of the product's future usability. In turn, behavioral intentions pertaining to product use (Davis 1989) should be stronger for insight-driven learners. Formally,

H_5: Users who experience insight (vs. those who do not) during learning have greater usage intentions.

H_6: The effect of insight on usage intentions is mediated by affect.

Thus, Study 2 focuses on how insight is related to critical product adoption factors such as affect and future usage intentions, thereby enriching the technology adoption model (Dabholkar and Bagozzi 2002; Davis 1989) and adding to extant research on consumer judgments in skill-based product categories (Burson 2007).

Method

One hundred forty-seven undergraduate marketing students participated in the study in exchange for course credit. The overall method and procedure is similar to Study 1. A brief description of Audacity was shown to all participants, and a set of six identical tasks were administered. Completion times for all trials were collected unobtrusively, which was the basis for plotting the learning curves. Participants' affective state was measured immediately after the learning phase (and before dependent measures and covariates) using the positive and negative affect schedule (Watson, Clark, and Tellegen 1988).

The occurrence of insight during learning was coded following the protocol used in Study 1 (Krippendorff's $\alpha = .82$) from the cognitive responses. Usage intentions (three-item modified behavioral intentions scale), demographic variables, and other covariates—technological anxiety, relevance, and prior knowledge—were collected at the end of the session. As in the previous study, two independent coders categorized individual learning curves into discontinuous and power law curves. Intercoder agreement was high (Krippendorff's $\alpha = .84$), and disagreements were resolved by discussion. Curve fit analyses indicated that the coders' classification was robust (Table 2).

Results

Replication. Replicating H_1, the power law fit for aggregate learning curves was supported ($R^2_{Power} = .95$) and compared well with the benchmark linear regression ($R^2_{Linear} = .82$). In addition, replicating H_2, we observed that overall, 44% of the participants were discontinuous learners ($\chi^2 = 467.76$, $p < .001$). Moreover, replicating H_3, insight significantly and positively related to discontinuous learning curves (Wald $\chi^2 = 13.05$, $p < .001$).

Affect. To test H_4, we estimated a mediation model using the Preacher–Hayes bootstrapping procedure (Preacher and Hayes 2004) with discontinuous learning (yes/no) as the predictor, affect as the criterion, and insight (yes/no) as the mediator. We included final completion times and individual learning rates as control variables. In support of H_{4a}, the effect of discontinuous learning on affect (without mediating paths) was positive and significant ($t = 2.18$, $p < .03$). Furthermore, the effect of discontinuous learning on affect was fully mediated by insight. The bias-corrected 95% confidence interval of the IV → M → DV path did not include 0 (1.1595, 5.3156), and the direct effect of discontinuous learning on affect after removing the effect explained by the mediating path was not significant ($p > .3$). The effects for control variables were not significant ($p > .10$). These results support a fully mediated model of discontinuous learning leading to greater positive affect through the occurrence of insight (H_4).

Usage intentions. A regression with usage intentions as the criterion and insight as the predictor showed that insight significantly and positively predicted usage intentions ($\beta = .17$, $t = 2.02$, $p < .05$), lending support to H_5 (Table 3). We tested the mediation hypothesis (H_6) using the Preacher–Hayes procedure. In the model with insight

TABLE 3
Affect and Usage Intentions by Insight: Study 2

	Affect	Usage Intentions
Insight	4.23	7.55
No insight	–2.42	6.06

Notes: Individual column comparisons of means were significantly different at the .05 level or less.

leading to greater usage intentions through positive affect, the direct effect of insight on usage intentions was not significant ($t = .54$, $p > .5$), whereas the mediated path (insight → affect → intentions) was significant and positive (95% confidence interval: .5002, 1.8607), indicating full mediation.

Discussion

Study 2 replicates key findings from Study 1 and provides additional evidence in support of a qualitatively different form of learning: insight-based learning. An important substantive consequence of this alternative route is that the occurrence of insight leads to greater positive affect, which in turn influences consumer intentions critical to predicting successful usage adoption (Moreau and Dahl 2005; Shih and Venkatesh 2004; Wood and Moreau 2006).

Thus, in addition to providing evidence on the robustness of discontinuous learning, Study 2 also offers a fresh view of consumer-level drivers of usage adoption. Notably, we find that insight-driven discontinuous learning during initial product trial has direct positive consequences for adoption beyond what might be expected from traditional power law learning. Notably, these stronger intentions do not seem to arise out of any differences in proficiency but largely from the experience of insight. Final completion times for insight-versus non-insight-driven learners did not differ, but behavioral intentions did.

Thus, fostering discontinuous learning offers one way to enhance usage intentions. Specifically, designing features or setting up initial trials to enhance the likelihood of an Aha! experience offers a new way to ensure that product adoption goes beyond purchase and extends into usage (Shih and Venkatesh 2004). Theoretically, the mediation results from this study directly contribute to enriching the technology adoption model (Dabholkar and Bagozzi 2002; Davis 1989; Meuter et al. 2005) by highlighting the role of the type of learning in the product usage situation. Given the possible impact of insight on product usage, we now turn our attention to antecedents of insight-based learning. In Study 3, we lay out and test our expectations regarding the role of exploration in product usage.

Study 3: Antecedents of Insight-Driven Learning

In Studies 1 and 2, we focused on outlining the different learning routes by analyzing completion time trends. The broad theoretical basis for expecting discontinuous learning stems from the notion of discovery during initial product trial. The experience of insight acts as a key driver affecting proficiency and perceptions. Discovery-based learning predicates exploration as a factor facilitating learning (Yechiam, Erev, and Gopher 2001) and subsequent performance. The underlying rationale is that because exploration encourages a more complete examination of the usage space, it should enhance the likelihood of discovering different (and possibly better) strategies in performing a task with the product, thereby fostering the experience of insight. Consistent with this expectation, exploration should lead to broader learning and the development of a flexible knowledge base with regard to using a product. In particular, as a person tries out different aspects of the product, he or she is more likely to acquire a deeper understanding of the product layout, product features, and how the features hang together, thereby enhancing his or her mental model of the product (Norman 2005). In contrast, low exploration during initial learning should limit the experience of insight and lead to limited how-to knowledge—notably, knowledge that is specific to the product usage task. Thus, exploration (vs. no exploration) during initial trial should lead to more flexible and generalizable knowledge (Taatgen et al. 2008), which should be reflected in consumers' mental models. Formally,

> H_7: Encouraging exploration during learning (vs. not) leads to greater overall quality of consumers' mental models.

The enhanced flexibility in knowledge gained along with greater effectiveness in using a product should be particularly evident in usage contexts in which prior knowledge is limited (Taatgen et al. 2008). Transfer tasks present one such context. A transfer task is one that is related to but different from the task initially performed. Transfer contexts are especially relevant when considering products with multiple functionalities. For example, people may initially learn different modes of image capture in a digital camera but, over time, may use different features (e.g., various resolution settings, timer setup). How well consumers learn to use these related but previously unlearned features may strongly affect how much they eventually use the product and, in turn, how easily or quickly the product diffuses through the market (Shih and Venkatesh 2004).

Because exploration leads to more flexible and generalizable knowledge (Taatgen et al. 2008), it should be well suited to improve performance in new usage contexts (i.e., a transfer task). However, the overall beneficial effect of exploration on transfer task performance should be moderated by the type of task—in particular, its complexity. When transfer task complexity is high, the steps involved in using the product should be more difficult to uncover and perform (than a low complexity task). With high exploration during learning, people are more likely to (1) make linkages between steps involved in using the product, (2) make connections between different features of the product and how they come together, and therefore (3) get a better overall sense—a more comprehensive mental model—of the product. When faced with a complex transfer task, the availability of a good mental model should lead exploration-based learners to perform better than those not engaging in exploration during initial learning. However, when the transfer task is not very complex, the steps involved are relatively easier to uncover and perform, thereby yielding no discernible advantage for the exploration-based learner (compared with those not engaged in exploration during learning). Thus:

H_8: (a) Encouraging exploration during learning (vs. not) leads to better transfer task performance, and (b) performance improvement is greater (less) when transfer task complexity is high (low).

In addition to experimentally manipulating exploration in Study 3, we recruited two new measures to assess the (1) quality of performance and (2) consumers' mental models generated during learning. First, we devised a new transfer task in Study 3 to tap how well consumers are able to use a product. This task generated unique participant-specific output, which could then be analyzed for performance quality. Second, to measure the quality of insight generated during learning, we adapted the concept-mapping procedure developed by Novak and colleagues (e.g., Novak 2002; Novak, Gowin, and Johansen 1983). This procedure calls on participants to generate a pictorial representation of the knowledge gained during product use and thus builds on the verbal protocol methods used in usability research. We detail these procedures in the next section.

Method

Study 3 used a 2 (learning type: exploration vs. no exploration) × 2 (transfer task: complex vs. simple) between-subjects full-factorial design with proficiency on a transfer task as the dependent measure. Sixty-six undergraduate students completed the study in exchange for course credit. We developed a new task involving Audacity and constructed objective measures derived from this task for performance assessment. Specifically, we designed the task such that each participant produced a unique file whose acoustic quality could then be analyzed using the Audacity software. The transfer task entailed converting a music file into a mobile phone ringtone, which is a relevant task for this sample (for details, see Part 2 of the Web Appendix at http://www.marketingpower.com/jmnov11). In essence, it 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 completing these steps, participants saved their output files and proceeded to the next section of the study. We subsequently analyzed these individual files for (1) deviation from the ringtone length specified in the instructions and (2) amplitude of bass frequencies in the ringtone. Using the acoustic analysis features in Audacity, an independent judge determined each participant's performance on these two dimensions from their unique output file.

The exploration manipulation was administered by encouraging the participants in this group to "explore the product and try out its different features." We asked participants to rate the extent of exploration during their learning trials on a seven-point scale (1 = "did not play around," and 7 = "played around with the software"), and analyses revealed that participants in the exploration condition engaged in greater exploration than the no-exploration group ($M_{Explore} = 2.9$, $M_{No\text{-}Explore} = 2.3$; $p < .05$). We manipulated task complexity by introducing an additional step to the conversion task for the high-complexity condition. Specifically, the additional step required participants to combine two parallel stereo tracks into one at the time of saving the output. This step does not change the acoustic characteristics of the output file, which enabled us to have measures that are directly comparable across groups. At the end of the study, we obtained complexity ratings for the transfer task on a seven-point scale (1 = "very simple," and 7 = "very complex"). As we expected, participants rated the complex transfer task significantly more complex than the simple transfer task ($M_{complex} = 4.76$, $M_{simple} = 4.27$; $p < .05$).

Immediately after the learning trials, concept map measures were collected (Novak 2002). Participants drew a boxes-and-arrows diagram of their understanding of the product features and how the product is used to modify digital music. Following the overall procedure outlined in Besterfield-Sacre et al. (2004), two independent coders rated individual concept maps on a nine-point scale (1 = "low," and 9 = "high") across three dimensions: correctness (reliability = .83), comprehensiveness (reliability = .87), and organization (reliability = .89). In particular, correctness was assessed by comparing the features and relationships between features described by the participant with the actual relationships and features derived from the product's description. Coders judged comprehensiveness on the degree to which the participants' concept map covered the set of product features and actions/outcomes that could be ascertained through usage during the experimental task. They judged organization according to the degree to which different concepts and relationships were logically interrelated in the map. A summated score constructed from these items formed our measure of quality of insight (Cronbach's $\alpha = .91$).

The cover story and overall procedure was similar to previous studies, except the number of learning trials was reduced to three (because exploration was explicitly encouraged in this study). After the learning trials, the conceptual mapping measures, and a common filler task, participants completed the transfer task. We also measured prior history, relevance, involvement, focused attention, and technological anxiety as covariates, and we report them in the analyses if significant.

Results and Discussion

Quality of mental models. We expected the mental models to be consistently better for the exploration (vs. no-exploration) group. A regression of the concept map scores on exploration revealed a main effect in the expected direction ($M_{Exp} = 16.76$ vs. $M_{NoExp} = 14.98$; $t = 1.98$, $p < .05$), in support of the hypothesized impact of exploration on insight (H_7).

Performance. Because the deviations from optimum ringtone length followed a Poisson distribution (most deviations close to 0 and a few extending to almost 70 seconds) we conducted a Poisson regression with amount of deviation (error length) as our dependent measure. Exploration and type of transfer task served as the independent variables, with technological anxiety, involvement, attention, and prior history as covariates. We observed a significant main effect for exploration ($z = 7.02$, $p < .001$). A significant two-way interaction ($z = 2.94$, $p < .001$) qualified this effect. Planned contrasts revealed that the average error length was significantly lower for the exploration group for both the complex ($M_{Comp\_Exp} = 8.92$ seconds vs. $M_{Comp\_NoExp} = 23.73$ seconds; $z = 7.02$, $p < .001$) as well as simple transfer tasks ($M_{Sim\_Exp} = 11.58$ seconds vs.

$M_{Sim\_NoExp} = 22.49$ seconds; $z = 3.97$, $p < .001$). This difference was greater for the complex (vs. simple) group, as indicated by the significant two-way interaction. The effects of involvement and attention were negative (in the direction expected) and significant (ps $< .05$).

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 exploration was positive and significant ($t = 3.2$, $p < .003$), and a significant two-way interaction qualified this effect ($t = 2.03$, $p < .05$). Planned contrasts showed that in the complex transfer task, exploration during learning led to significantly better quality (i.e., higher relative volume of bass frequencies in the ringtone: $M_{Comp\_Exp} = -37.57$ decibels vs. $M_{Comp\_NoExp} = -49.1$ decibels; $t = 3.21$, $p < .003$), but in the simple transfer task, the difference was not significant ($M_{Sim\_Exp} = -36$ decibels vs. $M_{Sim\_NoExp} = -42.38$ decibels; $t = .49$, $p > .5$). The effect of involvement was positive (in the direction expected) and significant ($p < .05$). Thus, across both measures, we find that exploration leads to better performance and that the improvement is greater for complex (vs. simple) transfer tasks (H_8). Further exploration-based learning also led to greater usage intentions ($M_{Exp} = 4.69$ vs. $M_{NoExp} = 4.00$; $t = 1.89$, $p = .06$).[2]

As the results of Study 3 indicate, encouraging exploration during initial product trial leads to the formation of a broader, more flexible mental model and enhances consumers' ability to use the product in different contexts. Moreover, enhanced exploration seems to lead to greater behavioral intentions, similar to those observed in Study 2 as a result of insight. This brings to the fore the issue of whether current practices in marketing are conducive for insight-driven learning. We turn to this issue in Study 4.

Study 4: Are Marketing Practices Conducive for Insight-Driven Learning?

Because consumer learning is critical to new product adoption, firms often engage in practices aimed at easing the process. Providing step-by-step instructions is a common practice, and instruction manuals exemplify this approach. Given that insight-based learning has positive effects on perceptions, it is important to understand whether current marketing practices with regard to instructions are conducive to fostering insight-driven learning.

Although instruction manuals have advantages (Wright 1983), providing instructions to first-time users has also been shown to have no impact (Rettig 1991; Scharer 1983) or even reduce performance (Allwood 1990). Because tasks vary across studies, it becomes difficult to compare across these conflicting findings. Therefore, analyzing usage learning and taking into account the type of learning might better explain these contradictory expectations.

The assumption underlying the use of manuals is that the availability of instructions helps people learn the sequence of steps needed to use a product feature. However, availability of instructions during actual product usage may encourage users to refer to them more often, thereby impeding active exploration. In this connection, the exploration hypothesis posits that inadequate exploration leads to suboptimal usage strategies. Allowing for sufficient trial and error with the feature will lead to optimal strategies and help performance. Thus, providing usage instructions with the product (i.e., before the consumer has explored the usage space) may lead to short-term performance benefits but is also likely to reduce the experience of insight during the initial trial by suppressing potential exploration (Yechiam, Erev, and Gopher 2001). In turn, this limits the individual-specific, discontinuous gains that are possible with exploration-driven learning. Formally,

> H_9: Providing usage instructions (vs. no instructions) leads to (1) reduced exploration and (2) reduced likelihood of discontinuous learning.
>
> H_{10}: The negative effect of instructions on discontinuous learning is mediated by exploration.

Design and Procedure

Study 4 employed a single factor (instructions: present vs. absent) between-subjects design using the same overall experimental protocol as Studies 1 and 2. All participants were exposed once by computer to stepwise instructions on how to use the product to complete the experimental task. Subsequently, these instructions were provided (not provided) as a printout to the instructions-present (instructions-absent) group and formed our instructions manipulation. Data were collected on computers, and the experimental task involved using software (Audacity) to modify digital music. We used a different task for this study: introducing a fade-off effect to the music. Instructions explicitly specified the feature to be used, and the steps needed to complete the task, as would be typical in a product usage manual.

A set of six identical tasks (on differently named files) were administered, and completion times were measured unobtrusively, which formed the basis of the coding of two types of learning curves (intercoder reliability = .88).[3] Coders resolved disagreements by discussion. This classification was also verified using the alternative model fits

[2]The exploration and no-exploration groups did not differ in terms of attention, involvement, and motivation (all ps $> .25$). Furthermore, controlling for these factors, a one-way analysis of variance on the average time taken during learning trials revealed no significant effect for the exploration manipulation ($p > .2$), ruling out the alternative explanation that participants in the exploration group worked harder or paid greater attention to the product.

[3]To verify the robustness of coder-based classification, we employed an objective, time-based criterion similar to autoregressive moving average modeling. We defined a discontinuity when the drop in completion times between any two trials exceeded 150% of the average intertrial completion time drops for each participant. This classification yielded results similar to the coders' and was in general agreement with it (percentage agreement across three studies ranged between 89% and 93%). The results of other analyses using this mathematically defined discontinuity were also consistent with current patterns and do not change the overall inference from our research.

and found to be robust (Table 2). Participants' thought protocols were collected and coded for evidence of exploration (1 = "low," and 7 = "high"; reliability = .81) during the experimental task. Words or phrases such as "played around with," "fiddled around with," "tried out different things," and so on, were coded as evidence of high levels of exploration, and words or phrases suggesting that participants just repeated the basic steps were coded as low in exploration.

Results

Exploration and discontinuous learning. Seventy-three undergraduate marketing students at a large midwestern university participated in the study in exchange for course credit. We estimated a regression model with exploration as the dependent measure; presence (absence) of instructions as the factor; and involvement, motivation, and prior knowledge as covariates. None of the covariates had significant effects and thus were excluded from further analyses. The model revealed a significant, negative effect of instructions on exploration ($\beta = -.43$, $t = 4.03$, $p < .001$), in support of H_{9a}.

Similarly, we estimated a logistic regression with discontinuity in learning curves (yes/no) as dependent measure and instructions (present/absent) as the explanatory variable. The model revealed a significant effect of instructions (Wald $\chi^2 = 5.11$, $p < .025$), and the parameter was negative, indicating that providing instructions reduced the likelihood of discontinuous learning, in support of H_{9b}. Importantly, the relationship between exploration and discontinuity in learning curves was also supported. A logistic regression on discontinuity with exploration as the predictor revealed a significant, positive effect of exploration on the likelihood of a discontinuous learning curve (Wald $\chi^2 = 4.45$, $p < .03$).

Mediation analysis. We estimated a mediation model using the Preacher–Hayes bootstrapping procedure with discontinuity as the dependent variable, exploration as the mediator, and instructions as the predictor variable. We observed that the total indirect path (IV $\rightarrow$ M $\rightarrow$ DV) was significant and the bias-corrected 95% confidence intervals of the indirect path did not include 0 (−.2283 to −.0087). The direct effect of instructions on learning curve discontinuity was not significant ($p > .10$). In combination, the results from this analysis support the fully mediated pattern of effects predicted in H_{10}.[4]

Discussion

The results from Study 4 lend support to H_9 and H_{10}, the hypotheses outlining the effects of usage instructions on discontinuous learning. Counter to lay expectations, we find that providing usage instructions, such as the step-by-step written instructions commonly found in user manuals, reduces discontinuous learning. Availability of instructions during the initial trial process potentially leads new users to rely on them and, as a consequence, reduces exploration of the product. In this sense, instructions become a prop (or even a security blanket) that deters users from trying out aspects of the product, in turn reducing the odds of discontinuous learning.

These findings have important consequences for product adoption and the design and marketing of new products. In particular, standard, user-manual-style written instructions seem to reduce the likelihood of insight-driven learning and thus the opportunity of greater positive affect and usage intentions that go with it. Because firms deploy user manuals as an important aid in learning to use products, they often direct consumers to manuals at the first available opportunity for further guidance (the online equivalent being the "Help" files commonly found in software or websites). Our findings suggest that such practices might be counterproductive in some contexts and may need to be tempered when consumer-led or self-directed learning is of interest. This research does not dispute the overall value of a readily available user manual and also notes that legal considerations often necessitate making one available to consumers. However, our findings suggest that even with written instructions made available, actively encouraging exploration may help firms attain the benefits of insight-driven learning.

General Discussion

This study's purpose is to develop and test a framework for how consumers learn to use products. Table 4 summarizes the findings. The core finding is the demonstration of

TABLE 4
Summary of Findings

Study	Hypothesis	Result
1	Power law fits better than linear trend for aggregate learning curves. (H_1)	Supported
1	Discontinuous curves also present for individual learners. (H_2)	Supported
1	Discontinuous learning more likely to relate to insight. (H_3)	Supported
2	Discontinuous learning leads to positive affect. (H_{4a})	Supported
2	Effect of discontinuous learning on affect mediated by insight. (H_{4b})	Supported
2	Discontinuous learning correlates with greater usage intentions. (H_5)	Supported
2	Effect of discontinuous learning upon usage intentions mediated by affect. (H_6)	Supported
3	Exploration leads to higher quality of mental models. (H_7)	Supported
3	Exploration leads to better transfer performance. (H_{8a})	Supported
3	Effect of exploration on transfer performance is evident for more complex tasks but not less complex tasks. (H_{8b})	Supported
4	Instructions reduce exploration. (H_{9a})	Supported
4	Instructions reduce discontinuous learning. (H_{9b})	Supported
4	Negative effect of instructions on discontinuous learning mediated by exploration. (H_{10})	Supported

[4]Comparisons between the instructions versus no-instructions group revealed no significant differences in terms of attention, involvement, motivation (all ps > .5), and average task times for learning trials ($p > .17$), thereby ruling out the alternative explanation that printed instructions served as a distraction.

discontinuous learning and its connection to a qualitatively different learning mechanism: insight. In contrast to views of usage learning that conceptualize learning as a gradual process, discontinuous learning seems to be driven by an Aha! experience accompanied by abrupt jumps in skill. Enhanced likelihood of better conceptual learning through insight also seems to accompany this form of learning (Study 1). From the firm's standpoint, this route to learning offers the benefit of not only better consumer learning but also more favorable consumer perceptions and future intentions (Study 2). Given these positive effects, firms may foster this form of learning by structuring initial product trial to encourage exploration (Study 3). Firms can execute this concept in multiple ways: Structuring product tutorials that boost exploration and fostering in-store salesperson interactions that encourage consumers to explore are just a few such ways to secure the benefits of exploration and discontinuous learning. However, following the often-repeated process of giving step-by-step written instructions seems to diminish the incidence of insight-based learning (Study 4). Thus, the form of instruction and reliance on such instructions must be tempered with the odds of reducing the likelihood of an Aha! experience during learning.

Theoretical Implications

This research adds to theory on how consumers learn to use products. Our theoretical framework describes how learning to use products might follow different paths depending on the relative extent to which declarative and procedural knowledge interact during learning. This is a fertile area for further research because the form of interaction between declarative and procedural knowledge could vary substantially depending on context. For example, while this research shows one form in which insight occurs, other types of interaction such as top-down learning (declarative → procedural) or bottom-up learning (procedural → declarative) could lead to different consequences for product usage.

Further research could also examine other forms of insight and their role in consumer behavior. Whereas we examined one type of insight, the creativity literature also offers other diverse conceptualizations of insight (Schilling 2005) that may provide fodder for examining other contexts. A theoretically impactful area for further research might stem from a consideration of when alternative types of insight (e.g., insight via overcoming mental blocks, insight due to analogy) relate to product perceptions and usage.

Our research framework could also be used to seed new research on how consumers learn to use highly complex products. Do instructions and exploration play a similar role as they do in this study, or does their role change due to the complexity of the product? Furthermore, is insight as likely in such contexts, and what factors stimulate insight? On a related note, given the considerable attention devoted to incremental versus radical innovation (e.g., Chandy and Tellis 2000), a relevant question that prompts empirical research is whether insight is fundamentally related to learning to use radically new products.

The framework we have developed here might also be used to stimulate more sophisticated modeling approaches. For example, formally incorporating heterogeneity in curve parameters could enhance the discovery and modeling of individual differences in learning. In addition, hierarchical models (with Bayesian estimation) that predict learning types according to performance or latent class models classifying individuals according to learning trajectories could substantially enhance theory development in consumer learning.[5]

Finally, while extant research in marketing has identified procedural knowledge as a key component in preventing brand switching—variously recognized as human capital (Murray and Häubl 2007) and cognitive switching costs (Johnson, Bellman, and Lohse 2003; Wernerfelt 1985)—the route to achieving such capital has not been systematically studied. Our research fills this gap by developing theory on insight-driven learning. As the consumer either overcomes initial learning costs (power law) or derives benefits from initial learning (discontinuous learning), he or she develops procedural knowledge (in the form of user skills) that could eventually contribute to the development of tacit knowledge over time (Matthew and Sternberg 2009; Nickols 2000).[6] As immediate memory for the physical usage fades and the actual usage becomes habituated, proficiency with using a product might move into the domain of tacit knowledge, thereby adding to the human capital that the consumer has invested in the brand (Murray and Häubl 2007). Our research also suggests that insight-driven learning may indeed offer additional human capital by way of the positive emotion generated during initial learning.

Managerial Implications

With respect to consumers acquiring product usage knowledge, the predominant perspective guiding extant marketing thought and practice has been the learning-cost view. Viewed from this lens, initial trial represents a hurdle that consumers surmount to become proficient users. As a result, product design for consumer technology products has been dominated by ease-of-use concerns. Our research shows that initial trial also might present an opportunity to add value to the overall customer experience by enhancing the possibility of an Aha! experience. Experiencing an Aha! moment and forming a mental model for the product through insight could lead to positive affect and, consequently, product attachment. Therefore, it is important to acknowledge insight-based learning during use as an alternative to the ease-of-use mantra (e.g., "Geico: So easy a caveman can do it").

Indeed, in some situations, encouraging discontinuous learning might require consumers to deal with difficulty. For example, the TrackPoint (red button inside the keyboard) with which the Thinkpad line of laptops is strongly associated is not, at first glance, an easy-to-use and familiar interface. It involves using a small button embedded in the middle of the keyboard to navigate the on-screen cursor instead of a touchpad that most laptops feature. However, when a new customer "gets it," it acts as a veritable hook to enhance the usage experience and perceived satisfaction. Indeed, this specific feature has generated substantial customer involvement and attachment (Hill 2009) to the

[5]We thank an anonymous reviewer for this recommendation.
[6]We thank an anonymous reviewer for this insight.

extent that it has now become part of the ThinkPad brand identity. Notably, the ThinkPad logo sports the red button prominently (Hill 2007). This level of attachment to individual features is also evident with other firms' products. For example, Apple has leveraged insight-driven consumer learning to successfully (re)introduce previously struggling platforms such as the tablet PC. By positioning the iPad as an entertainment device and designing it such that users discover its features through actual trial, the tablet platform has been rejuvenated from the initial forays by Microsoft (Fontana 2010; Vilches 2010).

Insight-driven learning offers a different route to salespeople's persuasion attempts, rooted in the notion of exploration and discovery. Understanding how insight during initial trial might positively influence customer affect could provide a model for salespersons to encourage this process. New customers may be explicitly encouraged to try out different product features, wherein the exploration is designed to lead them along the Aha! path. This form of persuasion could help with not only short-term firm objectives (sales) stemming from positive affect but also long-term objectives (satisfaction, repeat purchase). This form of persuasion has been famously championed by Steve Jobs with his "one more thing" act at most Apple new product launches.

Finally, because modern technologies direct customers toward making choices between platforms rather than choices between brands, it is even more important for firms to allow for and, wherever possible, enhance insight-driven learning. The success of the motion-sensitive Wii platform has paved the way for Nintendo's subsequent cash flow from the games it sold on this platform. Similarly, the success of the touch-screen interface allowed Apple to leverage it into a remarkably profitable platform suitable for different products. Novel product design and new product trials that facilitate creativity, exploration, and discovery may offer ways for firms to encourage insight. Competitions that engage consumers in using the product more effectively or in new ways (e.g., "find ten uses for a Post-it Note") may help them explore the product space more fully and lead to an Aha! moment. Actively engaging in social media and online forums can also expose consumers to insights from other sources—namely, existing customers. Insight-based learning during initial product trial thus offers a readily accessible route to confer usage and affective benefits for the customer experience.

Appendix

Subjective Knowledge (Items Anchored at 1 and 7)

As regards audio editor and recorder software, you are:

1. "Not at all knowledgeable/highly knowledgeable."
2. "A complete beginner/an expert."
3. "Begun using recently/been using for a long time."
4. "Know much less than most people/know much more than most people."

Relative to the rest of the population's knowledge about audio editor and recorder software, you are:

5. "One of the least knowledgeable people/one of the most knowledgeable people."

As regards computer software in general, you are:

6. "Not at all knowledgeable/highly knowledgeable."

Technological Anxiety (Items Anchored at 1 = "Strongly Disagree," and 7 = "Strongly Agree")

1. In general, I feel apprehensive about using technology.
2. Technical terms sound like confusing jargon to me.
3. I have avoided technology because it is unfamiliar to me.
4. I hesitate to use most forms of technology for fear of making mistakes I cannot correct.

Product Category Relevance (Items Anchored at 1 and 7)

How do you rate the job that this product does in terms of its general significance to you as a consumer?

1. "Irrelevant/relevant."
2. "Unimportant/very important."
3. "Not applicable/highly applicable."

Involvement (Items Anchored at 1 and 7)

How do you rate the task that you performed during the experiment? To me, the task was:

1. "Unexciting/exciting."
2. "Mundane/fascinating."
3. "Uninvolving/involving."
4. "Boring/interesting."

Focused Attention (Items Anchored at 1 and 7)

While using this software,

1. "I was not deeply engrossed/deeply engrossed."
2. "Not absorbed intently/absorbed intently."
3. "My attention was not focused/focused."
4. "I did not concentrate fully/concentrated fully."

Need for Cognitive Closure (Items Anchored at 1 = "Strongly Disagree," and 7 = "Strongly Agree")

1. I think that having clear rules and order at work is essential for success.
2. Even after I've made up my mind about something, I am always eager to consider a different opinion.
3. I don't like situations that are uncertain.
4. I dislike questions which could be answered in many different ways.
5. I like to have friends who are unpredictable.
6. I find that a well ordered life with regular hours suits my temperament.
7. I enjoy the uncertainty of going into a new situation without knowing what might happen.
8. When dining out, I like to go to places where I have been before so that I know what to expect.
9. I feel uncomfortable when I don't understand the reason why an event occurred in my life.
10. I feel irritated when one person disagrees with what everyone else in a group believes.
11. I hate to change my plans at the last minute.
12. I would describe myself as indecisive.
13. When I go shopping, I have difficulty deciding exactly what it is I want.
14. When faced with a problem I usually see the one best solution very quickly.

15. When I am confused about an important issue, I feel very upset.
16. I tend to put off making important decisions until the last possible moment.
17. I usually make important decisions quickly and confidently.
18. I have never been late for an appointment or work.
19. I think it is fun to change my plans at the last moment.
20. My personal space is usually messy and disorganized.
21. In most social conflicts, I can easily see which side is right and which is wrong.
22. I have never known someone I did not like.
23. I tend to struggle with most decisions.
24. I believe orderliness and organization are among the most important characteristics of a good student.
25. When considering most conflict situations, I can usually see how both sides could be right.
26. I don't like to be with people who are capable of unexpected actions.
27. I prefer to socialize with familiar friends because I know what to expect from them.
28. I think that I would learn best in a class that lacks clearly stated objectives and requirements.
29. When thinking about a problem, I consider as many different opinions on the issue as possible.
30. I don't like to go into a situation without knowing what I can expect from it.
31. I like to know what people are thinking all the time.
32. I dislike it when a person's statement could mean many different things.
33. It's annoying to listen to someone who cannot seem to make up his or her mind.
34. I find that establishing a consistent routine enables me to enjoy life more.
35. I enjoy having a clear and structured mode of life.
36. I prefer interacting with people whose opinions are very different from my own.
37. I like to have a plan for everything and a place for everything.
38. I feel uncomfortable when someone's meaning or intention is unclear to me.
39. I believe that one should never engage in leisure activities.
40. When trying to solve a problem I often see so many possible options that it's confusing.
41. I always see many possible solutions to problems I face.
42. I'd rather know bad news than stay in a state of uncertainty.
43. I feel that there is no such thing as an honest mistake.
44. I do not usually consult many different options before forming my own view.
45. I dislike unpredictable situations.
46. I have never hurt another person's feelings.
47. I dislike the routine aspects of my work.

Positive and Negative Affect (PANAS) Scale (Items Anchored at 1 = "Very Slightly," and 7 = "Extremely")

The following are a number of words that describe different feelings and emotions. Read each item and then check the appropriate button below that word. Indicate to what extent you have felt this way during this experiment.

> "interested," "distressed," "excited," "upset," "strong," "guilty," "scared," "hostile," "enthusiastic," "proud," "irritable," "alert," "ashamed," "inspired," "nervous," "determined," "attentive," "jittery," "active," "afraid"

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