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ORIGINAL EMPIRICAL RESEARCH

Productive play time: the effect of practice on consumer demand for hedonic experiences

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Abstract In this paper we explain how practice, prior knowledge and task difficulty interact to affect demand for hedonic experiences. As predicted by the human capital model, we propose that the key determinant of demand for hedonic experiences is the increase in performance efficiency that can be gained through practice. In addition, we argue that the nature of the effect of practice is distinctly different in hedonic consumption, compared to utilitarian consumption. Specifically, for hedonic experiences, practice allows consumers to extract greater value within a given period of time, rather than reduce the amount of time spent on a (utilitarian) task. Finally, we argue that if changes in performance efficiency across repeated hedonic experiences adhere to the power law of practice, then both prior knowledge and task difficulty will be important moderators of the main effect of practice on demand. These predictions are tested in two experiments that use an online panel to examine consumer demand for videogames.

Keywords Experience · Power law of practice · Human capital model · Videogames · Internet · Hedonic products · Utilitarian · Prior knowledge · Decision making

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Consumers spend a lot of their money and time on hedonic experiences. Indeed, some have argued that we live in an "experience economy" and that managing consumers' experiences is the key to avoiding commoditization and price-based competition (Pine and Gilmore 1999). Yet relatively little is known about how consumers choose among the enormous variety of experiences that are available to them. We address this question by examining one potentially critical, yet under-researched, driver of consumer choice among hedonic experiences. Specifically, we are interested in better understanding how practice—that is, the acquisition of knowledge and/or skill through repeated performance (Newell and Rosenbloom 1981)—affects consumer demand for hedonic experiences.

Prior research has demonstrated that the demand for utilitarian goods and services can be dramatically influenced by practice (Johnson et al. 2003; Murray and Häubl 2007). Specifically, it has been shown that practice increases demand for utilitarian products or services because it makes such consumption more efficient—i.e., practice reduces the time required to complete a particular consumption task. Yet, for many hedonic experiences, it seems counter-intuitive to suggest that more efficient consumption will increase demand. For example, would consumers prefer to take shorter holidays, play games that end sooner, eat meals faster, or watch condensed movies?

We argue that efficiency gained through practice does, in fact, increase demand for hedonic experiences. However, the nature of that efficiency is different in the context of hedonic consumption than it is for utilitarian consumption. While practice reduces the amount of *time* required for utilitarian consumption (thus allowing people to consume the same product or service more efficiently), practice increases the amount of *enjoyment* that can be gained through hedonic consumption within the time available (thus allowing people to more efficiently extract enjoyment from an activity).

For example, consider a researcher who for years has used SPSS software for statistical analyses. Having extensive practice with this particular software, s/he is able to complete the next analysis much more efficiently with SPSS than with another statistics program. Prior research has indicated that when such a utilitarian product can be used more efficiently, its "total cost"—i.e., time and effort, as well as price—is reduced (e.g., Wernerfelt 1985). As a result, all else being equal, given the choice between SPSS and competing software, s/he will tend to choose SPSS. Therefore, as consumers have practice using utilitarian products (like SPSS), the "price" falls and demand increases. That is, in a utilitarian context, practice increases demand by increasing efficiency and reducing the cost of consumption (Johnson et al. 2003; Murray and Häubl 2007; Ratchford 2001; Wernerfelt 1985).

We predict that efficiency is also a critical driver of demand for hedonic experiences. However, rather than reduce the time of consumption, practice allows consumers to more efficiently extract value from a given experience. For example, a wine connoisseur will tend to find more to enjoy in a glass of wine than will a consumer tasting wine for the first time. Similarly, a practiced player will tend to enjoy a round of golf more than a beginner. Even watching a television series can be a more pleasurable experience with practice—i.e., regular viewing of a TV series leads to a deeper knowledge of the characters and their history—than it is for someone who is watching the same show for the first time. In other words, because the wine connoisseur, golf pro, and regular TV watcher have more practice with those experiences, they are able to extract more value from them (relative to a consumer who is new to the same experience). In general, as the value of a hedonic experience increases, demand for that experience should also increase.

This paper contributes to the literature in marketing and consumer research in a number of important ways. First, we demonstrate and explain the powerful effect that practice can have on consumer demand for a hedonic experience. Other potentially relevant theories—for example, Berlyne's (1970) two factor theory, or the "Peak-End Rule" (Ariely and Zauberman 2000; Kahneman 1999)—are unable to account for the effects that we observe. In fact, prior theories that explain how people evaluate repeated hedonic experiences struggle to directly address the effects of practice on demand.

However, there is one theory that does provide an explicit explanation of the effects of practice on consumer demand: human capital theory (Becker 1993, 1996; Ratchford 2001). Prior tests of this theory have demonstrated that it is a powerful general framework for explaining the effects of practice on demand for utilitarian products. The research reported in this paper is the first to test the predictions of this theory in the hedonic domain. Importantly, we find that although the general framework of human capital theory can also explain consumer demand for hedonic experiences, the effect of practice on consumption efficiency is distinctly different from what has been proposed for utilitarian consumption. In particular, we find that in the hedonic realm, practice increases the value that can be extracted from an experience within a given period of time. As a result, this research contributes to our understanding of how human capital affects demand and provides an important extension to this theory. We further contribute to theory by applying to hedonic tasks a mathematical "law" of the nonlinear effect of practice (the power law of practice: Newell and Rosenbloom 1981), which has previously been used only with utilitarian tasks to characterize the effects of practice within the human capital model (Murray and Häubl 2003). This law states that all practice sessions are not equally productive. In fact, each new practice session for a particular task is slightly less productive than the last one.

In addition, our research design allows us to test a number of theoretically important variables that have the potential to moderate the effect of practice on consumer demand. First, unlike most previous studies in this area (an exception is Putrevu and Ratchford 1997), we use a sample recruited from an online panel that varies widely in prior knowledge about related tasks. In addition, we employ an experimental methodology that allows us to manipulate a hedonic experience's level of difficulty. We find that both prior knowledge and task difficulty are important moderators of the effect of practice on consumers' demand for hedonic experiences.

In the following sections of the paper we introduce the human capital model (Becker 1993, 1996; Ratchford 2001). We argue that this model is particularly relevant to the study of the effect of practice on demand and is the only model that clearly and directly predicts such effects. The results of two studies demonstrate that practice allows people to consume a hedonic experience more efficiently (i.e., by reducing time spent unproductively) and increases demand for that activity. We conclude with a discussion of the limitations of our studies and the practical and theoretical implications of our results.

Literature review and hypotheses

In this section, we introduce the human capital model (Ratchford 2001) and, from this general framework, derive a set of specific hypotheses within the domain of hedonic consumption. First, we predict that practice has an effect on demand for hedonic experiences. Next we explain how practice has this effect, by proposing that the typically nonlinear effect of practice (the power law of practice) characterizes the learning process for hedonic experiences—i.e., the knowledge and/or skill that is acquired through repeated performance. We also make an important theoretical distinction between the nature of efficiency in utilitarian and hedonic consumption. This section concludes with a discussion of the unique predictions of the human capital model related to two important moderating variables: prior knowledge and task difficulty.

The human capital model

The human capital model describes how the demand for activities, and the goods used to produce them, will vary over time as consumers learn more about these activities. The model predicts that the value of an experience depends on the knowledge and skill that people have previously acquired through practice.

For example, Murray and Häubl (2007) conducted a series of experiments in which participants were asked to search two specially-constructed online news sites for target information. The two versions were identical apart from the navigation interface; version A used pull-down menus, whereas version B used radio buttons. Pre-tests had shown that this difference had no objective effect on performing the search task. Participants were randomly assigned to one of these interfaces (A or B), and also to one of nine task conditions: one search task or nine search tasks. After completing their allotted number of searches, they then used the alternative interface (B or A) to complete a further search task. Finally, they were asked which of the two versions they would prefer to use in one last search task. After just one search, participants were indifferent between the two versions, but after three repetitions, the majority of participants preferred the version they had used the most, even though both were functionally identical. Murray and Häubl explained this apparently irrational preference, or “cognitive lock-in” (Johnson et al. 2003; Zauberman 2003), by showing that increased usage reduces the time taken to complete the search task, so participants were maximizing the productivity of their time when they used the most efficient interface (which was the one they had the most practice using).

The basis of the human capital model is the assumption that a household maximizes the utility of its *activities* rather than its purchases (Stigler and Becker 1977). The potential demand for any activity i at time j (Z_{ij}) is a function of the prices of the goods consumed by the activity (a vector, $\mathbf{X_j}$), such as the ingredients of a meal, the cost of time allocated to the activity (T_{ij}), and the prior knowledge or human capital (another vector, $\mathbf{K_j}$) built up from the multiple activities performed in the past that now make this particular activity more or less productive (Ratchford 2001):

$$Z_{ij} = Z_i\left(\mathbf{X_j}, T_{ij}, \mathbf{K_j}\right) \quad (1)$$

In the studies reported below, we test the human capital model in the context of playing videogames, for four reasons. First, videogames, like other hedonic experiences, are intrinsically rewarding; consumers minimize unrewarding time spent on utilitarian activities to maximize time spent on these rewarding experiences (Hirschman and Holbrook 1982). Second, videogames offer experimenters great control over the emotional responses and engagement experienced by participants (van Reekum et al. 2004). Third, previous research using videogames “suggests the presence of learning phenomena comparable to those that characterize the acquisition of any other skill” (Holbrook et al. 1984, p. 737; Schilling et al. 2003). Fourth, videogames also tend to be played repeatedly, which makes them a good general context for studying the effect of practice on consumer demand for hedonic experiences.

Playing a videogame is a hedonic activity very similar to the example of music appreciation used by Stigler and Becker (1977). Demand for the game would be (mainly) a function of the time that would be spent playing the game, and how productive that time is forecast to be, which is determined by how skillful the player is—that is, the player’s accumulated prior knowledge related to game playing. Mittal and Sawhney (2001) define two dimensions of consumer knowledge: (1) process-oriented, or “how to,” knowledge, which can be acquired only from usage, and (2) content-oriented, or “what,” knowledge, which can be learned without actual usage. Process knowledge is applicable only to similar processes, but content knowledge can be applied to many processes and may sometimes dominate product experience (Hoch and Deighton 1989). Therefore, the m types of knowledge or expertise available for use at time j (K_{mj}) consist of knowledge gained from past consumption of a player’s repertoire of $\mathbf{Z_j}$ activities (at times $\mathbf{j}$−1, $\mathbf{j}$−2, etc., i.e., process knowledge) plus education and other sources of related knowledge (E_j, i.e., content knowledge):

$$K_{mj} = K_m\left(\mathbf{Z}_{\mathbf{j}-1}, \mathbf{Z}_{\mathbf{j}-2}, \mathbf{Z}_{\mathbf{j}-3}, \ldots, E_j\right) \quad (2)$$

Stigler and Becker (1977) show that while the quantity of “output” from a hedonic task like music appreciation (or videogame playing) may be hard to measure, the shadow price (π) of an activity i at time j equals its marginal cost (c) minus the estimation at time j of the future gains (s) from accumulated knowledge about that activity (Ratchford 2001):

$$\pi_{ij} = c_{ij} - s_{ij} \quad (3)$$

If s=0, then the consumer expects no future benefits, and the decision to engage in the activity is based on current costs alone. But if the consumer expects that future usage will be even more productive, reaping the benefits of accumulated knowledge, then the desire for the activity will be influenced not only by current productivity but also by the extent of this knowledge. Expectations of future benefits could also extend beyond the next occasion to predict that practicing a task that is not productive in the medium term will eventually make that task very productive. For example, listening to a new style of music can be an unpleasant and confusing experience at first, but with more practice listening to that style of music becomes more productive, and the new style may come to dominate over less productive styles a person listens to. In this way, the human capital model can be used to explain why people choose to practice a variety of activities from listening to music to playing videogames.

In an experiment, we can ask people to self-report their demand for an activity, which allows us to directly test the unique implications of the human capital model. The first of these implications is that practice can increase demand. Therefore,

H1: Practice has a positive effect on demand for a hedonic experience.

Human capital and the nonlinear effect of practice

We have argued that for both utilitarian and hedonic consumption, practice results in more efficient performance. Moreover we contend that, while improved utilitarian efficiency is about reducing task completion times, hedonic efficiency is about extracting more value from an experience within a given amount of time. Nevertheless, we expect that improvements in hedonic efficiency will follow the same nonlinear function of practice (the power law of practice; Newell and Rosenbloom 1981) that has accurately characterized utilitarian consumption (Johnson et al. 2003; Murray and Häubl 2007).

Specifically, this nonlinear function of practice, often called the "learning curve," has the form of a power function, which means this curved function is a straight line when graphed in log-log space; hence the term "the power law of practice." The power law function and its equivalent log-log linear form are:

$$\begin{aligned} T &= BN^{\alpha} \\ \log(T) &= \log(B) + \alpha\log(N) \end{aligned} \tag{4}$$

in which T is task completion time, B is the baseline time to complete the first practice trial, N is the current trial number, and α is the slope of the learning curve; a negative α means that time-on-task decreases with practice.

However, as we have argued above, for many hedonic experiences the consumer does not want to decrease task completion times. Fortunately, the power law of practice can be applied to dependent variables other than task completion times, such as the number of correct responses, or the amount accomplished per unit of time (Stevens and Savin 1962). For videogames, we could use score achieved per second to gauge increases in productivity. However, an even better measure of increasing efficiency at game playing is a decrease in ineffective game time—that is, a reduction in game time that is not associated with scoring points. Just like inefficient time in goal-directed search or shopping, ineffective game time should decline with practice, in accordance with the power law. The effects of practice on this dependent variable should be negative and therefore directly comparable to previous research on utilitarian consumption that has employed the power law of practice (e.g., Johnson et al. 2003; Murray and Häubl 2007). Therefore,

H2: Ineffective time (T) during hedonic experiences is characterized by a power law function ($T = BN^{\alpha}$) of baseline time (B, the duration of the first experience), and the number of repetitions (N), with a negative slope (α, i.e., practice reduces inefficiency). Therefore, early practice trials should be more productive at reducing inefficient game time than later trials are.

Hypothesis two is important, because if supported, it suggests that we can use the power law of practice to specify the functional form for the effects of practice within the general model of human capital. Using a power function to describe the acquisition of human capital (i.e., knowledge and skill) through repeated performance also has important implications for the potential moderating effects of prior knowledge and task difficulty.

Prior knowledge

To this point, we have developed our predictions of the effect of practice on demand assuming that the consumer is new to the hedonic experience (i.e., s/he has little or no relevant prior knowledge). Intuitively, greater prior knowledge should allow the consumer to have a deeper and more meaningful experience. For example, the wine connoisseur should have a deeper experience when tasting a wine. To the extent that the value of an experience increases as it becomes deeper and more meaningful, greater prior knowledge should lead to an increase in demand for that experience. This is not, however, what the human capital model would predict.

The nonlinear nature of the effect of practice means that repeated experience results in improved performance, but at a decreasing rate. In other words, consumers who have prior knowledge of a hedonic experience will make smaller gains with each repeated experience. For example, although a novice wine drinker may become considerably better at extracting enjoyment from a glass of wine after a tasting seminar, a wine connoisseur would see only a marginal improvement from the same experience.

Prior knowledge effectively increases the total number of times the task has been practiced. In an experiment, we can account for prior knowledge by adding to the number of practice trials observed in the experiment an estimate of the unobserved number of times the person has practiced the task in the past, or tasks that are very similar. The overall effect of practice would then be based on the number of current trials (N) plus prior knowledge (K), which is treated as if the individual had practiced the task K times before[1] (this is the general form of the power law of practice: Newell and Rosenbloom 1981):

$$T = B(N_{TOTAL})^{\alpha}$$
$$T = B(N + K)^{\alpha}$$
$$\log(T) = \log(B) + \alpha \log(N + K) \; . \tag{5}$$

A consumer who has a long history of experience with a hedonic task, and therefore a high level of prior knowledge (K), will also have a high number of total practice trials (N_{TOTAL}), and therefore be far along the learning curve, where it flattens out as it approaches the asymptote of performance efficiency. Current practice trials, therefore, will exhibit little gain in efficiency. On the other hand, the total number of practice trials for a novice player with little or no prior knowledge will be almost entirely made up of current practice trials. The total number of trials for a novice player will therefore map onto the steeply sloping early part of the learning curve, where practice produces dramatic improvements in performance. As a result, adopting a nonlinear functional form for the effect of practice within the human capital model implies that we should observe a moderating effect of prior knowledge on current practice. Specifically, the effect of current practice will be significant only for novices (i.e., consumers with low prior knowledge). Therefore,

H3: There is a significant two-way interaction between prior knowledge and practice, such that the positive effect of practice on demand for a hedonic experience is significant only for consumers with low prior knowledge.

Task difficulty

Another potential moderator of the effect of practice on the demand for hedonic experiences is the difficulty of performing the task. If the task is very easy to learn (e.g., a game of pure chance such as a lottery, or a slot machine game, in which skill is not required; Cotte and Latour 1999), then practice will not generate much improvement in skill and will not change consumer demand for the experience. This is precisely what Murray and Häubl (2007) found when they made their search task Web sites easy to use (2 intermediate pages) versus hard to use (6 intermediate pages). Practice had no effect on demand for the easy interface but a strong effect on demand for the hard interface; after one trial the majority rejected it in favor of the easy alternative, but after nine practice trials the majority preferred the harder-to-use interface they were more familiar with.

Therefore, a nonlinear effect of practice implies that demand will increase for repeated experiences only when practice can result in the acquisition of additional human capital (i.e., knowledge and/or skill). This implies that when a game is so easy to play that even a beginner can quickly reach the asymptote of the learning curve, the moderating effect of prior knowledge will disappear. In other words, H3 should hold only when the task is difficult enough that practice increases performance efficiency. This leads to the prediction of a three-way interaction between practice, prior knowledge, and task difficulty. Specifically:

H4: Practice, prior knowledge, and task difficulty interact in such a way that the two-way interaction between practice and prior knowledge is significant only when the task is difficult.

Summary of hypotheses

The human capital model predicts that practice should have a positive effect on consumer demand for hedonic experiences. We extend this model by specifying a nonlinear functional form for the effect of practice (i.e., the power law of practice), which in turn allows us to derive two additional hypotheses that predict important boundary conditions on the main effect. In addition, we argue that the nature of the effect of practice is distinctly different in hedonic consumption, compared to utilitarian consumption. Specifically, practicing hedonic tasks leads to greater value within a given period of time, rather than a reduction in the time spent on the task. The following sections describe two experiments designed to test our four hypotheses.

Overview

We carried out two experiments, using an online videogame as an example of a hedonic task. This allowed us to readily

[1] Note that if it were difficult to convert a measure of K into the same units as N so they could be summed, potentially a different slope could be estimated for each kind of practice.

manipulate the difficulty of the task and the number of times it is practiced. In addition, we recruited the samples for each experiment from an online panel expected to vary widely on a third factor, prior knowledge, specifically, prior knowledge related to videogame playing. Experiment 1 used a 2 (game difficulty) × 2 (practice) design in which game difficulty and practice were manipulated and prior knowledge was measured. In the first experiment, the three-way interaction between practice, prior knowledge, and difficulty was not significant. In Experiment 2, we modified our experimental design to further explore that interaction. Specifically, in the second experiment we manipulated practice in the same way (2 levels), but used only one moderately difficult version of the game, and measured both difficulty (i.e., perceived difficulty) and prior knowledge. In this second experiment, we found support for H4, as the predicted three-way interaction was significant.

Experiment 1

Design

Experiment 1 used a 2 (game difficulty: Low [slow game] vs. High [fast game]) × 2 (practice: 1 game vs. 10 games) design in which game difficulty and practice were manipulated and prior knowledge was measured. Each participant was randomly allocated to one of the four between-subjects conditions on arrival at the videogame site.

Participants

A total of 207 participated out of 655 members of an Australian online panel (response rate = 32%), who had been invited by email to participate in a videogame playing study for the chance to win a $300 (AUD) Apple iPod prize. The panel had previously been recruited from the general public, and therefore it was expected to vary widely in prior knowledge of videogame playing. The prize was awarded via lottery, weighted by performance (score), to motivate all players to take the task seriously and do their best. To play the game, panel members first had to enter their panel ID number so they could be contacted if they won the prize. Duplicate entries were deleted. There was evidence of a slight self-selection effect on participation: there were more males than females in the final sample, and compared to the general population, the sample was relatively young (Table 1). The level of game-playing ability in this sample, therefore, was likely higher than it would be in a random sample of the general population.

Stimuli: the online videogame

The online videogame we used was a modified fighter jet game similar to the old arcade game *Galaxian*. It was developed specifically for use in our two experiments and was designed to allow us to manipulate difficulty by increasing the speed at which the game was played. The object of the game was to score points by shooting enemy targets while at the same time avoiding obstacles and incoming fire. The game ended when the player's jet sustained critical damage, which means that longer playing times indicate greater skill and also more opportunities to score. The aircraft, viewed from above on screen, could be moved left or right with the mouse and its guns could be fired by clicking the left mouse button. The game was played on the Internet, and for each game played we unobtrusively recorded its duration and the score achieved. In the low-difficulty game, the obstacles advanced at a leisurely pace, while in the high-difficulty game, they rushed down the screen at a rapid speed.

Measurement

For both theoretical and empirical reasons, we expected the dependent variable, *demand*, to be a composite based on six candidate measures. These included three self-reported Likert-type items, all measured on seven-point scales in a post-test online survey ("I liked playing the game," "I enjoyed playing the game," and "I would play this game again"), and positive affect measured using the 20-item PANAS Indices (Watson et al. 1988; α=.88). Positive affect was measured because it is the outcome that positive hedonic experiences should produce. However, we also measured it to test whether demand for hedonic tasks is influenced by positive emotion, as previous investigations using utilitarian tasks have proposed that the effect of practice on demand does not require a positive attitude (Johnson et al. 2003). Two further objective measures were gathered automatically during each game; its duration in seconds, and its final score. Five other seven-point Likert items included in the online survey were expected to measure *prior knowledge* of videogame playing ("I play videogames often," "I love playing videogames," "I am comfortable using computers," the number of times the player had played games like this one before, and perceived difficulty ["the game is easy to play," reverse coded]).

The first theoretical reason for expecting our dependent variable to be a composite measure is that the human capital model has its roots in economic theory, and its formal dependent variable is demand, which in the secondary data typically analyzed by economists might be sales, or dollars. Ratchford (2001), however, describes how demand can be operationalized in consumer research

Table 1 Sample characteristics for Experiments 1 and 2

Measure	Exp. 1 (n=207)	Exp. 2 (n=114)	Test
Gender			
Female	42.0%	31.6%	$\chi^2(1)=3.40$ $p=.073$
Male	58.0	68.4	
Age			
Age in years at time of study	35.70 (14.13)	34.25 (14.30)	$t=.88$, $p=.382$
Education			
High school or less	38.6%	40.4%	$\chi^2(3)=.52$ $p=.915$
Post high school training	30.0	26.3	
Bachelor degree	21.7	23.7	
Postgraduate qualification	9.7	9.6	
Occupation			
Retiree	6.3	7.9	$\chi^2(10)=6.55$ $p=.767$
Not currently employed	3.9	1.8	
Household duties	9.7	12.3	
Student	24.6	28.9	
Laborer	1.4	1.8	
Operator or driver	.5	.0	
Clerical, sales, or service	11.6	12.3	
Tradesperson	3.4	4.4	
Semi-professional	7.2	2.6	
Professional	21.7	21.1	
Manager or administrator	9.7	7.0	
Internet use			
Used the Internet in the last week	98.6	99.1	$\chi^2(1)=.20$ $p=1.000$
Videogames expertise			
Prior knowledge (0–6, 3 items)	2.86 (1.41)	2.99 (1.52)	$t=-.74$, $p=.458$
Perceived difficulty (0–6)	3.48 (1.80)	3.33 (1.97)	$t=.69$, $p=.492$

Standard deviations in parentheses. Degrees of freedom for all t-tests = 319

studies like ours, in which no measure of "sales" or "dollars" is available. He suggests that multiple items can be used as reflective indicators of an underlying latent variable that measures "demand," and that the items used will very likely vary according to the circumstances of the study. According to the *Oxford Dictionary of Economics*, demand is the "desire and ability to acquire a good or service," a description that definitely suited at least three of our six candidate items.

The second theoretical reason is that Berlyne (1970) defined "hedonic value," which should be the key driver of demand for hedonic experiences, as having both evaluative and behavioral dimensions. According to Berlyne, hedonic value is "a term meant provisionally to cover both reward value, as judged by the capacity of a stimulus to reinforce an instrumental response, and preference or pleasure, which is reflected in verbal evaluations" (Berlyne 1970, p. 284). In addition, including a measure of intention in our index of demand allows our results to be comparable to previous and future studies that measure choice behavior, as well as product or service evaluations (e.g., Murray and Häubl 2007).

The empirical results largely conformed to our expectations. As shown in Table 2, an exploratory factor analysis revealed that three of our six candidate items for demand, two evaluative items and one intention item, loaded on the same "demand" factor but had low cross-loadings on two other factors, one labeled "prior knowledge" and the other labeled "score" (which was closely related to game duration). Score emerged as a factor unrelated either to demand or prior knowledge. Positive affect also loaded as expected on the demand factor, but its loading was below .7 (Hair et al. 1998).[2]

A surprising result was that perceived difficulty loaded on the demand factor, rather than the prior knowledge factor, although with a loading below .7, and a cross-loading (on score) with an absolute value greater than .3 (Hair et al. 1998). This was because in Experiment 1, prior knowledge had only a small, although negative, correlation

[2] As we report below, the pattern of results was not substantially different whether we measured demand with three items (including intention) or with just the two evaluative items; however, conceptually (as explained above), intention is an important component of demand.

Table 2 Exploratory factor analyses for Experiments 1 and 2

Item	FACTOR					
	1 (Demand)		2 (Prior Knowledge)		3 (Game Score)	
	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2
Demand						
I liked playing the game	**.91**	**.92**	.02	−.11	.12	.11
I enjoyed playing the game	**.91**	**.91**	.04	−.06	.12	.15
I would play this game again	**.80**	**.83**	.001	−.15	−.02	−.04
Positive Affect Index	.61	.54	.04	.20	−.17	−.21
Perceived difficulty (the game is easy to play, reversed)	−.53	−.53	−.05	−.10	−.46	−.32
Prior knowledge						
I play videogames often	.07	.02	**.90**	**.89**	−.04	.08
I love playing videogames	.17	.14	**.90**	**.88**	−.03	.09
Number of times playing games like this one	.07	.02	**.83**	**.82**	.15	.17
Comfortable using computers	−.15	−.23	.43	.56	.17	−.08
Game score						
Final time (duration of final game played)	−.09	−.08	.02	−.01	**.90**	**.84**
Final score (score in final game played)	.10	.21	.18	.21	**.86**	**.72**

Items used to define scales in bold. Extraction method: principal components analysis. Rotation method: Varimax with Kaiser normalization. Variance explained: 67.61% (Exp. 1), 65.52% (Exp. 2). KMO = .72 (Exp. 1), .74 (Exp. 2); Bartlett's Test of Sphericity: $\chi^2(55)=1111.64$, $p<.001$ (Exp. 1), $\chi^2(55)=593.10$, $p<.001$ (Exp. 2)

with perceived difficulty ($r=-.12$, $p=.099$). The low correlation between prior knowledge and perceived difficulty may seem counterintuitive and requires further explanation. If someone has played the game or games like it several times before, which is our definition of prior knowledge, then according to the power law of practice that person should be approaching their asymptote of performance at playing the game. However, this doesn't necessarily mean that high prior knowledge reduces the perceived difficulty of playing the game. Perceived difficulty can be a relatively stable perception. Consider Paganini's notoriously difficult *Caprices*, which only a handful of violinists have dared to perform or record. They remain difficult even though, with practice, they can be played. The correlation between prior knowledge and perceived difficulty remained small even when we defined prior knowledge exclusively by the number of times a person had played similar games, rather than general experience with videogames ($r(207)=-.18$, $p=.011$). In addition, we measured prior knowledge, but not ability to play videogames, and it is very likely that individual players varied widely in their potential asymptotic performance. Again, this makes it possible to have a high prior knowledge score, yet still perceive a videogame as difficult to play.

We calculated demand and prior knowledge as the mean of the items on each factor with loadings above .7 (α for demand = .88; α for prior knowledge = .78). None of these items had cross-loadings higher than .17 (absolute value), and in a test of discriminant validity (Fornell and Larcker 1981) using confirmatory factor analysis (CFA; model fit: $\chi^2(13)=9.21$, $p=.325$, GFI = .99, NFI = .99, CFI = .99, RMSEA = .03), average variance extracted (AVE) for both demand (.75) and prior knowledge (.71) was not only above .50 but also higher than the square of their correlation ($r=.14$). Also, this correlation's 95% confidence interval (−.04 to .31) did not include "1."

Game difficulty manipulation check

The game-speed manipulation of task difficulty was successful. The high-difficulty game ($n=103$) was perceived as significantly more difficult compared to the low-difficulty game ($n=104$, $M_{\text{HIGH-}D}=3.87$ vs. $M_{\text{LOW-}D}=3.10$, $p=.002$). This was likely due to the fact that completion times—i.e., the amount of time before a player's fighter jet was destroyed—were, on average, 41% faster for the high-difficulty game ($M_{\text{HIGH-}D}=17.41s$ vs. $M_{\text{LOW-}D}=29.51s$, $p<.001$).

Results

The results support H1, that is, practice had a significant positive correlation with demand ($r(207)=.15$, $p=.026$).

H2 predicted that the efficiency gains made through practice would adhere to the power law of practice, by reducing the amount of game playing time that was ineffective in a nonlinear fashion. We tested this hypothesis using data from the participants who played ten games. The results indicate that, in the ten-game sub-sample, there is no difference between the playing times on the first and tenth games ($M_{\mathrm{FIRST}}=21.64s$ vs. $M_{\mathrm{TENTH}}=21.48s$, $t(103)=.10$, $p=.917$). However, while game playing time was flat across the ten games played, these players achieved increasingly higher scores in these games ($M_{\mathrm{FIRST}}=171.15$ vs. $M_{\mathrm{TENTH}}=341.35$, $t(103)=-4.92$, $p<.001$), or in other words, became more productive with practice, scoring more points per second ($M_{\mathrm{FIRST}}=8.51$ *pps* vs. $M_{\mathrm{TENTH}}=16.19$ *pps*, $t(103)=-4.51$, $p<.001$).

To further reveal this "hidden productivity," we estimated the effect of practice on ineffective game-playing time—that is, game time unrelated to scoring points. First, we estimated overall game-playing time (log-transformed) from score achieved during the game (also log-transformed), using individual-level regressions (Johnson et al. 2003; Lorch and Myers 1990):

$$\ln(T) = b_0 + b_1 \ln(S + 1), \tag{6}$$

where $\ln(T)$ is the natural log of the duration of the game, $\ln(S + 1)$ is the natural log of the score achieved in the game (+ 1 in case the score was 0), b_0 is the intercept, and b_1 is the change in (log) time associated with each (log) point scored. We then used the residuals from these individual-level regressions as the dependent variable for a second set of individual-level regressions. These estimated ineffective game-playing time (T), using Eq. 4. As predicted by H2, the slope of the learning curve for ineffective game time, α, was negative ($M=-.03$, $SD=.18$, $t(101)=-1.87$, $p=.030$ [1-tailed]), indicating that practice significantly increases game-playing efficiency.

Moderating effects of prior knowledge and difficulty

The main effect of practice remained significant when it was included in a regression model that also included prior knowledge, task difficulty, and their interactions (see Table 3). However, this main effect was qualified by the significant two-way interaction between practice and prior knowledge predicted by H3.[3]

To illustrate the effect of this two-way interaction, we used a median split on the three-item prior knowledge index ($M=3$) to classify participants as high or low in prior knowledge. The effect of practice on demand was positive only for consumers with low prior knowledge (see Fig. 1). When only the low prior knowledge sub-sample is analyzed (using simple t-tests), practice significantly increases demand ($M_{\text{1-GAME}}=3.32$ vs. $M_{\text{10-GAMES}}=4.38$, $t(98)=-3.30$, $p<.001$ [1-tailed]), whereas in the high prior knowledge sub-sample, the effect of practice is not significant ($M_{\text{1-GAME}}=4.27$ vs. $M_{\text{10-GAMES}}=4.18$, $t(105)=.29$, $p=.771$).[4]

To further illustrate the moderating effect of prior knowledge on practice, we used the general form of the power law of practice to estimate inefficient game-playing time using Eq. 5. We interpreted the maximum possible on the (0–6) prior knowledge scale as equivalent to having played a similar game six times previously. An alternative specification, treating prior knowledge as a logarithmic scale (i.e., 0 to 402 previous games), explained slightly less variance, although the difference was not substantial (R^2: $M_{\mathrm{LINEAR}}=11.9\%$ vs. $M_{\mathrm{LOG}}=11.8\%$). When prior knowledge was controlled for, the effect of practice was no longer significant (i.e., α was not significantly negative: $M=-.04$, $SD=.32$, $t(101)=-1.40$, $p=.082$ [1-tailed]). In other words, whether or not practice will increase game-playing efficiency depends on the amount of prior knowledge.

H4 had predicted a three-way interaction between practice, prior knowledge, and task difficulty, but this (practice × prior knowledge × difficulty) interaction did not have a significant effect on demand (see Table 3). We examine potential explanations for this null result in the "Discussion" section below and revisit our test of H4 in Experiment 2.

Discussion

Overall, the results of this first experiment were consistent with the hypotheses derived from the human capital model. As predicted, we find that practice has a positive effect on demand (H1).

[3] Our results were virtually identical when we deleted the intention item from our measure of demand and instead used a measure based on the two evaluative items ($r=.89$; Spearman Brown split half reliability = .94). The main effect of practice ($\beta=.51$, $p=.001$) was qualified by a marginally significant two-way interaction between practice and prior knowledge ($\beta=-.30$, $p=.055$). There was also a marginally significant interaction between prior knowledge and difficulty ($\beta=-.30$, $p=.056$), but the three-way interaction between practice, prior knowledge, and difficulty was not significant ($\beta=.09$, $p=.557$).

[4] Following the suggestion of an anonymous reviewer, we confirmed this test of H3 using a two-group structural equation model (SEM), in which demand was a latent variable and the two groups were high and low prior knowledge. Using Anderson and Gerbing's (1988) two-step approach, the first-step's unconstrained model had satisfactory fit indices ($\chi^2(18)=4.61$, $p=.100$, GFI = .99, NFI = .99, CFI = .99, RMSEA = .08), although ideally RMSEA should be below .05. In the second step, the fit of the model was not significantly worse after constraining the measurement weights to be equal in both groups ($\chi^2(16)=4.15$, $p=.272$, GFI = .99, NFI = .99, CFI = 1.00, RMSEA = .04; difference $\chi^2(2)=.54$, $p=.765$). However, further constraining the structural path from practice to demand to be equal for both groups did significantly affect fit (difference vs. measurement weights model: $\chi^2(1)=7.11$, $p=.008$). Practice had a significant positive effect only for the low prior knowledge group (standardized $\beta=.51$, $p=.002$, vs. high prior knowledge $\beta=.10$, $p=.369$).

Table 3 Estimators of demand

Independent Variable	EXPERIMENT 1		EXPERIMENT 2	
	B (*SE*)	β	*B* (*SE*)	β
Intercept	**3.69** (.25)***		**5.56** (.63)***	
Practice (−1 = *1 game*, 1 = *10 games*)	**.70** (.25)**	**.44**	**−1.58** (.63)*	**−.94**
Prior knowledge (0–6, 3 items)	.12 (.08)	.11	−.04 (.19)	−.03
Difficulty				
Manipulated (−1 = *low*, 1 = *high*)	.11 (.25)	.07		
Measured (*Perceived Difficulty*: 0–6)			**−.35** (.15)*	**−.41**
Practice × Prior knowledge	**−.16** (.08)*	**−.33**	**.40** (.19)*	**.80**
Practice × Difficulty	−.02 (.25)	−.02	**.47** (.15)**	**1.08**
Prior knowledge × Difficulty	−.11 (.08)	−.22	−.02 (.05)	−.10
Practice × Prior knowledge × Difficulty	.03 (.08)	.06	**−.12** (.05)**	**−.93**

Bold coefficients are significant ($p<.05$). *SE* = standard error. R^2: Study 1, 8%; Study 2, 28%. Maximum condition indices: Study 1, 5.23; Study 2, 15.95

***$p<.001$, ***$p<.01$, *$p<.05$

We also observed the "hidden" mechanism proposed by the human capital model to explain why practice increases demand for hedonic tasks. Practice improves consumption efficiency by allowing players to improve their performance within a given period of time (i.e., score more points per second), over repeated experiences (H2). The results also support H3: the effect of practice on demand is moderated by prior knowledge, such that demand for playing the game increased with practice for players with low prior knowledge, but did not change for those with high prior knowledge. This interaction is not consistent with the intuition that prior knowledge allows for a deeper experience, which would presumably increase demand.

However, we failed to find evidence supporting H4, which predicts that the positive effect of practice, for players with low prior knowledge, will only be significant if the game is difficult to play. In this first experiment, although our manipulation of game difficulty was successful, this hypothesized three-way interaction among practice, prior knowledge, and difficulty was not significant. A possible explanation for this is that the sample for our first experiment had a relatively low level of videogame playing ability, compared to videogame players in general, even though the level of videogame playing ability in the sample was probably higher than it is in the general public. This would explain why even the low-difficulty version of the game was not rated significantly below the midpoint on our (0–6) scale of perceived difficulty (one-sample *t*-tests: $M_{\text{LOW-}D}$=3.10, vs. 3 [midpoint]: $t(103)=.54$, $p=.593$; $M_{\text{HIGH-}D}$=3.87, vs. 3: $t(102)=5.23$, $p<.001$). If both the low and the high difficulty versions of the game were difficult for this first experiment's sample, then our manipulation of game difficulty was not effective. In our second experiment, we recruit a sample with an even higher level of videogame playing ability.

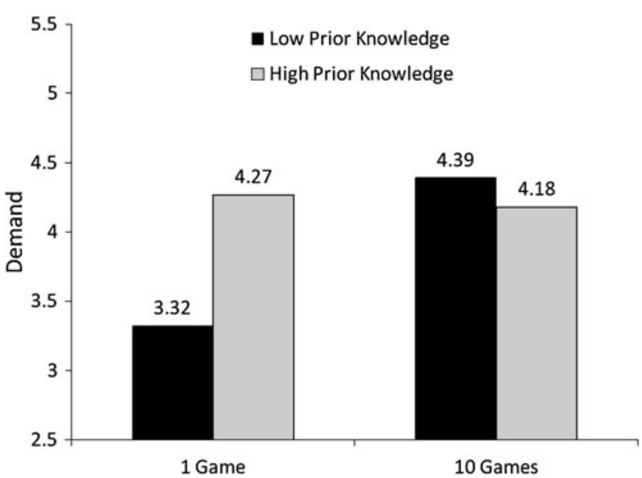

Figure 1 Moderating (interaction) effect of prior knowledge on the effects of practice (Experiment 1).

Experiment 2

In our second experiment, we deliberately targeted young males from the online panel who did not participate in the first experiment, in an effort to increase the level of videogame playing ability in the sample. In addition, instead of manipulating game difficulty, we used just one version of the game, in which the plane flew at a medium speed roughly midway between the low-difficulty (slow) and high-difficulty (fast) versions used in the first experiment, and measured perceived difficulty. This procedure allowed us to more effectively test H4.

Design

The design of Experiment 2 used just one between-subjects factor: practice (2 levels: 1 game vs. 10 games). Both game difficulty and prior knowledge were measured. Participants were randomly allocated to one of the two practice conditions.

Participants

A total of 114 participated out of 200 primarily young and male members of an Australian online panel (response rate = 57%), who had again been invited by email to participate in a videogame playing study for the chance to win a $300 (AUD) Apple iPod prize. The age, gender, and other demographics of the panelists were collected by the sign-up survey which consumers completed to join the panel, so that demographic characteristics could be used to select email addresses. Although the final sample for Experiment 2 contained a marginally higher proportion of males (Table 1), it was not significantly different on any other measures, including age. Nevertheless, the sampling procedure was successful in that half of this sample perceived the game to be low in difficulty (see below).

Stimuli: the online videogame

The same online videogame used in Experiment 1 was used again in this experiment. The only difference was that the speed of the game was set to a medium level, between the fast and slow versions used in the first experiment, and all participants played this same medium-difficulty version of the game.

Measurement

Experiment 2 used the same items as in Experiment 1 to measure demand and prior knowledge. As in Experiment 1, the three items measuring demand (α=.90), and the three items measuring prior experience (α=.79), were the only three items that loaded above .7 on their expected factors and had low cross-loadings on the other two factors (Table 2). Once again, score was a separate factor, and perceived difficulty loaded on the demand factor, as it continued to have a low correlation with prior knowledge ($r(114)=-.12$, $p=.202$). In a CFA ($\chi^2(13)=8.39$, $p=.396$, GFI = .98, NFI = .98, CFI = 1.00, RMSEA = .02), the demand and prior knowledge scales passed the same two tests of discriminant validity used in Experiment 1. AVE was above .50 for both scales (demand = .78; prior knowledge = .71) and higher than their squared correlation ($r=.003$). Also, the 95% confidence interval for this correlation (−.22 to .25) did not include “1.”

Results

As indicated in Table 3, practice had a significant main effect on demand in the full regression model, but in the opposite direction to that predicted by H1. However, this main effect of practice averages over significant interactions between practice, prior knowledge, and difficulty, including the two-way interaction predicted by H3, and the three-way interaction predicted by H4. We analyze these interaction effects in more detail below.

First, though, it is important to note that in our second experiment the effect of practice on efficiency again adhered to the power law of practice, as predicted by H2. The slope of the learning curve for ineffective game time, α, was significant and negative ($M=-.10$, $SD=.29$, $t(54)=-2.63$, $p=.006$ [1-tailed]). As in Experiment 1, practice made no difference to playing time ($M_{\mathrm{FIRST}}=20.15s$ vs. $M_{\mathrm{TENTH}}=21.74s$, $t(54)=-.33$, $p=.741$), but significantly increased the score achieved in this time ($M_{\mathrm{FIRST}}=238.18$ vs. $M_{\mathrm{TENTH}}=434.55$, $t(54)=-2.71$, $p=.009$), or in other words, productivity, measured in points per second ($M_{\mathrm{FIRST}}=18.10$ *pps* vs. $M_{\mathrm{TENTH}}=32.28$ *pps*, $t(54)=-2.64$, $p=.011$). And again, controlling for prior knowledge using the general form of the power law reduced the significance of the effect of practice (α; $M=-.18$, $SD=.55$, $t(54)=-2.39$, $p=.010$ [1-tailed]).

To illustrate the significant interaction effects revealed by the main regression analysis, we dichotomized the continuous variables using median splits, as in Experiment 1. We created two prior knowledge groups, low and high, using a median split on prior knowledge ($M=3$, the same as Exp. 1 since prior knowledge was not significantly higher in Exp. 2 [see Table 1]). We also used a median split on perceived difficulty ($M=3$) to classify individuals as low or high in perceived difficulty. The low-difficulty group clearly evaluated the game used in Experiment 2 as low in difficulty relative to the mid-point of the scale (one-sample t-test: $M_{\mathrm{LOW}\text{-}D}=1.69$, vs. 3 [the midpoint]: $t(58)=-8.73$, $p<.001$), whereas the high-difficulty group perceived it to be significantly higher in difficulty than the midpoint ($M_{\mathrm{HIGH}\text{-}D}=5.09$, vs. 3: $t(54)=19.39$, $p<.001$). Importantly, because of the low correlation between prior knowledge and perceived difficulty in both our experiments, there were roughly equal numbers of low- and high-prior knowledge players in each difficulty group (low-difficulty: Low-K/High-K = 44%/56%; high-difficulty: Low-K/High-K = 53%/47%; $\chi^2(1)=.86$, p = *ns*).

As reported in Table 3, the results support H4, as the three-way interaction (practice × prior knowledge × difficulty) was significant.[5] Figure 2 illustrates the effect of this interaction. In a follow-up ANOVA, using factors

[5] The three-way interaction between practice, difficulty, and prior knowledge predicted by H4 was also significant when we used a two-item measure of demand that did not include the intention item ($\beta=-.82$, $p=.017$). The main effect of practice was negative ($\beta=-.84$, $p=.025$), as was the main effect of perceived difficulty ($\beta=-.45$, $p=.009$), but both these main effects were qualified by the significant three-way interaction, and also a significant two-way interaction between practice and difficulty ($\beta=1.04$, $p=.002$).

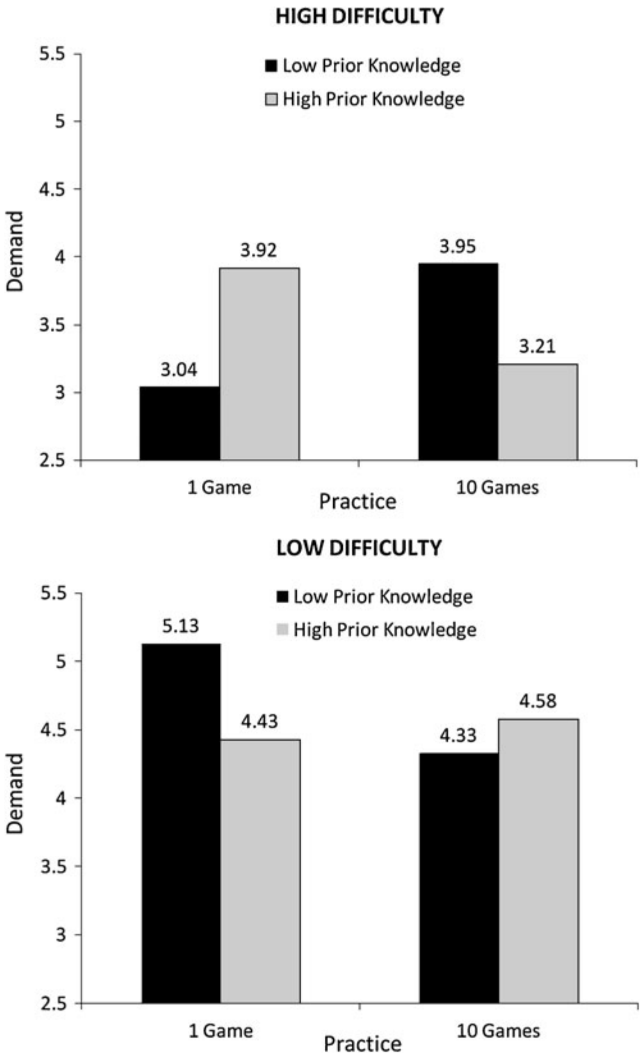

Figure 2 Three-way interaction between practice, prior knowledge, and task difficulty (low vs. high; Experiment 2).

defined by the median splits, the two-way interaction between practice and prior knowledge, predicted by H3 and found in Experiment 1, was marginally significant in Experiment 2 only for players who perceived the game as difficult (see the right-hand panel of Fig. 2: $F(1, 51)=3.34$, $p=.073$). For the high-difficulty game, practice increased demand (in simple t-tests), if players had low prior knowledge ($M_{1\text{-GAME}}=3.04$ vs. $M_{10\text{-GAMES}}=3.95$, $t(27)=-1.54$, $p=.068$ [1-tailed]). The effect of practice was not significant, however, if players had high prior knowledge, whether they played the high-difficulty game ($M_{1\text{-GAME}}=3.92$ vs. $M_{10\text{-GAMES}}=3.21$, $t(24)=1.07$, $p=.295$) or the low-difficulty game ($M_{1\text{-GAME}}=4.43$ vs. $M_{10\text{-GAMES}}=4.58$, $t(31)=-.28$, $p=.390$ [1-tailed]; see the left-hand side of Fig. 2). The interaction between practice and prior knowledge was not significant for the low-difficulty game ($F(1, 55)=1.34$, $p=.252$). For the low-difficulty game, practice did not increase demand, even for low-prior knowledge participants ($M_{1\text{-GAME}}=5.13$ vs. $M_{10\text{-GAMES}}=4.33$, $t(24)=1.28$, $p=.211$).

Collapsing across the two levels of difficulty, the two-way interaction between practice and prior knowledge predicted by H3 was once again significant in Experiment 2, but its coefficient was also in the opposite direction compared to Experiment 1 (Table 3). This was because the positive effect of practice for low-prior knowledge players playing a high-difficulty game was cancelled out by the null effect of practice for low prior-knowledge players playing a low-difficulty game, so that the overall effect of practice for low-prior knowledge players was not significantly positive ($M_{1\text{-GAME}}=4.09$ vs. $M_{10\text{-GAMES}}=4.12$, $t(53)=-.07$, $p=.474$ [1-tailed]). On the other hand, aggregating across low and high levels of difficulty only amplified the negative effect of practice for high-prior knowledge players (although this effect was not significant in follow-up t-test: $M_{1\text{-GAME}}=4.22$ vs. $M_{10\text{-GAMES}}=3.94$, $t(57)=.63$, $p=.528$), so that, collapsing across levels of prior knowledge, the main effect of practice was negative (although again not significant in a simple t-test: $M_{1\text{-GAME}}=4.15$ vs. $M_{10\text{-GAMES}}=4.02$, $t(112)=.41$, $p=.686$; see Table 4). We discuss potential reasons for this negative effect of practice, mainly for players with high prior knowledge, in the "General Discussion" section below.

General discussion

Our aim in these two experiments was to demonstrate the utility of the human capital model of consumer behavior, and in particular to show that it applies to hedonic experiences as well as it has to the goal-directed, utilitarian tasks that have been examined in previous studies (Johnson et al. 2003; Murray and Häubl 2007). As predicted by the human capital model, demand for a videogame, a hedonic activity, increased with practice (i.e., the more times people played the game). In addition, this increase in demand was not due to savings in overall task completion time, in contrast with most previous studies of practice effects, which have focused on utilitarian products (e.g., Murray and Häubl 2007). Instead, we found that game playing time stayed flat over ten practice trials, but with practice this time had become more productive. Furthermore, we were able to reveal the "hidden productivity" within these unchanging game playing times by showing how unproductive game time—that is, game time unrelated to scoring points—decreased in line with the power law of practice.

We also tested the unique predictions of the human capital model related to the moderating effect of prior knowledge. We found that prior knowledge behaved as if it consisted of additional practice trials, as it is modeled in the general power law of practice (Newell and Rosenbloom

Table 4 Cell means for Experiments 1 and 2

Dependent variable	EXPERIMENT 1		EXPERIMENT 2	
	1 Game (n=103)	10 Games (n=104)	1 Game (n=59)	10 Games (n=55)
I liked playing the game (1–7)	**3.53** (1.68)	**4.21** (1.58)**	4.05 (1.97)	3.98 (1.60)
I enjoyed playing the game (1–7)	**3.47** (1.71)	**4.39** (1.55)***	3.95 (1.98)	4.02 (1.56)
I would play this game again (1–7)	4.34 (1.99)	4.21 (1.97)	4.46 (2.06)	4.07 (1.76)
Demand (1–7)	**3.78** (1.60)	**4.27** (1.57)*	4.15 (1.87)	4.02 (1.47)
I play videogames often (1–7)	3.60 (1.86)	3.72 (1.74)	3.83 (1.90)	3.75 (2.02)
I love playing videogames (1–7)	4.53 (1.61)	4.80 (1.35)	5.00 (1.45)	4.64 (1.72)
Number of times playing games like this one (0–6)	2.25 (1.56)	2.25 (1.28)	2.58 (1.46)	2.09 (1.57)
Prior knowledge (0–6)	2.80 (1.56)	2.92 (1.25)	3.14 (1.44)	2.82 (1.59)
Final game time (seconds)	24.26 (21.32)	21.48 (22.06)	22.41 (30.83)	21.74 (37.54)
Final game score (points)	272.82 (398.82)	341.35 (394.28)	422.03 (559.88)	434.54 (511.07)

Bold means are significantly different. Standard deviations in parentheses. MANOVA tests of the effect of practice on these dependent variables (not including demand or prior knowledge): Study 1, Wilks' Λ=.82, F(8, 192)=5.22, p<.001; Study 2, Wilks' Λ=.87, F(8, 99)=1.87, p=.073

***p<.001, ***p<.01, *p<.05

1981). Another contribution of this study to future research and theorizing using the human capital model was that we were able to show that this general power law can be used to relate previous usage of a product to its efficiency of use (Ratchford 2001; Stigler and Becker 1977). Since practice has diminishing returns, current practice has significant effects on game-playing productivity for novice players with little prior knowledge, and therefore on their demand for the game. However, current practice has little improving effect on the efficiency of experts with extensive prior knowledge.

Comparing the human capital model to alternative explanations

No alternative explanation for our results is as comprehensive as the human capital model. The Peak-End Rule (Ariely and Zauberman 2000; Fredrickson and Kahneman 1993; Kahneman 1999), for example, contends that the overall evaluation of an experience will be correlated with the average of the "peak" measure during the experience and the "end" measure of the experience. In one of the few studies that have applied the Peak-End Rule to positive experiences, Fredrickson and Kahneman (1993) asked their participants to use a slider to continually rate their emotional reactions during a series of pleasant film clips. The peak (the maximum real-time slider rating) and the end (the average slider rating over the last 10 s) each supplied unique information towards the formation of an individual's global retrospective evaluation of each clip.

We did not measure real-time evaluations during games, but one measure that we did collect for every game played by those who played the game multiple (i.e., 10) times was the score achieved in the game. We investigated whether the average of an individual's peak and end scores was correlated with demand for the game. In both experiments, however, the Peak-End average was not significantly correlated with demand (Exp. 1: r=−.03; Exp. 2: r=.03), as score was unrelated to demand in our experiments. Nevertheless, future studies could measure evaluations of individual games to see if the Peak-End Rule does correlate with prospective evaluations (demand) for hedonic tasks.

However, what we were particularly interested in is the effect that practice—i.e., knowledge or skill gained through repeated performance—has on demand. The Peak-End Rule was not developed to directly address this domain (Kahneman 1999). The Peak-End Rule is more appropriately applied to understanding how a person evaluates a single experience than to predicting the effects of practice on consumer demand across a series of experiences (Kahneman 2000; Schrieber and Kahneman 2000). Also, the Peak-End Rule does not offer clear predictions about how prior knowledge or task difficulty might moderate the effect of practice.

Berlyne's (1970) two-factor theory, however, does suggest that task difficulty and practice will interact in a manner that is not easily accounted for by the human capital model. The two factors in Berlyne's theory are *familiarity* and *tedium*. Moderate levels of familiarity produce more hedonic value than low or high levels. At extremely high levels of familiarity, tedium depresses hedonic value even further, below its low-familiarity level. In an influential experiment, Berlyne (1970) predicted and found a two-way interaction between task difficulty and practice. The task was evaluating reproductions of paintings, some of which were complex (high-difficulty) while others were simple (low-difficulty), and this evaluation task was repeated (practiced) 46 times. The low-difficulty paintings familiarized rapidly, so their evaluations declined in straight-line fashion, consistent with the effect of tedium. But because the high-difficulty paintings took longer to familiarize, they delayed the onset of tedium, and their evaluations exhibited the inverse-U effect of familiarity.

In our second experiment, we observed an interaction between practice and difficulty similar to that predicted by Berlyne's two-factor theory. Demand was higher for the low-difficulty game compared to the high-difficulty game (see Fig. 2), but this gap narrowed with practice, in a way consistent with tedium reducing demand for the low-difficulty game and the inverse-U effect of familiarity delaying the effect of tedium for the high-difficulty game (after 1-game, the gap was 1.33 [4.76 vs. 3.43, $p=.005$]; after 10-games, it was 0.9 [4.48 vs. 3.58, $p=.022$]). Berlyne's theory also offers an explanation for why practice had a negative effect on demand for high-prior knowledge players in our second experiment. Since high-prior knowledge players presumably could familiarize themselves with the game faster, their demand for the game was more likely to be affected by tedium.

However, Berlyne's theory does not explicitly incorporate prior knowledge and, therefore, cannot account for the significant three-way interaction we found in Experiment 2. Only the human capital model predicted that the two-way interaction between practice and prior knowledge is qualified by task difficulty. Moreover, familiarity, in Berlyne's theory, is based on prior exposure to the *same* stimulus, rather than analogical transfer from similar stimuli, which is addressed in the human capital model by the acquisition of transferable skills. For example, Murray and Häubl (2002) showed how practice "locked-in" demand only when the skills acquired were not transferable to other tasks. According to Berlyne's theory, the two-way interaction between practice and task difficulty should not be affected by prior knowledge gained from analogous tasks (e.g., other paintings, or other videogames).

It is also possible to draw a corollary from the human capital model that can explain the negative effect of practice on demand at high levels of prior knowledge, without having to invoke Berlyne's theory. Assuming a fixed budget for time allocated to hedonic tasks, if practice increases demand for one task, it reduces demand for another, most likely a well-practiced task for which further practice will not significantly increase productivity. The reverse must also occur if person already has high prior knowledge of a task. Further practice would *reduce* demand for that task in comparison to other hedonic tasks that could benefit from further practice. This line of argument suggests that in contrast to utilitarian tasks, for which the human capital model predicts that practice will encourage cognitive lock-in, for hedonic tasks practice may encourage variety seeking among people with high prior knowledge. Future research should test this possibility by offering participants, with varying levels of prior knowledge, a range of practiced and unpracticed hedonic tasks to choose from.

Limitations

This study has a number of limitations, which future research could address. First, we used just one videogame to test the predictions of the human capital model for all hedonic products and experiences. Clearly, there is a need to replicate our results, not only with other types of games, but also with other hedonic activities. For example, the utility of the human capital model depends on how much skill and other forms of prior knowledge contribute to enjoyment of the game. The model clearly applies to participants and viewers of TV quiz shows, but should not apply to casino gambling games based on luck, although players may think their skill is involved. A future experiment might manipulate the number of times players win a "no skill" game. For other hedonic activities, such as music appreciation, or wine tasting, the model should apply, but may be difficult to test, as increases in productivity are likely to be well hidden.

Second, our manipulation of task difficulty was unsuccessful in our first experiment, and for this reason we measured perceptions of task difficulty for an unvarying task in our second experiment. But because we did not randomly assign participants to task difficulty conditions, we cannot rule out other explanations for its apparent causal effects (Aronson et al. 1998). A key task for future research in this area is to replicate our findings using effective manipulations of task difficulty for a hedonic experience.

Third, we are unable to rule out two sources of error in our measurement of prior knowledge, which may have led to an over- or an under-estimation of its effects. First, two of the three items we used assumed that there is a common skill set across all videogames and therefore practice on one transfers to another. While this is true to some extent, it is also true that most games require skills that are unique to the specific game, and a high score on these two items would over-estimate the contribution of prior knowledge to skill using the current game. Also, all three items we used measured actual game playing, but it is possible that players could accumulate prior knowledge from watching others play the game or games that are very similar. In this case, our measure of prior knowledge may have under-estimated its effects.

Fourth, we forced the amount of practice our players engaged in, but in real life people make the decision not only to play the game again but to practice the game even when in the medium term alternative activities may be more productive. The human capital model provides one of the most plausible explanations for why people would choose to practice an activity that is not currently enjoyable, such as when a novice plays the piano. We leave it to future research, however, to test hypotheses about why people would choose to engage in practicing hedonic activities.

Finally, future research should use multiple-item measures of enjoyment, attitude, and intention so that the chain of influence between these constructs can be investigated for hedonic tasks. Demand for a hedonic activity could then be clearly measured by intention to perform the activity again, and future research could examine the antecedents of this intention, which likely include attitude toward the activity and enjoyment, in contrast to utilitarian activities. Furthermore, we used mainly self-report measures, but future research would benefit from the use of a wider range of measures. In particular, demand should be measured behaviorally, by offering players a choice between the game they have practiced and an alternative (e.g., Murray and Häubl 2007). Also, the effects of repeated game playing on emotional responses such as arousal could be measured directly using psychophysiological measures (for example, skin conductance; van Reekum et al. 2004). Such continuous measures during game play would provide a better test of the alternative Peak-End Rule explanation of demand for hedonic experiences.

Conclusion

We have shown that the human capital model of consumption can be applied to the explanation of demand for one hedonic activity: playing a videogame. This demand can be explained, usefully, by knowledge and usage effects, which are potentially under managerial control (Hoch and Deighton 1989; Ratchford 2001; Stigler and Becker 1977); for example, by advertising, or offering free trials. Our findings also have implications for the design of hedonic products and the metrics used to evaluate their effectiveness. Namely, for products like videogames, practicing to use a product more productively increases its value, just as practice increases "cognitive lock-in" to Web sites (e.g., Johnson et al. 2003). However, for intrinsically rewarding hedonic tasks like playing videogames, in which there can be positive returns from flat or increasing time-on-task, increases in productivity may be hidden, rather than clearly and unobtrusively observable in reductions in task completion times. For the videogame we used, game duration and score allowed us to unobtrusively calculate a metric for increasing productivity: ineffective game-playing time. Videogame developers could use this metric to predict demand for a game based on the value that players are able to accrue through practice relative to substitute products or activities. We note though, that for other hedonic activities, efficiency metrics like this one may be harder to find.

This work may also have implications for understanding how videogame playing can become addictive. Consistent with previous work on addiction (Becker 1996; Stigler and Becker 1977), we find that with practice the amount of utility that can be derived from playing videogames may grow relative to other activities. In the extreme, videogame playing could dominate all other activities.

Although we have applied the human capital model to videogame playing, we expect that the model has the potential to explain demand for many other hedonic experiences. In fact, the number of consumer experiences (activities, products, services, etc.) that are hedonic in nature is likely to be much larger than the number that are utilitarian, which research into the human capital model has concentrated on until now. In particular, consumer information search is an activity that can be hedonic (browsing), as well as utilitarian (buying), and the human capital model has already proven useful for investigating this key topic in consumer research (Putrevu and Ratchford 1997). Finally, the consistent finding that knowledge and usage effects explain differences in demand suggests wider questions about the allocation of time to various activities (Cantor and Sanderson 1999). For example, a human capital perspective suggests that people, and especially parents and educators, should take a forward-looking, even life-span, view when selecting experiences and how much time to budget toward them (Ratchford 2001). Relationships, between partners, or parents and children, or companies and their customers, are another class of hedonic experiences that benefit from knowledge developed over time (e.g., Ford et al. 2002).

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