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Organizational Behavior and Human Decision Processes 91 (2003) 128–139
ORGANIZATIONAL BEHAVIOR AND HUMAN DECISION PROCESSES
www.elsevier.com/locate/obhdp

Differential partitioning of extended experiences☆

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Abstract

This article focuses on the effect of the perceived cohesiveness of experiences, whether composed of single or multiple parts, on their overall hedonic evaluations. Four experiments demonstrate the effects of partitioning on decision makers' evaluation of extended experiences. First, patterns (i.e., improving vs. deteriorating trends) strongly influence how experiences are evaluated. Second, increased partitioning of an experience reduces the effect of the overall trend and results in more equal weighting of its parts. Third, breaking experiences at strategic points (i.e., local maxima and minima) influences the overall evaluation of experiences as well as the prediction of their future levels. These results suggest that components of sequences are evaluated similarly to the way whole sequences are evaluated and that experiences composed of multiple components are evaluated relatively more on the basis of their individual intensity and less based on their overall pattern.

Keywords: Hedonic evaluations; Experience-partitioning; Intertemporal choice; Time

Introduction

Many experiences, such as visiting a health club, eating at a restaurant, and using telecommunication services, extend over time. During such extended episodes, the quality of the experience often changes, creating a profile of utility over time (which we refer to as a *pattern*). For example, imagine a person who experiences a sequence of encounters with an Internet service provider. Assume that the quality of the service changes over time: some of the usage occasions are smooth with no communication errors, whereas others are difficult with varying levels of connectivity. For simplicity, assume that the pattern is quite orderly and follows either an improving trend from mediocre to very good or a deteriorating trend from very good to mediocre. Now imagine that at the end of the day, that person evaluates her overall daily satisfaction with the service. How will she form this evaluation and on which aspects of the pattern will she base her evaluation? In the current article, we focus on how the perceived cohesiveness of an experience, whether perceived as a single unit or as composed of multiple parts, moderates these overall evaluations.

Recent research on intertemporal choice suggests that the patterns of extended experiences significantly influence their perceived overall attractiveness (Loewenstein & Prelec, 1993). Moreover, work in this area has demonstrated that preferences toward sequences of outcomes cannot be deduced simply from preferences toward their components (Ariely, 1998; Hsee & Abelson, 1991; Varey & Kahneman, 1992). Instead, decision makers seem to extract only a few key aspects of these sequences (which we refer to as *gestalt characteristics*), and rely on these gestalt characteristics when forming overall evaluations of sequences. The experiences' rate of change and their final intensity are two such features.

Although the evidence for preferences for improving patterns is accumulating, we recently demonstrated that this tendency is not uniform across all types of experiences and depends on the level of cohesiveness (Ariely & Zauberman, 2000). Specifically, we examined two general types of experiences: cohesive (continuous) experiences and experiences that are composed of multiple

☆ The authors thank Jim Bettman, John Lynch, and George Loewenstein for their helpful comments on a previous draft. In addition, the authors acknowledge the helpful comments of the editor and three reviewers.

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doi:10.1016/S0749-5978(03)00061-X

components (partitioned). Although cohesiveness is a matter of degree, cohesive experiences generally progress without breaks or interruptions, and are perceived as a single unit. Examples of such experiences include movies, morning commutes, and voice messages. Partitioned experiences, which take place over multiple periods or with interruptions, include plays (with an intermission), educational courses, concerts, and multi-day vacations. Using both annoying sounds and hypothetical investment scenarios, we demonstrated that, compared with continuous experiences, partitioned experiences are less influenced by the way they progress over time and more by the mean intensities of their components.

When we examine the world around us, it seems easier to generate real-life examples of experiences that are partitioned than real-life examples that are strictly continuous (ones without any break or interruption). If the distinction between continuous and partitioned experiences moderates the impact of patterns on decision makers' overall evaluations and if many, if not most, of daily experiences are partitioned to some extent, then understanding the effects of patterns on partitioned experiences is important. Following this line of reasoning, the current work further examines the effect of partitioning on the evaluations of patterns and, in doing so, provides more robust evidence for the moderating effects of partitioning.

The remainder of the article is organized as follows: We first provide a brief overview of prior research on evaluation of single experiences and present a synthesis of initial evidence regarding differences between single and partitioned experiences. Then, we present four experiments examining the moderating effect of partitioning on the relationship between patterns and overall evaluations. We conclude with a discussion of the experimental results and their implications.

Evaluating experiences over time

Over the past decade, there has been growing interest in the relationship between the way that experiences change in intensity over time and their corresponding overall retrospective evaluations (Ariely, 1998; Hsee & Abelson, 1991; Loewenstein & Prelec, 1993; Varey & Kahneman, 1992). For example, Ariely (1998) demonstrated that experiences with equally painful components are evaluated differently, depending on their pattern over time. Experiences that increase in intensity over time (2, 3, 4, 5, 6) are evaluated as more painful than are constant experiences (4, 4, 4, 4, 4), which in turn are evaluated as more painful than experiences that decrease in intensity over time (6, 5, 4, 3, 2). Preferences for improving sequences seem to be robust and have been demonstrated in many domains, such as monetary payments (Loewenstein & Sicherman, 1991), life experiences (e.g., vacations; Loewenstein & Prelec, 1991, 1993), emotional episodes (Fredrickson & Kahneman, 1993; Varey & Kahneman, 1992), television advertisements (Baumgartner, Sujan, & Padgett, 1997), queuing experiences (Carmon & Kahneman, 1996), pain (Ariely, 1998; Ariely & Carmon, 2000), discomfort (Ariely & Zauberman, 2000; Kahneman, Fredrickson, Schreiber, & Redelmeier, 1993; Schreiber & Kahneman, 2000), medical outcomes and treatments (Chapman, 2000; Redelmeier & Kahneman, 1996), gambling outcomes (Ross & Simonson, 1991), and academic performance (Hsee & Abelson, 1991).

Sequences of experiences that extend over time can be characterized by several different aspects (gestalt characteristics), and indeed multiple aspects have been shown to impact overall evaluations. Some of the most important aspects include the trend of the experience (Loewenstein & Prelec, 1993), its rate of change (Hsee & Abelson, 1991; Hsee, Abelson, & Salovey, 1991), and the maximum and final intensities associated with the experience (Fredrickson & Kahneman, 1993; Kahneman et al., 1993; Ross & Simonson, 1991; Varey & Kahneman, 1992). Taken together, these components seem to account for overall evaluations, which suggests that it is these components (and not an integral of the intensity) that decision makers use when constructing their overall evaluations.

Effects of partitioning: Multiple versus single experiences

Research that relates momentary evaluations to overall evaluations has generally concentrated on hedonic profiles of single experiences and their overall evaluation. However, research also suggests that when decision makers encounter prolonged naturally occurring experiences, they divide them into components and use the partitioning imposed by these components to organize the information from their experiences (Lassiter, Briggs, & Bowman, 1991; Newtson, 1973; Newtson, Rindner, Miller, & LaCross, 1978). Moreover, research from behavioral games (Andreoni, 1988; Croson, 1996) and bargaining (Roth, Murnighan, & Schoumaker, 1988) demonstrate that when a sequence of games is broken, participants think differently about the instances within and between the game parts.

Additional work examining the effects of partitioning the probability space (e.g., Fox & Rottenstreich, 2003) demonstrates that judgments that rely on ignorance priors (equal prior likelihood) are sensitive to the extent of the partitioning. That is, the number of events in which the sample space is divided influences the judged probability of occurrence. In the context of decision analytic models, Ravinder, Kleinmuntz, and Dyer (1988) and Kleinmuntz (1990) demonstrate the importance of decomposing complex problems into smaller, simpler judgments, for increasing consistency in decision making. In general, multiple streams of research indicate that even arbitrary breaking points in a series of repeated events cause decision makers to treat events that are not separated by breaks as a unit and to "reset" their strategy at breaking points.

When these findings are generalized to decision makers' integration of extended experiences, they suggest that evaluations can be influenced by arbitrary partitions. Following this logic, we demonstrated that the relationship between a pattern of an experience and its overall retrospective evaluation might be different if the experience was perceived to be cohesive (singular) or partitioned (multipart) (Ariely & Zauberman, 2000). In these demonstrations, partitioning moderates the effect of patterns: partitioning improving sequences result in less favorable evaluations whereas partitioning declining sequences result in more favorable evaluations. In the current research, we examine this phenomenon in more detail to enhance our understanding of the underlying process.

Hypotheses

Earlier, we briefly described research on integration of sequences, as well as evidence regarding the effects of partitioning. In the current article, we integrate these ideas and study the effects of partitioning on evaluations of extended experiences. We suggest that many, if not most, extended experiences that people face in their day-to-day life are partitioned to some extent; therefore, it is important to understand the effects of partitioning on integration of experiences. Moreover, understanding the effects of partitioning can enable us to better understand the mechanisms that underlie the robust, yet currently unexplained, preferences for improving sequences. On the basis of the ideas presented previously, we propose the following hypotheses:

H1a. Increased partitioning will attenuate the preference for improving sequences.

H1b. Compared with decision makers' overall retrospective evaluation of a cohesive experience, their overall evaluations of partitioned experiences will be based relatively less on the way the experiences evolve over time (their pattern) and more on their mean intensity (Ariely & Zauberman, 2000).

There are several implications of these ideas. For example, if a breaking point resets the evaluation process, partitioning experiences might be sensitive to the composition of the components, holding the overall sequence constant. If the same integration rules of continuous experiences are also used when evaluating the separate components, and if the overall evaluations are based on the summary evaluations of the separate component and not on the global pattern, then specific characteristics of each component (such as the pattern just preceding a break) could have a significant effect on the overall evaluation of the global experience. That is,

H2a. The overall evaluation of a multicomponent experience will be based more on the summary representations of the individual components and less on the overall patterns.

H2b. The location of the break will influence overall retrospective evaluations, such that partitioning experiences at local peaks will lead to more positive evaluation than partitioning at local dips.

We test these hypotheses in four experiments. In experiments 1, 2, and 3, we demonstrate that the preference for improvement is a function of partitioning, with reduced relative impact of the overall trend compared to the overall mean intensity. Experiment 3 provides additional support to the idea that each component of a multicomponent experience is evaluated similarly to overall experiences. In experiment 4, we demonstrate that the impact of the trend of the experience is diminished with increased partitioning, by examining its effect on predictions rather than retrospective evaluations. Because the basic experimental method is similar across all the experiments, we provide greater details for the methods of experiment 1 and focus mainly on the differentiating design elements in subsequent experiments.

Experiment 1: Increased partitioning

Experiment 1 was designed to replicate and extend Ariely and Zauberman's (2000) findings. The current experiment tested the extent to which partitioning is important by manipulating partitioning on three, rather than two, levels (one-part, two-parts, and four-parts). We expect that the effect of the trend of the experience (increasing vs. decreasing) will diminish with increased partitioning (H1a).

Method

Participants

Forty-five students participated in the experiment and were paid $6 for their time. Participants were randomly assigned to the three experimental conditions.

Design

The experiment included a 3 (partitioning) $\times$ 2 (trend) $\times$ 4 (trend-variations) mixed design. Partitioning was manipulated between-participants and includes a three level manipulation of the cohesive structure of the hedonic profiles: (1) at the lowest level of partitioning, the service was presented as cohesive (the one-component condition, see Fig. 1A, for illustration); (2) at the intermediate level of partitioning, the service was presented as composed of two parts, each with equal duration (the two-component condition); and (3) at the

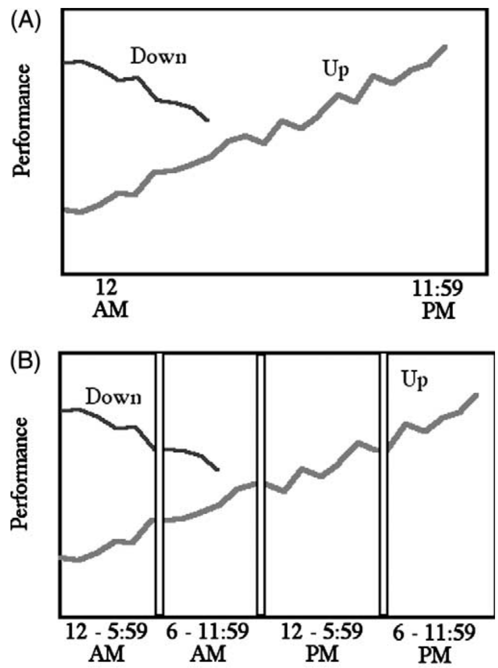

Fig. 1. Schematic display of the partitioning manipulation and the two types of trends. During the trials, the information was reveled over time from left to right over a period of 45 s. In this figure, the snapshot of the up trend is taken near the end of the service period, and the snapshot of the down trend is taken near the beginning of the service period. (A) Top panel illustrates the progression of a continuous experience. (B) Bottom panel illustrates the progression of a multicomponent experience.

highest level of partitioning, the service was presented as composed of four parts, each with equal duration (the four-component condition). Note that the partitioning manipulation did not change the integral of the information that was displayed (i.e., the overall level was equal across conditions). Instead, we introduced break points by adding vertical separators that shifted the information graph to the right by a distance equal to the width of the break point. Fig. 1B represents the same improving and declining trends in the four-component condition, with three visual separators that divide the x-axis. These visual separators do not hide any of the information; instead, they shift the x-axis by a given width, so that the overall width of visible space is preserved. We manipulated the within-participant factors, trend, and trend-variations by varying the quality of service (in percentage) over the day. There were two types of sequences (trends): an overall improving trend (upward trend) and an overall deteriorating trend (downward trend). Within each trend, there were four versions (trend-variations) that varied on their starting point, ending point, mean intensity, and rate of change. We chose these trend-variations by selecting two low (15 and 25%) and two high (75 and 85%) points along the performance scale, and setting all possible combinations of increasing and decreasing trends between these sets of points (see Table 1, Panel A). We added a small random component of ±4% to each point along the sequence to give it a more realistic character.

Table 1
A numerical representation of the stimuli

	Improving trends		Declining trends	
	Starting (%)	Ending (%)	Starting (%)	Ending (%)
*A: Experiment 1**				
Trend-variation 1	15	75	75	15
Trend-variation 2	15	85	85	15
Trend-variation 3	25	75	75	25
Trend-variation 4	25	85	85	25
*B: Experiment 2**				
Trend-variation 1	5	35	35	5
Trend-variation 2	5	65	65	5
Trend-variation 3	5	95	95	5
Trend-variation 4	35	65	65	35
Trend-variation 5	35	95	95	35
Trend-variation 6	65	95	95	65
*C: Experiment 3**,**				
Trend-variation 1	10	50	50	10
Trend-variation 2	10	70	70	10
Trend-variation 3	10	90	90	10
Trend-variation 4	30	70	70	30
Trend-variation 5	30	90	90	30
Trend-variation 6	50	90	90	50
*D: Experiment 4**,**				
Trend-variation 1	20	40	40	20
Trend-variation 2	20	60	60	20
Trend-variation 3	30	60	60	30

* The progression included a small random component of ±4%.
** The progression changed its directions multiple times as in Fig. 3.

Procedure

Participants were instructed to evaluate the performance level of several communication providers. Each trial provided information about, and asked for, an evaluation of a different provider. We indicated the performance level of each of the communication providers by plotting the proportions of successful information packets that had been transferred by that communication provider as a function of the hour in the day. The vertical axis was marked 0% success rate on the bottom and 100% success rate on the top. The horizontal axis was marked 12:00 a.m. on the left and 11:59 p.m. on the right, representing a period of 24 h (see Fig. 1A). At the beginning of each trial, participants were faced with a blank grid. Once participants indicated that they were ready to observe the next information provider, the performance graph was plotted, starting from the left (12:00 a.m.) and, over 45 s, building upward toward the right side of the graph, at a constant rate. Fig. 1A represents an improving trend and a declining trend in the one-component condition: The snapshot for the improving sequence (upward) is taken near the end of the service period; the snapshot for the deteriorating sequence (downward) is taken near the beginning of the service period. Note that if the snapshot represented in Fig. 1 had been "taken" at the end of the 45 s trial, the pattern would have extended all the way to the right edge of the box. The snapshots are presented this way to illustrate the buildup process of the trials.

In the two partitioned conditions (the two-component and four-component conditions), the progress was not continuous and included narrow gaps that created the partitioning (see Fig. 1B). Participants viewed the progress of the sequence without interruption. At the end of each trial, all participants were asked to report their overall satisfaction with the performance of that particular information provider. Participants reported these overall retrospective evaluations on a scale ranging from 0 ("not satisfied at all") to 100 ("extremely satisfied").

Results and discussion

We computed an overall analysis of variance (ANOVA), with trend and trend-variations as within-participant factors, and partitioning as a between-participants factor. Consistent with the well-documented preference for improving sequences, the mean satisfaction for the improving trend was significantly higher ($M = 65.15$) than the mean satisfaction for the declining trend ($M = 33.45$), $F(1, 42) = 1790.4$, $p < .001$. More important, a statistically significant trend by partitioning interaction, $F(2, 42) = 665.4$, $p < .001$ qualified this result. This interaction indicates that the difference in satisfaction between the improving and declining trends was not uniform across all three conditions (see Fig. 2). Rather, the effect of the trend (the difference between the improving and declining trends) was highest in the one-component condition ($M = 44.73$), lower in the two-component condition ($M = 31.18$), and lowest in the four-component condition ($M = 19.18$). These results show that whereas participants' evaluations of single prolonged experiences were highly influenced by the way the experiences progress over time (the overall trend), their evaluations of the partitioned experiences became increasingly less sensitive to overall trends as the number of partitioning increased. As the number of partitioning increased, participants' overall evaluations were based relatively more on the experiences' momentary performance (actual valance) and less on their global pattern.

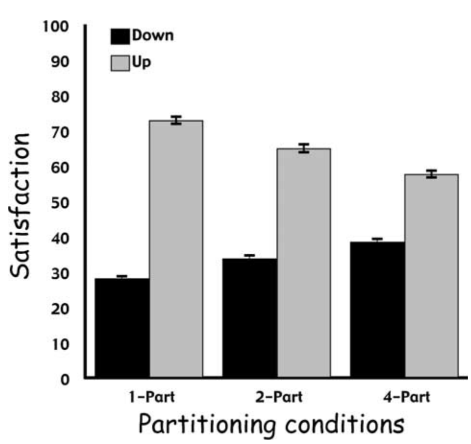

Fig. 2. Mean satisfaction in experiment 1 as a function of the two trends and the three partitioning conditions. *Notes.* Error bars are based on standard errors.

Experiment 2: Partitioning and gestalt characteristics

Experiment 1 demonstrates the effect of partitioning on overall retrospective evaluations. Experiment 2 directly examines the extent to which increased partitioning changes the relative impact of two gestalt characteristics of the sequences: mean value and trend. We hypothesized that increased partitioning will decrease the relative weight of the global trend and increase the relative weight of the mean quality.

Method

Participants

Sixty-six students participated in the experiment and were paid $6 for their time. Participants were randomly assigned to the three experimental conditions.

Design and procedure

The design was a 3 (partitioning) $\times$ 2 (trend) $\times$ 6 (trend-variations) mixed design. We manipulated partitioning between participants and trend and trend-variations within participants. The novel aspect of experiment 2 was the way that trend-variations were manipulated. The different trend-variations were not simple replications of one another; instead, they were designed to have different starting points, ending points, mean intensities, and slopes (see Table 1, Panel B). Note that these four characteristics (starting points, ending points, mean intensities, and slopes) are not independent—any two of these characteristics can fully describe each individual trend. However, this structure of the trend-variations manipulation enabled us to extract the decision-weights for two of the four characteristics of the patterns. Based on our predictions, we describe each of the trends based on its trend and mean, testing how these two parameters were combined into an overall evaluation and how partitioning influenced their relative effects.

Results

We computed an overall ANOVA, with trend and trend-variations as within-participant factors, and partitioning as a between-participants factor. As can be seen in Fig. 3, the results indicate a significant main effect for trend, $F(1, 63) = 50.26$, $p < .001$, and a trend by

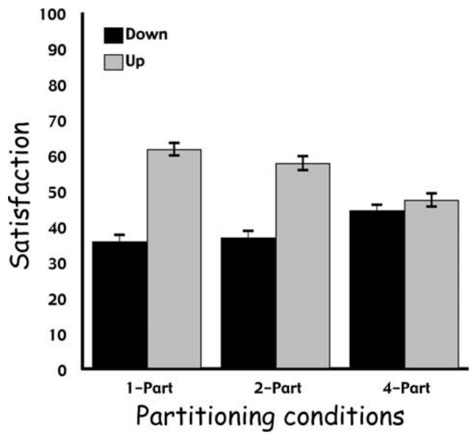

Fig. 3. Mean satisfaction in experiment 2 as a function of the two trends and the three partitioning conditions. *Notes.* Error bars are based on standard errors.

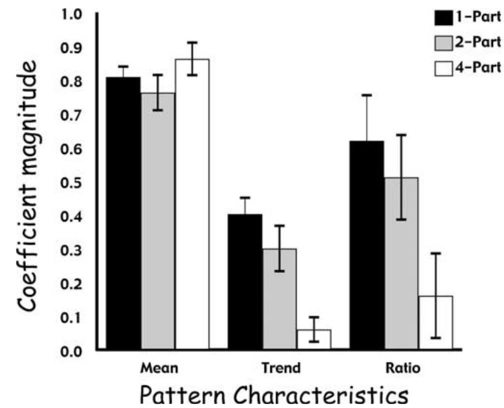

Fig. 4. Mean standardized coefficients for mean-intensity, trend, and their ratios in experiment 2 as a function of the three partitioning conditions. *Notes.* Error bars are based on standard errors.

partitioning interaction, $F(2,63) = 8.91$, $p < .001$. In addition, there was a significant main effect for the trend-variations, a significant trend by trend-variations interaction, and a marginally significant trend by trend-variations by partitioning three-way interaction. Without presenting these results in depth, it is important to note that they do not qualify any of our main results. Note also that the results of experiment 2 (Fig. 3) show a weaker effect of trend compared with the results of experiment 1 (Fig. 2). This reduction is due to the increased range of trend-variations, some of which have very shallow slopes (compare panels A and B in Table 1).

The novel contribution of experiment 2 centers on its ability to test which aspect of the patterns (mean value or trend) drives the differences between the various partitioning conditions as shown in experiment 1. For each participant, we computed an individual regression model in which the respondent's overall evaluations for all 12 stimuli were regressed on two main aspects of the sequences (the rate of change and the mean intensity). We used the standardized regression coefficients as the individual level measures, and performed all statistical analyses on this measure. For each subject, we computed three measures: the standardized regression coefficient of the slope (rate of change), the standardized regression coefficient for the mean intensity, and the ratio of the two (slope/mean intensity). The hypothesis was that with partitioning, the relative weight of the slope would decrease, compared to the relative weight of the mean. As can be seen in Fig. 4, the results support our main hypotheses. While the weight of the mean (size of coefficient) remained roughly equal across the partitioning conditions, the weight of the slope decreased with partitioning and most importantly, so too did the ratio of the two coefficients. The mean trend to mean ratio was highest in the one-component condition ($M = .62$), lower in the two-component condition ($M = .51$), and lowest in the four-component condition ($M = .16$). A planned contrast analysis of the effect of partitioning on the relative impact of the trend and the mean showed a statistically significant effect ($p = .017$). The same results were replicated with a two-group Mann–Whitney nonparametric tests, i.e., the trend to mean values differ significantly; the ratio of trend to mean value differs significantly between the one-component and four-component conditions ($U = 59.00$, $p < .001$), and between the two-component and four-component conditions ($U = 122.00$, $p = .013$), yet not between the one-component and two-component conditions ($U = 198.00$, $p = .42$). Also important, the total variance accounted for by the trend and mean rule was the same under all three partitioning conditions ($F(2,61) = .14$, $p = .87$): the R^2 was .90 for the one-component condition, .88 for the two-component condition, and .88 for the four-component condition.

Discussion

The goal of experiment 2 was to examine more closely the effect of partitioning on the integration process of experiences over time. To this end, we tailored the stimuli in this experiment in a way that enables an estimation of two gestalt characteristics: the mean intensity and the trend. The analysis of the individual regression coefficients demonstrates that with increased partitioning, the relative impact of the rate of change compared with the mean value decreased in importance. This supports the idea that partitioning decreases the relative role of the rate of change and increases the relative role of the mean levels of the experience. The results also indicate that although the relative impact of intensity and trend varies with increased partitioning, the overall efficiency of the rule does not change and the two parameters account for the same portion of the variance across all conditions.

The results of experiments 1 and 2 support the first two hypotheses. Consistent with prior research, these results show that overall retrospective evaluations of cohesive experiences are based on the way the experiences evolve over time (Ariely, 1998; Kahneman et al., 1993; Loewenstein & Prelec, 1993). The results also show that when experiences are partitioned, the relative effect of the trend diminishes and the relative role of the mean intensity increases. The R^2 associated with the trend and mean intensity captures much of the variance across the three partitioning conditions. Because the variance accounted for was similar across the three conditions, and because there was a significant shift in the relative weight of each parameter, there seems to be an actual shift in the integration process.

Nevertheless, the results of partitioning could still be attributed to increased error and regression to the mean. Consequently in experiment 3, the partitioning manipulation controls the starting point, ending point, number of parts, and the overall trends of sequences, while manipulating only the location of the break points. This manipulation will test this alternative explanation, while also providing a test for the evaluation of the components (H2).

Experiment 3: Differential partitioning

Experiments 1 and 2 provide evidence that partitioning decrease the impact of patterns on overall evaluations. Experiment 3 investigates whether each of the components is evaluated separately (as proposed in H2a and H2b) and how the components are combined. To answer these questions, we examine whether the reliance on gestalt characteristics that takes place when decision makers evaluate an entire sequences (e.g., end intensity and slope) also influences evaluations of experience-components. In particular, experiment 3 explores whether the trend of the pattern that takes place just before the breaking points influences overall evaluations. This manipulation enables us to simultaneously test hypotheses 2a and 2b, namely, that the end of a sequence effect is similar to the end of sequence-component effect, and that the integration across sequence components relies on the components' summary evaluations and not on the global pattern. On the other hand, if the trend of the sequence just before the end of a component does not have such an effect, this could be due to either different evaluation rules for components (ones that are not influenced by the final trend) or a holistic overall evaluation that is not based on the separate components.

Method

Participants

Sixty students participated in the experiment and were paid \$8 for their time. Participants were randomly assigned to three experimental conditions.

Design and procedure

The design was a 3 (partitioning) $\times$ 2 (trend) $\times$ 6 (trend-variations) mixed design. Partitioning was manipulated between participants and trend and trend-variations were manipulated within participants. There were two important differences between experiment 3 and experiments 1 and 2: the manipulations of the sequences and the manipulation of the partitioning. The sequences in experiment 3 were not monotonically changing from the starting point to the ending point but had systematic fluctuation in the way they progressed over time (again with some additional small random variability). These fluctuations caused the declining trends to have overall decreasing performance levels, with temporary increases in performance throughout the sequence. The same was true for the improving trends, in which overall performance was increasing but with some temporary decreases throughout the sequence (see Fig. 5 and Table 1, Panel C). In all cases, the increase (decrease) in each component was proportionally the same: Fluctuations were such that after an increase (decrease) of a given magnitude X, there was a decrease (increase) of magnitude $X/2$. For example, an increase of 20 points (from 10 to 30) would be followed by a reduction of 10 points (from 30 to 20). Using such fluctuating sequences is important to examine the issue of partitioned experiences at local peaks and troughs.

Most critical to the current work was the manipulation of the location of the partitioning. In the no-partitioning condition, respondents evaluated continuous sequences (used as a control). In both the upward- and downward-partitioning conditions, participants evaluated experiences that all had three components, but with different locations of the two breaking points relative to the sequence's local peaks and troughs. In the upward-partitioning condition, participants evaluated services that were broken at local peaks. In the downward-partitioning condition, participants evaluated services that had been broken at local troughs (see Fig. 5).

Results and discussion

We computed an ANOVA, with overall evaluations as the dependent variable, trend and trend-variations as within-participants factors, and partitioning as a between-participants factor. The results showed a significant main effect for trend ($F(1,57) = 239.77$, $p < .001$). As expected, the overall evaluations of the improving patterns were higher ($M = 47.28$) than the declining pattern ($M = 28.78$). We also found a significant main effect for partitioning ($F(2,57) = 8.49$, $p < .001$), and more important, a significant interaction between partitioning and trend ($F(2,57) = 17.53$, $p < .001$). As shown in Fig. 6, the effect of the trend (the difference between the increasing and decreasing trends) was higher for the no-partitioning conditions ($M = 28.43$)

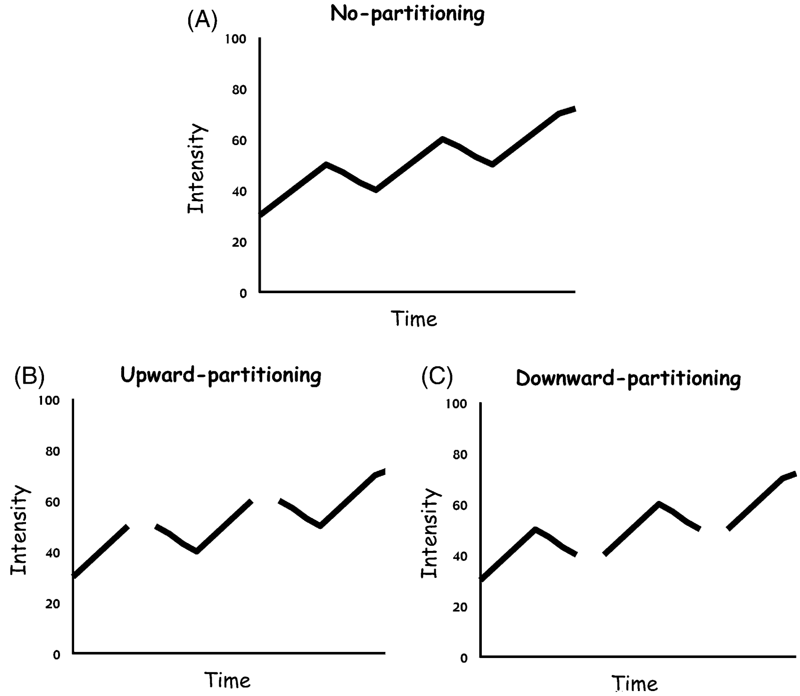

Fig. 5. A schematic display of the three partitioning manipulations used in experiment 3. (A) No-partitioning condition; (B) upward-partitioning condition; and (C) downward-partitioning condition.

than for both the upward- ($M = 14.52$) and the downward-partitioning ($M = 12.54$) conditions, $F(1, 57) = 34.92$, $p < .001$, supporting hypotheses 1 and 2. The effect of the trend was similar for the upward- and the downward-partitioning, $F(1, 57) = .8$, $p = .37$, which demonstrates that the location of the partitioning did not differentially influence the overall effect of the trend. The reason for this similarity stems most likely from the fact that both partitioning conditions utilized the same patterns and the same number of components.

The most important aspect of the predictions is the comparisons of the overall evaluations for the upward- and downward-partitioning conditions. As illustrated in Fig. 6, overall evaluations in the upward-partitioning condition were higher ($M = 40.84$) than those in the downward-partitioning condition ($M = 34.15$), $F(1, 57) = 22.85$, $p < .001$. This result supports the idea that people do not use the entire pattern across all components when forming their overall evaluations. Rather, decision makers seem to base their judgment to a large extent on the separate evaluations of the components. If this were not the case (and evaluations were based on the entire sequence), there would be no effect for partitioning location. The difference in the two partitioning conditions also suggests that the integration rules that people use to evaluate components of an experience are highly sensitive to the last part of the experience (be it the end intensity or its final rate of change). This integration rule is similar to the way people evaluate cohesive sequences, which suggests that when a component is

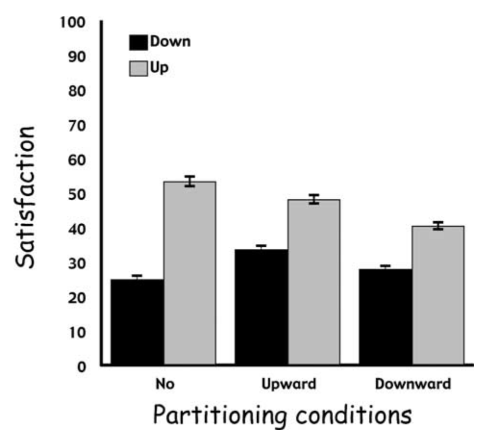

Fig. 6. Mean satisfaction in experiment 3 as a function of the two trends and the three partitioning conditions. *Notes.* Error bars are based on standard errors.

over, decision makers treat it as a stand-alone sequence. Finally, the results of this experiment also show that the effect of partitioning cannot be attributed to increased error and regression to the mean, because both the upward- and downward-partitioning conditions have the same level of partitioning.

In summary, the results presented in the first three experiments show that whereas the overall retrospective evaluation of a cohesive experience is based on the way the experience changes over time, overall evaluations of partitioned experiences are based less on the way experiences change over time and more on their mean intensity. The results also show that the evaluations of the pattern-components are influenced by their final trend, much like complete patterns, and that the overall evaluation of a multicomponent experience is based more on the summary representations of the individual components and less on overall patterns.

Experiment 4: Prediction

The first three experiments examined the effect of partitioning of experiences on the way they are integrated retrospectively. The general findings from these three experiments, and experiment 2 in particular, suggest that the effect of partitioning is driven by attenuating the relative impact of the global trend of the experience. If we consider that the perception of the trend is particularly important for predicting future states (see Ariely & Carmon, 2000), one of the implications of partitioning is that the same manipulations should bring about similar influence on the predictions of future continuation of that experience. Experiment 4 extends the first three experiments by examining the effect of partitioning on another type of dependent measure: prospective evaluations. In this experiment, we used a similar partitioning manipulation to that used in experiment 3 (using only the upward- and downward-partitioning conditions), but asked participants to predict how the experience would progress in the next 24-h period. We expected that if the location of the partitioning influenced overall evaluations by implicitly influencing perception of trends, location of partitioning would also influence explicit predictions of future states. Specifically, the partitioning at local peaks should result in more positive evaluations than partitioning in local troughs.

Method

Participants

Eighty-two students participated in the experiment and were paid \$8 for their time. Participants were randomly assigned to the two experimental conditions.

Design and procedure

The design was a 2 (partitioning) $\times$ 2 (trend) $\times$ 3 (trend-variations) mixed design. We manipulated partitioning between participants and trend and trend-variations within participants. Overall, the procedure of this experiment was similar to experiment 3, with three notable differences: First, we did not use the no-partitioning condition because it does not make any unique predictions compared with the other two partitioning conditions. Second and most important, the dependent measures did not reflect participants' overall retrospective evaluations of the sequence, but instead asked them to predict the sequence for the next 24-h period. Participants were first exposed to the experience, and at the end of each sequence, they were asked to indicate a 90% confidence interval (an upper and lower bound), which reflected their prediction of the progression of the sequence in the next 24-h period. Participants were asked to draw this confidence interval in a way that would result in its containing 90% of all possible progressions of the sequence. Third, we used trend-variations that had a narrower range to avoid possible floor and ceiling effects in the predictions task. Because the task of responding to the prediction dependent measure was more time-demanding, we used only three trend-variations in each of the two trends (see Table 1, Panel D).

Results and discussion

First, we estimated a linear trend for each projection (taken as the center of the envelope at each point in time). Based on these measures, an overall ANOVA was carried out with pattern and pattern-version as within-subjects factors, and partitioning as a between-subjects factor. As can be seen in Fig. 7A, the overall results indicated a significant main effect for partitioning, $F(1, 80) = 10.98$, $p = .0014$, and a significant main effect for pattern, $F(1, 80) = 31.43$, $p < .001$. Inspection of these results indicates that improving patterns were projected to improve more in the future (linear trend of .47) compared with deteriorating patterns (linear trend of −.4), $F(1, 80) = 31.43$, $p < .001$. More important for the goals of the current work is the effect of partitioning on the slope of the future projection. Investigation of these results showed that the average predicted slope in the downward-partitioning condition (−.75) was lower that the average predicted slope in the upward-partitioning condition (−.1), $F(1, 80) = 10.98$, $p = .0014$. Note that the implementation of the upward- and downward-partitioning did not change the overall pattern of the service-profile; but only the locations of the partitioning.

An additional dependent measure that can be used to gain more insight into this issue is the mean prediction level. To do so, we computed for each subject a mean prediction measure for each of the six service-profiles they predicted. As can be seen in Fig. 7A, the overall ANOVA of these measures revealed a main effect for partitioning $F(1, 80) = 23.73$, $p < .001$, and a main effect for pattern $F(1, 80) = 231.21$, $p < .001$. The most important aspect of these results was that the partitioning manipulation influenced the mean predicted service quality. Participants predicted the service quality to be higher in the upward-partitioning condition than in the downward-partitioning condition ($F(1, 80) = 23.73$, $p < .001$).

In summary, for otherwise identical sequences, the location of the partitioning influenced both the

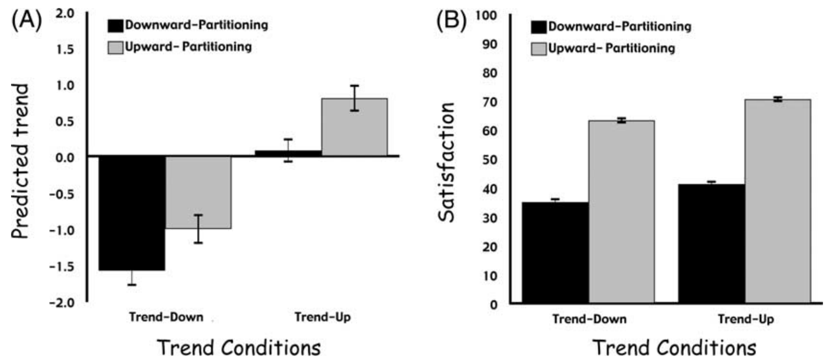

Fig. 7. Mean predicted trend (A) and mean intensities (B) in experiment 4. Predictions were made for a 24-h period, and are presented as a function of the two partitioning conditions, and the two main trends. Error bars are based on standard errors.

predicted trend and the predicted mean levels for the next 24-h period. These results support the idea that partitioning attenuates the effect of the overall trend and thus influences predictions. Lastly, these results also shed some light on a possible psychological process that gives rise to preferences for improving sequences. The results of experiment 4 and their relationship to the other experiments, especially experiment 3, demonstrate that the effects of partitioning on retrospective evaluations are similar to the effects of partitioning on predictions. This suggests that there might be a relationship between the two types of effects. That is, the effect of the trend is incorporated into hedonic evaluations not only in retrospective evolutions, but even in predictions.

General discussion

The main objective of the current work was to examine the way people evaluate experiences that extend over time. We are particularly interested in the way that the cohesiveness of the experience changed the effects of pattern on overall evaluations. Using simulated experiences, all four experiments replicated the known result that improving trends are evaluated more positively than deteriorating trends of equal objective level (Ariely, 1998; Loewenstein & Prelec, 1993). Within this context, the current work centers on the process that underlies the effects of partitioning sequences on the way decision makers perceive and evaluate them. The experiments used two different approaches to partitioning (increased partitioning and differential partitioning) and two different dependent measures (overall retrospective evaluations and predictions). Overall, the results demonstrate that the relationship between the pattern of the experiences and their overall evaluations is strongly influenced by the extent and location of the partitioning.

The findings also indicate that when decision makers evaluate experiences that consist of multiple parts, they use the intensity of the components relatively more and the overall pattern of the sequence relatively less as a basis for their judgments. Experiment 1 demonstrated the effects of partitioning on decision makers' overall evaluations, and experiment 2 demonstrated them on the integration process (the shift in the relative importance weight of the mean intensity and the pattern). Experiment 3 provided a more direct test for the effects of partitioning by taking an identical sequence and partitioning it at local minimum or maximum, while keeping the number of partitions constant. The results show that sequences that are partitioned at a local minimum have lower overall evaluations compared to sequences that are partitioned at a local maximum.

Experiment 3 is of particular importance because it also demonstrates that the patterns' intensity just before the partitioning point has a higher impact on the way sequences are globally evaluated, which is similar to the effect of ending in cohesive sequences. Thus, experiment 3 provides support for the idea that the integration rules used for evaluation of parts, namely, the large influence of the final intensity and slope, are similar to those used when entire sequences are evaluated. Finally, experiment 3 also demonstrated that partwise evaluations, and not the global pattern, are used to form the overall evaluations at the end of the entire sequence.

Experiment 4 further examined the effect of partitioning using a different dependent measure: the prediction of future progression of the pattern. The results show that the effects of partitioning on predictions are similar to their effects on overall retrospective evaluations.

Based on the similar effects of partitioning on retrospective evaluations and prediction tasks, it is interesting to speculate whether these two psychological processes are related. The relationship between these two judgments is consistent with the idea that preference for improvement stems from anticipation (Loewenstein, 1987) and "naïve extrapolation" (Ariely & Carmon, 2000). The naïve extrapolation account suggests that decision makers spontaneously think about the meaning of their experience and in particular about the implications of the experience for future states. Furthermore, this anticipation of future states is then incorporated into current evaluations, which results in preferences for improvements. For example, a burn patient whose pain is increasing is extrapolating a bad future, and this bad future and the fear it brings with it, increases his current pain evaluation. Similarly, a burn patient whose pain is decreasing is extrapolating recovery, and this promising future and hope improves his current pain evaluation. These results provide initial support for these ideas.

In summary, the findings from all four experiments suggest that decision makers use two types of processes to integrate experiences over time: one for cohesive experiences and the other for partitioned experiences. For single cohesive experiences, decision makers rely more heavily on the pattern of the experience and extract different gestalt characteristics from this pattern to form their overall evaluation (i.e., end, peak, and trend). For multicomponent experiences, decision makers use similar rules for each of the parts, but when evaluating the overall sequence, they use their partwise evaluations more heavily and in a less time-dependent manner (i.e., more equally weighted integration of the parts).

Understanding prospective and retrospective evaluations of sequences is important because these evaluations are likely to influence decision makers' attitudes as well as the likelihood of future choice. The implications of this work to these issues are straightforward. To illustrate, recall our example of the Internet service providers. Assume that a provider with limited resources must make choices about how to allocate its service quality over time. First, all else being equal, improving sequences are preferable to deteriorating ones. Second, service providers can strategically decide whether or not to partition their services. Services that are generally improving should not be partitioned. Services that are declining should be partitioned. Third, partitioning at local high points is preferable and should lead to higher evaluations. Fourth, when externally imposed partitioning occurs (such as the end of the fiscal year), effort would be better placed before rather than after this partitioning (i.e., a bonus at the start of the year can cause a deteriorating sequence, whereas the same bonus at the end of the year can cause an improving sequence).

On a final note, how can the knowledge about assessments of experiences enhance the quality of peoples' lives? Because intense pleasure and substantial improvement are weighted heavily and because breaking improving experiences causes them to be coded and assessed separately, people should experience a diverse and variable life. A few exhilarating experiences will triumph over many pleasant ones (see also Scitovsky, 1976). Taking breaks at high points (such as receiving a promotion) rather than at low points (such as having one's manuscript rejected) can be a recipe for greater joy and satisfaction.

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Received 21 March 2002