Following the Scent: Applying the Ecological Valence Theory to Odor Preferences

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Abstract

Preference is the primary dimension underlying odor perception. Therefore, to understand odor perception it is necessary to understand odor preferences. We propose that preference for an odor is determined by preferences for all objects and/or entities associated with that odor (extending Palmer and Schloss's (2010) Ecological Valence Theory of color preferences to odor preferences). Odor preferences were strongly predicted by preference for all associates with the odors (e.g., people liked the *apple* odor which was associated with mostly positive things like apples, soap, and candy and disliked the *fish* odor associated with mostly negative things like dead fish, trash, and vomit. Our model performed significantly better than one based on preference for the object the odors were designed to smell like (e.g., predicting preference for the *apple* odor based on preference for apples). These results suggest that odor preferences are a summary statistic, coding the valence of previous odor-based experiences.

Keywords: Odor preference; Hedonics; Associative Learning

Introduction

Odor perception is surprisingly complex, taking input from 350-400 functional olfactory receptors – far more than the 3 photoreceptors involved in normal color vision – and feeding it into a high-dimensional system (Herz, 2014). Several studies have tried to reveal the dimensional structure underlying odor perception, and all have shown that the first, most robust axis is preference (a.k.a., hedonic response, pleasantness) (e.g., Berglund, Berglund, Engen, & Ekman, 1973; Joussain, Chakirian, Kermen, Rouby, & Bensafi, 2011; Khan et al., 2007; Schifman, Robinson, & Erikson, 1977; Shiffman, 1974; Yeshurun & Sobel, 2010). Why is preference such an important dimension of olfaction? How are odor preferences formed? And why are some odors preferred to others?

It is commonly held that the olfactory system's primary function is to signal organisms to approach beneficial objects and situations and avoid harmful ones (e.g., Herz, Beland, & Hellerstein, 2004; Proetz, 1953; Yeshurun & Sobel, 2010; Zarzo, 2011). For example, rats have evolved the adaptive quality of being afraid when they smell cats, even if they have never encountered a cat before (Dielenberg & McGregor, 2001). Odor preferences are adaptive for an organism's success to the degree that it likes (dislikes) odors that are associated with positive (negative) outcomes (e.g., Proetz, 1953).

Although there may be some innate components to odor preferences, evidence suggests human odor preferences are largely determined by experience and are context-dependent (for reviews, see Herz, 2006; Yeshurun & Sobel, 2010). One mechanism by which odor preferences may develop is through *associative learning* (Bartoshuk, 1991; Engen, 1991; Herz, 2001). According to this account, when an odor is paired with an affectively charged experience, the affective valence of the experience transfers to degree of preference for the odor. For example, the positive experience of spending time with a friend who happens to be wearing new perfume would tend to cause an increase in one's preference for the smell of the perfume. However, the negative experience of getting the stomach flu while under that friend's care would tend to have the opposite effect, possibly even causing one to hate the smell of the perfume.

The associative learning account makes several testable predictions that have been empirically supported. First, it predicts that preferences for novel odors can be learned by pairing them with positive/negative experiences. Indeed, when Herz et al. (2004) exposed participants to a novel odor while they played a fun, monetarily rewarding video game, preference for that odor increased relative to baseline. Likewise, when a different set of participants played an annoying, monetarily penalizing version of the game, their preference for the odor decreased.

Second, the associative learning account predicts that two populations whose prior experiences with a given odor have different valences will have different preferences for that odor. For example, people in Britain strongly disliked wintergreen (methyl salicylate), where it was associated with sickness and medicine (Moncreiff, 1966), whereas people in the US strongly liked the same smell, where it was associated with delicious candies (Cain & Johnson, 1978) (see Herz, et al., 2004). Likewise, participants who were afraid of dental procedures found the odor of clove (eugenol, found in dental cement) particularly unpleasant, whereas those who were unafraid liked the odor (Robin, Alaoui-Ismaili, Dittmar, & Vernet-Maury, 1998).

A third, related prediction is that if people are prompted to associate particular positive or negative experiences with a given odor (semantic priming), they will like that odor correspondingly more or less. Indeed, participants liked the smell of an isovaleric-butyric acid mixture better when it was called "parmesan cheese" than when it was called "vomit" (Herz & von Clef, 2001). They also liked the smells of clean air and of isovaleric acid mixed with cheddar cheese more when they were labeled "cheddar cheese" than when they were labeled "body odor" (de Araujo, Rolls, Velazco, Margot, & Cayeux, 2005).

Odor preferences are thus biased by which objects are thought to produce the odor (de Araujo, et al., 2005; Herz & von Clef, 2001) and can be manipulated by contextual cues that activate particular associations. This idea that people's evaluation of a given stimulus is influenced by contextual cues is consistent with situated conceptualization (e.g., Barsalou, 2003). If olfaction truly exists to steer organisms to approach/avoid beneficial/ harmful objects, it would be adaptive if the olfactory system continually updates preferences as it gathers information about new odor-associated objects and/or entities and discerns which ones are most relevant based on contextual cues.

Here, we propose that preference for a given odor is determined by the cumulative effects of *all* previous experiences with that odor. This hypothesis is derived by analogy from Palmer & Schloss' (2010) Ecological Valence Theory (EVT) of human color preferences, which posits that preference for a given color is determined by the combined valence (liking/disliking) of all objects and/or entities associated with the color. For example, people generally like vivid blue, which they associate with mostly positive things like clean water and clear sky, whereas they dislike dark yellow (olive), associated with mostly negative things like biological waste and rotting food.

Applied to odors, the EVT dovetails with the associative learning account by claiming that preference for a given odor is based on a summary statistic, coding the valences of all things associated with that odor. We predict that "default" odor preferences, such as those assessed in the laboratory, are explained by the combined valences of all associated objects. However, we readily agree that in the real world, situational factors might make some associates more salient and contribute more to odor preference than others, as has be proposed for color preferences (Schloss & Palmer, in press; Strauss, Schloss, & Palmer, 2013).

In their original test of the EVT for color preferences, Palmer and Schloss (2010) compared average color preferences to what they called the Weighted Affective Valence Estimates (WAVEs) of the corresponding colors: the average of the preference ratings for all objects associated with each color, weighted by the how well the colors of the objects match the relevant test color. The WAVEs were calculated based on the data from three groups of participants. Group 1 viewed each of the 32 colors for 20-sec and wrote down all of the objects they associated with each color. Group 2 was presented with a condensed version[1] of the object descriptions produced by Group 1 as black text on a white background and rated the valence (positive/negative) of each object description. Group 3 was presented with object descriptions paired with each color that elicited that description and rated how well the color matched the color of the object described. The WAVE was computed for each color by multiplying the valence of each associated object by the match rating for that object-color pair (as a weighting factor) and then calculating the mean of the products. The WAVEs explained 80% of the variance in average color preferences with no estimated free parameters. People clearly liked colors that were associated with objects that, on average, had more positive valences and disliked the colors that were associated with objects that had more negative valences.

Two other relevant approaches have been used to account for odor preferences; *odor profiling* and *physiochemical properties*. An odor profile is a list of odor descriptors with ratings of how applicable the descriptors are for each odor (Dravnieks, Masurat, & Lamm, 1984). The goal of odor profiling was to predict how much people would like odors based on their preferences for the odor descriptors (e.g., soapy, floral, spicy, nutty). Although this approach resembles the WAVE procedure described above, odor profiling uses one list of descriptors that is the same across all odors; it does not attempt to predict odor preferences from *all* objects associated with the particular odors. The profiling approach was successful at predicting hedonic responses to various odor sets (roughly 72%-92% of the variance for 14-16 odors), based on hedonic responses to 146 descriptors in their odor profile (Dravnieks, 1983; Dravnieks, et al., 1984). However, to evaluate whether odor preferences are a summary statistic of all objects/entitles associated with the odor, it was necessary to use a WAVE-like procedure to compile a comprehensive list of the objects and entities associated with the odors.

The psychochemical approach tries to predict odor preference from the molecular structure of odorants (e.g., Joussain, et al., 2011; Khan, et al., 2007; Zarzo, 2011). For example, Kahn et al. (2007) conducted a *perceptual* principle component analysis (PCA) on 1565 odorants based on their odor profiles (cf. Dravnieks et al., 1984) and a *physiochemical* PCA based on their physiochemical descriptions (e.g., molecular weight and atom counts). The first component in the perceptual PCA, representing pleasantness, was significantly correlated with the first component in the physiochemical PCA, revealing a relation between molecular structure and odor preference. Zarzo (2011) subsequently found that larger molecules containing oxygen and at least six other non-hydrogen atoms were more preferred. Why do these specific molecular structures produce more preferable odors? Returning to the idea that odor preferences exist to steer organisms to approach/avoid beneficial/harmful outcomes, organisms may like/dislike the smell of odorants with certain physiochemical properties because those properties are markers of evolutionarily beneficial/harmful objects (Zarzo, 2011).

This study used a WAVE procedure for odors, analogous to that of Palmer and Schloss (2010), to evaluate the EVT's account of odor preferences and to compare it to two other potential explanations: (1) the *single-associate hypothesis*,

[1] See Palmer and Schloss (2010) for the condensing procedure.

according to which people would only associate one object with each odor (e.g., only listing "apples" for the apple odor), and preference for an odor (e.g., *apple*) would be determined by preference for the single object type that produced the odor (e.g., apples) and (2) the *namesake hypothesis*, according to which people associate several objects with each odor, but preference for a given odor (e.g., *apple*) is better predicted by preference for the namesake object the odor was designed to smell like rather than to the combined preferences of all associated objects. Our results are most consistent with the EVT hypothesis, according to which odor preferences are best explained by the combined valences of all objects/entities associated with the odors.

Experiment

The goal of the experiment was to determine whether average odor preference could be explained by preferences for objects associated with the odors (i.e., by odor WAVEs).

Methods

Participants The participants were Occidental College undergraduates who received course credit or cash payment for their participation. Each participant completed one of four tasks: odor-association descriptions (n = 32), odor-preference ratings (n = 30), object-valence ratings (n = 45), and odor-object match ratings (n = 15). All gave informed consent and the Occidental College Human Subjects Research Review Committee approved the protocol.

Materials The olfactory stimuli were 31 Sniffin' Sticks odor pens (Burghart Messtechnik GmbH), (Hummel, Sekinger, Wolf, Pauli, & Kobal, 1997). The odors tested were *apple*, *banana*, *chocolate*, *cinnamon*, *cloves*, *coconut*, *coffee*, *coke*, *fish*, *garlic*, *ginger*, *grapefruit*, *grass*, *honey*, *lavender*, *leather*, *lemon*, *lilac*, *licorice*, *melon*, *mushroom*, *onion*, *orange*, *peach*, *pear*, *peppermint*, *pineapple*, *raspberry*, *rose*, *smoked meat*, and *turpentine*. Some were derived from natural ingredients (e.g., *orange*), whereas others (e.g., *rose*) were synthetic. An air purifier (Sharp KC-86OU) was run during all tasks using the odor pens.

Design, Displays, and Procedure This experiment included four between-subject tasks: (1) odor preference ratings, (2) object descriptions, (3) object valence ratings, and (4) odor-object match ratings.

(1) Odor preference task. Participants first smelled 12 pens (selected to span the range of preference) one at a time in random order to get an idea of the range of odors they would be asked to rate. They were asked to consider which odor they liked most and which odor they liked least. This anchoring procedure was done so that participants understood what liking odors "not at all" and "very much" meant for them within the context of the present odors (Palmer, Schloss, & Sammartino, 2013). Participants then rated their preference for each of the 31 pens, one at a time in random order. To do so, they made a line mark rating on a slider scale that ranged from "not at all" (left end-point; -100) to "very much" (right end-point; +100). The center of the scale was marked to provide a neutral (0) point.

(2) Object description task. Participants were given one odor pen at a time, in random order. They were instructed to smell the odor and think of as many objects or concepts as they could that they associated with the odor (no time limit). They typed these objects/concepts into a text box displayed on a computer monitor and pressed "enter" to go onto the next trial. Participants were asked to be as specific as possible but not to name objects that would not be known by other people (e.g., "my best friend's perfume"). They were told that the experimenters were interested in all items the pens reminded them of, whether pleasant or unpleasant. Once participants said they were finished with a particular pen, it was recapped and they were handed another pen.

This procedure produced a total of 2832 object associations across all 32 participants. These items were then compiled into a condensed list using a procedure similar to that used by Palmer and Schloss (2010) for color-object associations. First, all of the redundant object associations were combined (e.g., several people reported "banana" for the banana smell). Unlike in Palmer and Schloss (2010), we included objects that were mentioned only once in order to accumulate a more comprehensive list. Objects were then grouped together in cases where synonyms were used (for instance, "cinnamon gum" and "Big Red gum" were combined and referred to as "Cinnamon gum (e.g., Big Red)"). This process resulted in a total of 791 separate items across all of the pens. Note that in many cases, the same object was listed for several pens (e.g., "forest" was mentioned for the grass, lavender, leather, mushroom, and rose odors).

(3) Object valence rating task. Participants were first given a list of 12 sample items (baked goods, dirty toilet water, furniture, grocery store, oranges, rotting trash, socks, unwashed stale man, vanilla, vacation, vomit, warm) to give them an idea of the range of descriptions they would see. They then were presented with each of the 791 object descriptions as black text on a white background, one at a time in a random order. They rated how much they liked each object/entity using the same line-mark sider scale as in the odor preference task. They were also given the option of indicating that they did not know what a given item (e.g. "terrarium") was instead of rating it. When calculating the average of the odor valence ratings, we excluded the cases where participants said they did not know what the objects were. We allowed this option because we had chosen not to exclude objects that might be more obscure (as Palmer and Schloss (2010) had done) so that the object description list would be as complete as possible. Of the 791 objects, 641 objects were recognized by all participants and 772 of the objects were recognized by all except 5 or fewer participants. The most unfamiliar objects were raspberry lime rickey (unfamiliar to 21 of the 45 participants), terrarium (13), castor oil (12) and sour grass (10).

Odor-object match rating task. Participants smelled each of the 31 odors one at a time in random order. For each odor, they were first given a list of all items that had been associated with that odor and were asked to consider which was the best match and which was the worst match for that particular odor. They were then presented with each item, one at a time in a random order, and rated how well the item's odor matched the pen's odor on a scale from "very poorly" to "very well." These data were collected on the same -100 to +100 scale described above, but rescaled to range from 0 to 1. Participants had the option of indicating that they did not know what a given item was instead of rating it. When calculating the average of the odor-object match ratings, we excluded the cases for which participants said they did not know what the objects were. Because some items were named for multiple different odors (e.g., "forest"), there were 1632 match trials in total.

Results and Discussion

Figure 1 shows the odor preferences for each pen, average across participants. The fruity and minty smells were generally most preferred and the savory, meaty smells were generally least preferred. These preference ratings are similar to the hedonics ratings from Hummel et al. (1997) for the 15 pens that were common to both studies (r = 0.76).

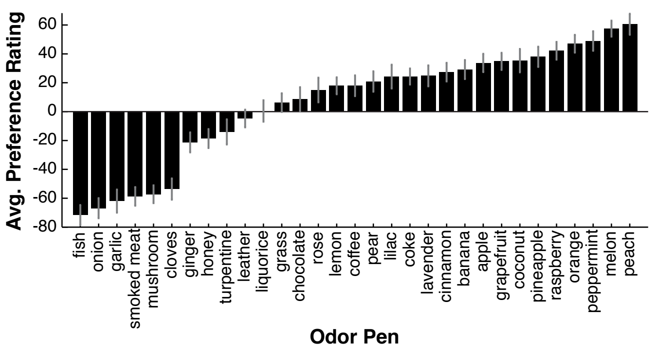

Figure 1: Average odor preference ratings (y-axis) for each 'Sniffin Sticks' odor pen (x-axis). The x-axis labels are manufacturer names of the pens. The error bars represent the standard errors of the means.

We calculated the Weighted Affective Valence Estimate (WAVE) for each odor pen (p), which is a measure of how positive the objects (o) are that are associated with the pen (v_o), weighted by how well the odors of the objects matched the odors of the pen (w_{po}), and n_p is the number of object descriptions ascribed to pen p (c.f. Palmer & Schloss, 2010):

$$W_p = \frac{1}{n_p}\sum_{o=1}^{n_p} w_{po} v_o$$

The WAVEs explained 76% of the variance in average odor preferences ($r = .87$, $p < .001$), with no free parameters. Figure 2 shows this strong relation between the preferences and WAVEs for each smell. It is worth noting that when the weighting factor (w_{po}) was eliminated from the equation, the resulting Affective Valence Estimate (AVE) explained as much variance (77%; r = .88) as the WAVE did. Therefore, smell preferences are strongly related to the average valence of the objects associated with the smells, irrespective of how well the object smells matched the smells of the pens).

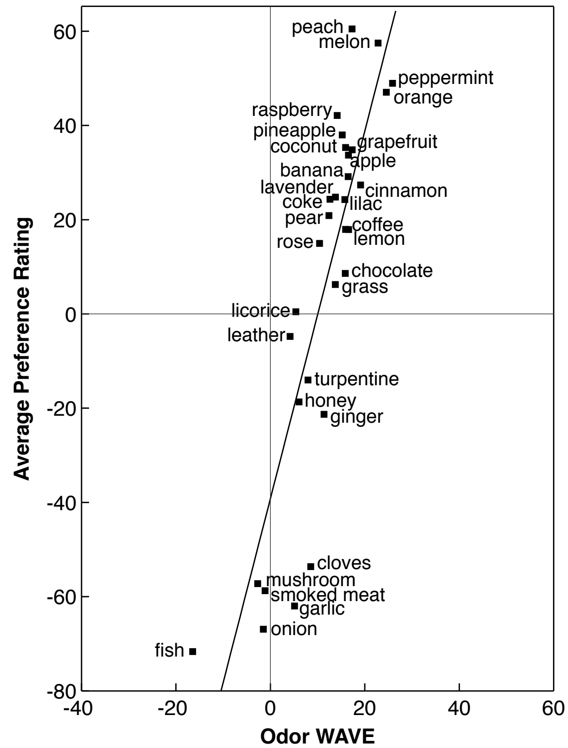

Figure 2: Average preference ratings as a function of the WAVE for each odor pen (i.e., the average valence of objects associated with each odor pen, weighted by how well the odor of the object matched the odor of the pen). The diagonal line represents the best-fit line between the preferences and WAVEs ($r = .87$, $p < .001$).

The odor WAVE results are analogous to those of Palmer and Schloss (2010), where color WAVEs explained 80% of the variance in average color preferences (r = .893). However, unlike for odors, the color-object match weighting factor was useful for predicting color preference, with the unweighted object preferences explaining substantially less variance (69%) than the weighted ones. It is unclear why there is this discrepancy between the usefulness of the weighting factor in predicting smell preferences vs. color preferences. Perhaps it is because odor recognition is relatively difficult and multiple objects – including those that are weak matches – are triggered by each odor.

One shortcoming of the odor WAVEs is that most of them are positive, even though several of the average odor preference ratings were negative. Palmer and Schloss (2010) reported a similar issue for color preferences and WAVEs. This discrepancy may be due to people underreporting negative objects if they were too shy to report gross and disgusting things (cf. Palmer & Schloss, 2010). Alternately, participants might be biased toward generating/thinking about positive objects. Even so, the fit between the odor preference and odor WAVEs is remarkably strong.

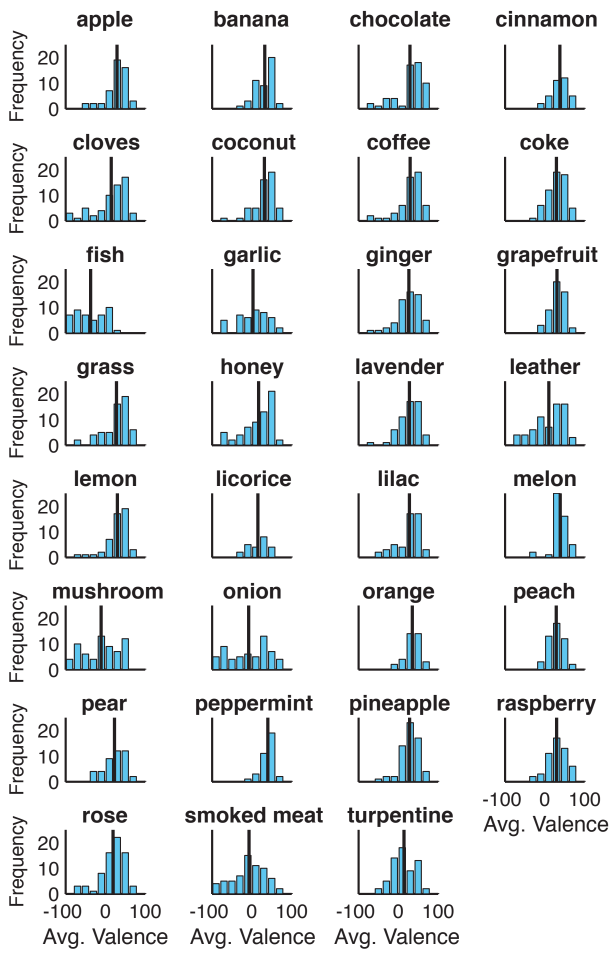

Figure 3: Histograms of the valences of objects associated with each pen. The x-axis represents the average valence rating for each object, divided in 10 equally spaced bins from -100 to +100. The y-axis represents the number of objects in each bin. The vertical line on each histogram represents the mean of the distribution.

We were initially concerned that there might be a one-to-one correspondence between the smell of a given pen and one particular object associated with that smell. If so, the present results would not be terribly interesting (e.g., if the *apple* pen smelled only like apples, and we could predict how much people liked the odor of the pen based on how much they liked apples). Not only did people produce many object descriptions for each pen (mean: 53; (range: 23-72), but the range of objects varied from negative to positive for every odor (see histograms in Figure 3).

Given that people associated many objects and entities with each odor, the next question is whether WAVEs (including all associates) predict odor preferences better than the valence of the object that each pen was produced to smell like (i.e., the "namesake" object). For example, does preference for "apples" account for the preference for the smell of the *apple* pen as well as the complete WAVE does? We addressed this question by correlating the smell preferences with the mean valence of the namesake objects (e.g., preference for the *apple* pen with the mean valence for "apples," preference for the *orange* pen with the mean valence for oranges, etc.). We had valence ratings for all of the namesake objects except for "turpentine," which was not listed during the object description task. We therefore computed the correlations between smell preference and namesake object valence for the remaining 30 pens. This correlation was .55 ($p < .01$) (30% variance explained), which is significantly lower than the correlation between the pen preferences and WAVEs for those 30 pens ($r = .87$, $p < .001$; 76% explained) (correlations compared using the Fisher r-to-z transformation; $z = 2.63$, $p < .001$). Thus, preference for a given odor is better predicted by valences of all the objects associated with the odor than by the valence of the odor's single namesake object.

General Discussion

The present study aimed at an increased understanding of what determines odor preferences. It was motivated by the Ecological Valence Theory (EVT) of color preferences, which posits that preference for a given color is determined by the combined valence (liking/disliking) of all objects associated with the color (Palmer & Schloss, 2010). Here, we extended the EVT to the olfactory domain by asking whether preference for a given odor could be explained by preferences for the objects and/or entities associated with that odor (as estimated by odor WAVEs).

Odor WAVEs explained 76% of the variance in odor preferences, supporting the hypothesis that odor preferences can be well understood as a summary statistic of people's affective responses to all things associated with the odor. This conclusion is consistent with associative learning of odor preferences (Bartoshuk, 1991; Engen, 1991; Herz, 2001). This view of odor preferences as summary statistic differs from the previous view that odor preferences are largely determined by emotional state of the observer when the odor is first encountered (e.g., Herz, 2001; 2006). Although the present data do not discriminate between these possibilities, subsequent research will address this issue.

Although the present results are correlational, there is already causal evidence that odor preferences are learned and manipulated by positive/negative experiences (e.g, video games) and associations (e.g., labels) with the odors (de Araujo, et al., 2005; Herz, et al., 2004; Herz & von Clef, 2001). This evidence is of a similar nature to that supporting the causal claim of the EVT for color preferences. For example, color preferences could be changed by priming people to thinking about positive/negative objects of particular colors (Strauss, et al., 2013).

In summary, we present evidence that odor preferences are determined by preferences for all of the objects and entities associated with the odors. These results mirror findings in the color preference literature, where color preferences are shaped by experiences with correspondingly colored objects and entities (Palmer & Schloss, 2010;

Schloss & Palmer, in press; Schloss, Poggesi, & Palmer, 2011; Strauss, et al., 2013; Taylor & Franklin, 2012). Thus, we believe that odor and color preferences may be governed by similar, associative learning mechanisms.

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