Testing Fundamentals of Salience Theory

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November 2020

Abstract

Different behavioral theories of decision making have argued that agents, when choosing among alternatives with multiple attributes, systematically overweight those attributes which stand out as particularly salient. However, the question of what exactly renders a choice attribute salient remains empirically untested. Is it the numerical value of an attribute or the utility that this attribute yields? In this paper, we propose two specifications, both capturing overweighting of salient attributes. One assumes that utilities define salience while the other one assumes that numerical values define salience. We then develop an experimental design which can distinguish between the two. We also implement a novel attention check to differentiate salience-based underweighting of aspects from selective attention. We find strong support that numerical values determine salience.

Keywords: Salience, Framing, Selective Attention, Memory.

JEL Classification Numbers: C91, D91.

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We thank Mats Köster for very valuable comments and suggestions. We are grateful to Viet A Ngyuen for her help in running the experiment. The experiment was preregistered in the AEA RCT Registry with the identifying number AEARCTR-0003164.

1 Introduction

A central theme in behavioral economics is that agents overweight a choice attribute that catches their attention. One well-known example (by Bordalo *et al.*, 2013) is the effect of varying mark-ups on the attention focused on prices. Suppose an agent contemplates whether to buy a low-quality wine for \$10 or a high-quality wine for \$20 at a wine store. As the high-quality wine is twice as expensive as the low-quality wine, the \$10 price difference is noticeable and attracts the agent's attention. As a consequence, she chooses the low quality wine. However, when choosing between the very same wines at a restaurant where both are marked up by \$40—that is, the wines cost \$50 and \$60, respectively—the price difference of "just" \$10 is less prominent and attracts much less attention. Hence, the agent focuses on quality differences instead and chooses the high-quality wine.

The behavioral economics and psychology literature has offered a number of different explanations for such behavior (e.g., Bordalo *et al.*, 2012, 2013; Tversky and Kahneman, 1981). What is common to them is that they typically rely on the idea of *diminishing sensitivity* (or a variant thereof) whereby a difference in one dimension (here: money) is perceived as being smaller when the overall payoff levels are larger. That is, the same price difference of \$10 is perceived to be smaller in the restaurant than in the store. As a consequence, prices are, using the terminology of Bordalo *et al.* (2012, 2013) less "salient" in the restaurant which renders the high-quality wine more attractive. Thus, the consumer is fully aware of all attributes, but weights them differently from a rational agent, depending on their salience.

While previous studies have detected such salience effects in a variety of domains, some underlying fundamentals of this theory are untested so far. Firstly, the existing literature is not very precise about what it is that attracts attention and thereby renders a choice feature salient. Crucially, there is no work that we are aware of that tests whether the salience of a choice feature is determined by the *numerical values* of the different attributes or the *utilities* derived from these attributes. To see why it nevertheless matters consider a modification of the example from above: What if the agent were to get reimbursed, e.g., by her employer, for her drinking expenses at a restaurant up to \$40? Would the price difference still be more salient in the restaurant than in the store, even though the personal financial outlay is the same across locations? Or, consider the store and restaurant to be located in Japan rather than in the United

States. Is a price difference of ¥1100 more or less salient than a difference of $10, even though they represent similar amounts? In this paper we test a version of salience theory, which we call *numerical salience* and which allows for such differences in presentation to affect decisions, against *utility salience* which posits that only the utility of an attribute matters for its salience.

In this paper, we present the results from an experiment which allows us to provide important insights into both of the aspects laid out above. Participants face a choice between two work contracts: a low wage/ low effort contract and a high wage/ high effort contract. Each contract specifies a number of real-effort tasks they have to work on, and the corresponding remuneration, but also informs the decision maker that a certain number of tasks have been pre-solved and (s)he just has to solve the remaining ones. Our treatment variation consists of a specific framing manipulation: we vary the number of pre-solved tasks together with the tasks specified in the two contracts in a way that the actual number of tasks to be solved is the same across treatments. Hence, while the *utility* (combining monetary gain and cost of effort) is unaffected by the treatment manipulation, if attention is affected by the *numerical values* appearing in the contract, this is predicted to lead to differences in choice behavior across treatments.

By varying the number of pre-solved tasks, our approach relies on altering the "conversion rate" in an additive manner. This is in contrast to a multiplicative framing where one could have, for example, presented wages in cents rather than euros. We do this because only additive framing manipulations allow numerical salience to make clear predictions. In an alternative design with a multiplicative conversion rate, the model of numerical salience does not provide unambiguous guidance whether this increases or decreases the salience of the respective dimension. In fact, under the sometimes invoked additional assumption of the salience function satisfying *homogeneity of degree zero*—which balances the two key properties of salience (i.e., ordering and diminishing sensitivity, see the next section) and gives invariance with respect to positive multiplicatives—utility salience and numerical salience make the identical prediction that behavior should be unaffected by the framing.[1]

We also complement the choice of contracts with a novel "attention check". Directly after participants have made their choice, they face a screen in which they have to recall the decision environment from the previous screen. More precisely, they have to recall the wage and the

[1] As a case in point for this prediction shared by both models, Drichoutis *et al.* (2015) find no effect on behavior when varying the conversion rates of experimental currency into euro amounts.

number of tasks specified in the two contracts, as well as the number of pre-solved tasks. This allows us to make inferences about how attentive participants were to certain features of the decision environment, in particular to the different dimensions. Models of salience predict that subjects are fully aware of all relevant information when choosing and therefore allow for perfect recollection of the choice environment. In contrast, models of selective attention which predict inattention to certain dimensions are consistent with selective recall of the more salient or more important dimension only. Notably, remembering all information is a sufficient, not a necessary condition for having precise knowledge of all options when making a choice. Altogether, we regard our memory-based attention check as a methodological contribution in order to distinguish between salience and approaches of selective attention (e.g. Mackowiak and Wiederholt, 2009; Caplin and Dean, 2015; Gabaix, 2014), which appears useful to us as in many contexts their predictions are identical (see for instance Mackowiak *et al.*, 2018).[2]

Our results can be summarized as follows. We find a sizable and highly significant treatment effect. When subjects decide in the frame where the number of pre-solved tasks is higher, they are 31.9% (or, equivalently, 16.3 percentage points) more likely to choose the high wage/ high effort contract. This is in line with the prediction of salience theory, provided we allow for numerical values rather than utilities to determine the salience of the different dimensions: due to *diminishing sensitivity*, if one shifts all values within one dimension upwards by the same amount, the differences between these values are perceived as being smaller. Accordingly, in our experiment, the "task dimension" becomes relatively less salient when the number of pre-solved tasks is increased. This shifts attention to the monetary dimension which is given more weight when deciding between contracts. Then, the contract that pays more is considered more attractive. Altogether, our results suggest that it is numerical values that render choice attributes salient.

We also observe extremely high recall rates. 78.4% of participants recall the decisions screen perfectly, and 94.0% make at most one mistake. This suggests that, by and large, subjects do not shift their attention away from certain dimensions, but instead evaluate all of them and then give more weight to the more important ones. Moreover, none of our results are driven by those

[2]While there is a substantial body of research on memory-related aspects in both economics and psychology, to the best of our knowledge there is no study that investigates how the salience of numbers affects whether or how these are remembered.

subjects who fail to recall properly. In particular, when we only include those who remember the decision screen perfectly, we find a (statistically significant) difference of 14 percentage points. We interpret this as suggestive evidence that our effects are more likely to be driven by salience than by selective attention. The latter, however, may of course still play an important role in other contexts, especially those where the number of attributes present is much larger than in our setting.[3]

Remarks. The question whether it is numerical or utility values that attract attention seems important to us also in light of various comments of readers which we received since we circulated versions of this paper. Their views represented very different opinions, in particular the question whether the model by Bordalo *et al.* (2012, 2013) builds on numerical or on utility salience seems to divide the community. (Incidentally, by equating payoffs and utilities right in the beginning, Bordalo *et al.* (2012) themselves circumvent this question.) Both views have been strongly suggested to us which, in our opinion, highlights the need for an empirical answer to this question. This is what we try to provide with this paper.

In addition, we would like to briefly clarify the role of the concept of numerical salience which we formally introduce in the next section. Even though the concept of numerical salience is not universally applicable, namely not to non-numerical dimensions, we still think that it is useful, mainly for the following reason: all existing evidence for salience effects (e.g., Dertwinkel-Kalt *et al.*, 2017; Hastings and Shapiro, 2013; Cosemans and Frehen, forthcoming) refers to numerical dimensions, mostly to price being more or less salient. But also those studies that vary the salience of qualities refer to numerical quality representations: those studies that suggest that the quality of a "product" could become salient through decoys (see, e.g., Heath and Chatterjee, 1995), use only hypothetical products that are represented by a price and some hypothetical numerical quality instead of real products. dimension. In incentivized decoy studies such as Lichters *et al.* (2017) decoys only extend the price dimension. Thus, the remark that numerical salience is often not defined does not invalidate the concept of numerical salience: it could well

[3]Of course, one may think of other explanations for our specific treatment effect which are not related to attention or salience. While we cannot fully rule out other ad-hoc explanations, we believe that they would be rather narrow in their scope beyond this specific setting. Given the evidence for salience effects in related choice situations we regard the analysis of the effects we documented as most promising within this class of models.

be the case that the main salience effect, the ordering property (or, as it is called in other studies, the *contrast effect*) indeed only matters for numerical dimensions such as prices, but not for non-numerical dimensions such as color.

2 Two Versions of Salience Theory

We consider a decision maker who chooses from a binary choice set $\mathfrak{C} = \{(w_1, e_1), (w_2, e_2) \in \mathbb{R}^2_{\geq 0}\}$ of working contracts. Each working contract $k := (w_k, e_k)$ is described by its wage w_k and its workload e_k with $w_1 < w_2$ and $e_1 < e_2$. In the context of the model, one can think of e_k to denote, for example, the physical effort needed, or the time required, to complete the work. Utility from wage and workload is additively separable with $u^w : \mathbb{R}_{\geq 0} \to \mathbb{R}_{\geq 0}$ denoting the utility from wage and $u^e : \mathbb{R}_{\geq 0} \to \mathbb{R}_{\geq 0}$ denoting the disutility of workload.

According to Bordalo *et al.* (2012, 2013), an agent overweights the attribute which is more salient. Salience is assessed via a *salience function* $\sigma : \mathbb{R}^2 \to \mathbb{R}_{\geq 0}$ which is symmetric and continuous and has the following two key properties: It obeys *ordering*, that is, $\sigma(x+\mu\epsilon, y-\mu\epsilon') > \sigma(x, y)$ for $\mu = sgn(x - y)$ and $\epsilon, \epsilon' \geq 0$ with $\epsilon + \epsilon' > 0$, and it exhibits *diminishing sensitivity*, that is, $\sigma(x + \epsilon, y + \epsilon) < \sigma(x, y)$ for all $\epsilon > 0$.

Given these properties, what still needs to be specified is how for a given choice set $\mathfrak{C}$, the arguments of the salience function are determined. In the notation from above, what are x and y? In Bordalo *et al.* (2012, 2013), the answer to this question is somewhat vague because they implicitly assume that the value functions $u^e(\cdot)$ and $u^w(\cdot)$, respectively, are given by the identity function, i.e., $u^w(w_k) = w_k$ and $u^e(e_k) = e_k$. Hence, it remains unspecified whether it is the utility derived from an attribute, e.g., the utility cost of the effort put in that determines the salience of the workload dimension, or whether it is the numerical value describing the amount of effort required, e.g., the number of tasks to complete. To address the issue, in what follows, we introduce two modified versions of salience theory. The first, which we denote *utility salience* (indexed by US), posits that it is utilities which determine the salience of a dimension and therefore deems any form of framing irrelevant. The second, called *numerical salience* (indexed by NS), takes the issue of framing seriously and assumes that it is the actual numbers by which the components of a contract are represented, that determines salience.

Utility Salience. For a salience function σ and a choice set $\mathfrak{C}$, a contracts k's workload is more salient the larger the value $\sigma(u^e(e_k), u^e(e_{-k}))$ is. Analogously, k's wage is the more salient the larger $\sigma(u^w(w_k), u^w(w_{-k}))$ is. We say that product k's workload is salient if $\sigma(u^e(e_k), u^e(e_{-k})) > \sigma(u^w(w_k), u^w(w_{-k}))$ holds, its wage is salient if $\sigma(u^e(e_k), u^e(e_{-k})) < \sigma(u^w(w_k), u^w(w_{-k}))$ and both are equally salient if $\sigma(u^e(e_k), u^e(e_{-k})) = \sigma(u^w(w_k), u^w(w_{-k}))$.

Ordering and diminishing sensitivity capture two essential features of sensory perception (Bordalo *et al.*, 2012). According to ordering, a contract's wage (workload) is the more salient the larger the utility range of wages (workloads) is. Diminishing sensitivity implies that the saliency of a good's choice dimension decreases if the utility that dimension yields uniformly increases for all working contracts in $\mathfrak{C}$ (Weber's law of sensory perception).

Without loss of generality, we assume, for each case, that option 1 is chosen if and only if the difference in utilities of options 1 and 2 is strictly positive. Under utility salience a salient thinker thus chooses option 1 if

$$\Delta^{US} := \sigma(u^w(w_1), u^w(w_2))(u^w(w_1) - u^w(w_2)) - \sigma(u^e(e_1), u^e(e_2))(u^e(e_1) - u^e(e_2)) > 0. \quad (1)$$

Numerical Salience. For numerical salience, we introduce two functions $f^w : \mathbb{R}^2 \to \mathbb{R}_{\geq 0}$ and $f^e : \mathbb{R}^2 \to \mathbb{R}_{\geq 0}$ which determine, for each dimension, the framing of the alternatives.[4] In particular, for a given *frame* z, $f^e(e_k, z)$ denotes the numerical value which appears in the description of the workload. $f^w(w_k, z)$ is defined accordingly. Hence, under numerical salience, the decision maker chooses option 1 if

$$\Delta^{NS} := \sigma(f^w(w_1, z), f^w(w_2, z))(u^w(w_1) - u^w(w_2)) - \sigma(f^e(e_1, z), f^e(e_2, z))(u^e(e_1) - u^e(e_2)) > 0, \quad (2)$$

so salience of contract k's effort level is given by $\sigma(f^e(e_k, z), f^e(e_k, z))$ and salience of contract k's wage is given by $\sigma(f^w(e_k, z), f^w(e_k, z))$. Compared to the case of utility salience from above, while the arguments of the salience function may be different, its properties are not. It thus continues to obey ordering and diminishing sensitivity, with the important difference that they are now based on the contract's numerical values rather than its utilities.

[4]We assume that when choosing between different options, i.e., contracts, all alternatives are framed in the same way, i.e., use the same frame for the same dimension. If not, this would require augmenting the model with a theory of how different frames are compared with each other, which is beyond the scope of this paper.

The Role of Framing. Now assume that the way in which the different contracts are presented is modified via a change in the framing of the workload-dimension from z to z^*. By definition, this does not change the decision of an agent who follows utility salience (or expected utility, for that matter), she will still decide according to (1). Under numerical salience, however, the salience of the workload-dimension is now determined by $\sigma(f^e(e_1, z^*), f^e(e_2, z^*))$, and the agent chooses option 1 if

$$\Delta_*^{NS} := \sigma(f^w(w_1, z), f^w(w_2, z))(u^w(w_1) - u^w(w_2)) - \sigma(f^e(e_1, z^*), f^e(e_2, z^*))(u^e(e_1) - u^e(e_2)) > 0. \tag{3}$$

Hence, if the change in frame is such that $\sigma(f^e(e_1, z^*), f^e(e_2, z^*)) < \sigma(f^e(e_1, z), f^e(e_2, z))$, it follows that $\Delta^{NS} > \Delta_*^{NS}$ (and vice versa). Thus, a frame that is chosen such that it changes the salience of a certain dimension can affect the choice of contracts.

Importantly, the way a change in the frame impacts on the salience of a dimension is not always straightforward to analyze in a generalized way. Given the properties of the salience function introduced above, however, a framing manipulation which makes use of *diminishing sensitivity* allows for unambiguous predictions. To see this, consider the function f^e to be additive with respect to the frame z: $f^e(e_k, z) = e_k + z$. Here, assume that the workload e_k represents the number of tasks which have to be solved, but, due to the framing z additional tasks are added in the presentation of the contract. This, however, represents a pure framing, which implies that somewhere in the description of the contract the decision maker is informed how to infer e_k from $f^e(e_k, z)$. Hence, in this example, for two different frames z, z^*, with $z^* > z$, it is then the case that

$$\sigma(e_1 + z^*, e_2 + z^*) < \sigma(e_1 + z, e_2 + z), \tag{4}$$

implying that under frame z^* the workload-dimension has become less salient for an agent who decides according to numerical salience. The experiment that we describe in the following makes use of such a change in framing of the contracts, which allows for testing numerical salience against utility salience. The next section describes the design in detail.

3 Experimental Design

In the experiment, each participant chooses between two contracts. Each contract consists of a specified number of real-effort tasks to be solved, and a payment, which participants receive at the end of the experiment, provided all tasks have been solved. The low wage contract consists of a payment of $w_l = 6$ EUR and $e_l = 5$ tasks that need to be solved. The high wage contract has $w_h = 9$ EUR and $e_h = 45$ tasks. Participants have to choose one of the two contracts.

As a real-effort task we employ a well-established encryption task (Benndorf *et al.*, 2019; Erkal *et al.*, 2011). Each single task involves encrypting a "word" which consists of eight random letters. Encryption is done by finding the corresponding three-digit number in a table below the word. This table is reshuffled after each correctly solved task, to avoid learning effects. If subjects make a mistake, they have to do the same task again, but the table is not reshuffled. Subjects on average take about 40 seconds to complete one task (see the Online Appendix, Section B for a screenshot of the task environment). Each subject solves two tasks before the contract choice, this ensures familiarity with the task at hand. After a subject has completed all the required tasks specified in the chosen contract, she is requested to fill out a short demographic questionnaire, she receives her earnings immediately at her cubicle and is free to leave without having to wait for the other subjects. This is made clear to subjects in the experimental instructions.

Our treatment manipulates the way the number of tasks that need to be solved under a given contract are presented to participants. In particular, each participant is told that "a certain number of tasks have already been solved", and that they would only have to solve what is left, i.e., the difference between the number of tasks specified in the contract and the number of tasks already solved. That is, using the notation from the previous section, the number of pre-solved corresponds to the value of z, while the number of tasks which appear in the description of each contract are given by $\hat{e}_l := f^e(e_l, z) = e_l + z$ and $\hat{e}_h := f^e(e_h, z) = e_h + z$, respectively. Importantly, note that we deliberately avoided being more specific about how and why these tasks have been solved.[5] This should mitigate the concern that subjects take the number of pre-solved task as a signal about the difficulty of the task or about the effort exerted by other subjects on this task. The two practice tasks furthermore ensure that it is clear to subjects how onerous this task is for them.

In treatment P-5, subjects are told that the low wage/low effort contract requires completion of $\hat{e}_l = 10$ tasks, but $z = 5$ tasks have already been solved. Accordingly, the high wage/high

[5] A translated version of the experimental instructions can be found in Section C of the Online Appendix.

effort contract specifies $\hat{e}_h = 50$. In treatment P-105, we set the number of pre-solved tasks to $z = 105$, as well as $\hat{e}_l = 110$ and $\hat{e}_h = 150$. This implies that while the numerical values which appear in the presentation of the contracts are shifted upwards in P-105, the actual amount of tasks to be completed, $e_l = \hat{e}_l - z$ and $e_h = \hat{e}_h - z$, respectively, is the same across treatments. Note that when participants see the two contracts on the screen, they also see the number of pre-solved tasks on that screen. Hence, this information is always present when deciding which contract to choose. Randomization into treatments is done at the individual level, i.e., within a given session, different subjects are exposed to different treatments.

Our design thus follows closely the theoretical exposition of the two distinct approaches. Note that under utility salience, in both treatments, the salience of the workload dimension is determined by $\sigma(u^e(5), u^e(45))$, because what matters is the actual number of tasks which have to be completed. Under numerical salience, however, in treatment P-5, the salience of the workload dimension is determined by $\sigma(10, 50)$, while in P-105 it changes to $\sigma(110, 150)$. As discussed in Section 2, by diminishing sensitivity $\sigma(10, 50) > \sigma(110, 150)$. Our theory of numerical salience thus delivers the following prediction.

Hypothesis 1. *The share of subjects choosing the high-wage, high-workload contract is higher in* P-105 *than in* P-5*.*

Salience theory predicts that subjects are fully aware of all relevant information when making a choice. Thus, salience effects are not driven by differences in the information people are aware of when choosing. As we cannot directly test awareness, we proxy it (in a conservative manner) by asking for recall. To this end, we surprise participants with a "memory task" immediately after they have made their choice. They are told that they have to recall all the elements of the previous screen, that is, $w_l, w_h, \hat{e}_l, \hat{e}_h$, and z. For each value they recall correctly, they receive 0.1 EUR on top of their earnings.

According to salience theory, the prediction formulated in Hypothesis 1 then continues to hold also only for those subjects that fully remember all relevant information:

Hypothesis 2. *The share of subjects choosing the high-wage, high-workload contract is higher in* P-105 *than in* P-5*, only looking at those subjects who remember all information correctly.*

In our pre-registration we planned to recruit 300 subjects. Due to more no-shows than expected, we obtained a sample of 285 participants in ten sessions in total. The experiment was run at the end of July 2018 at the Cologne Laboratory for Experimental Research (CLER). Participants were students from the University of Cologne from all disciplines. Each session lasted about 40 minutes, and participants earned 12.25 EUR on average, including a show-up fee of 4 EUR. The experiment was run using the software zTree (Fischbacher, 2007) and the recruiting of participants was done via ORSEE (Greiner, 2015).

4 Results

In order to test for treatment differences in contract choice, we focus on the share of participants who choose the high wage/ high effort contract in each of the two treatments. Throughout this section, we use non-parametric χ^2-tests, complemented by a parametric regression approach which allows us to additionally account for socio-demographic characteristics.

To investigate our first hypothesis, we do not exclude any subjects based on their performance in the memory task. As shown by Table 1, we find that when the contracts are presented as involving a high number of tasks (treatment P-105), participants are significantly more likely to choose the high wage/ high effort contract. In particular, 67.4% of them are willing to solve the higher number of tasks. In P-5, however, where both contracts have smaller numerical values, this is only true for 51.1% of participants. The difference of 16.3 percentage points is significant ($p = 0.005$, χ^2-test). This is in line with Hypothesis 1 because, as predicted by models of salience, when the number of pre-solved tasks is high, the effort dimension becomes less salient and, in turn, the monetary dimension of the problem becomes more relevant, leading subjects to choose the higher wage more often. When controlling for individual characteristics, we estimate a treatment effect of 15.5 percentage points ($p = 0.006$, Logit regression, Table 3).

For our second hypothesis, we first analyze how well subjects can recall the contents from the decision screen. Overall, we find remarkably high recall rates. 224 of the 285 participants (78.6%) are able to correctly reproduce the decision environment after making their choice. An additional 15.44 % (44 out of 285) make exactly one mistake. Recall rates range from 88.1% (for the number of presolved tasks) to 97.9% (high wage).[6] The high recall rate of the treatment

[6]Some of the differences in recall rates are significant. Participants are significantly less likely to remember the number of presolved tasks as well as the number of tasks associated with the low wage contract. See Table A5 in the Online Appendix for more details.

	(w_l, e_l)	(w_h, e_h)	
P-5	69 (48.9%)	72 (51.1%)	141
P-105	47 (32.6%)	97 (67.4%)	144
	116 (40.7%)	169 (59.3%)	285

$p = 0.005$

Table 1: Choice Frequencies (All participants)

	(w_l, e_l)	(w_h, e_h)	
P-5	61 (51.7%)	57 (48.3%)	118
P-105	40 (37.7%)	66 (62.3%)	106
	101 (45.1%)	123 (54.9%)	224

$p = 0.036$

Table 2: Choice Frequencies (Participants with perfect recall only)

variable (number of presolved tasks) is reassuring because it tells us that the vast majority of participants took this number into account when making a decision and agents were thus aware of the actual number of tasks they needed to solve in each of the two contracts.

With respect to Hypothesis 2, we analyze whether the effects predicted by the numerical salience model persist among those individuals who can perfectly recall all relevant information. Table 2 reports the corresponding choice frequencies and establishes that the treatment effect remains present. Among this subset of participants, we find that in P-5 48.3% of them choose the high wage/ high effort contract, compared to 62.3% in P-105. This difference of 14.0 percentage points is significant ($p = 0.036$). A similar conclusion can be drawn when using Logit regressions instead. We find very similar average marginal treatment effects (0.126 and 0.108, respectively, depending on the use of additional control variables, see Table 3), though due to the slightly larger imprecision due to the reduced sample, the estimates are only marginally significant.

Taken together, these results support the idea that behavior in our experiment is best described by those models of limited attention where the salience of the different dimensions is determined by the actual values of the attributes rather than their impact on utility. We emphasize here that this test allows us only to conclude that since subjects remembered the values on the screen, they must have paid attention to them. The converse is not true: if they had not remembered, we could not distinguish not paying attention to some dimension at all from paying full attention and subsequently forgetting. Hence, there is very limited support for the notion that subjects simply exclude those dimensions of the choice environment which they regard as minorly important for their choice.

	Full Sample		Perfect Recall Only	
	(1)	(2)	(3)	(4)
P-105	0.164	0.154	0.126	0.108
	(0.0565)	(0.0560)	(0.0650)	(0.0651)
	[$p = 0.004$]	[$p = 0.006$]	[$p = 0.053$]	[$p = 0.099$]
Observations	285	285	224	224
Session Dummies	YES	YES	YES	YES
Additional Controls	NO	YES	NO	YES

Note: The table reports the average marginal effects from a Logit regression with the dependent variable equal to one if the high wage/ high effort contract is chosen. P-105 is a dummy variable equal to 1 for participants in treatment P-105. Columns (3) and (4) exclude all subjects that made at least one error in the recall task. The additional control variables used in columns (2) and (4) are *Age, Age*^{2}*, Female, Field of Study* (classified according to the faculty of their degree). Standard errors in parentheses and p-values in square brackets.

Table 3: Treatment Differences in Choice Behavior

5 Concluding Remarks

In this paper, we presented the results from an experiment which allows to distinguish between the concepts of utility and numerical salience. Supporting the latter, we find that in our study it is just the numerical values, rather than the utility derived from them which determine the salience of attributes. This should not mean that utilities in general do not matter for salience effects, but it suggests that salience effects are particularly important for numerical dimensions and that purely the numbers (independent of how they translate into utilities) could already drive salience effects.

These findings have important implications for theoretical research as well as for marketing and policy making. Since the framing affects how a decision situation is perceived, it should not be missed by a model on perception and salience. Put differently, economic models of salience which insist on salience being based on differences in utility explicitly rule out differences in perception that are only due to framing to have an effect on behavior. Existing work which models consumers as salient thinkers (e.g., Bordalo *et al.*, 2013; Apffelstaedt and Mechtenberg, forthcoming; Inderst and Obradovits, 2020) neglects the role of numerical salience by either assuming that the salience of attributes is determined by its utility, or by not distinguishing between the two concepts. In both cases, as our paper shows, such models assume away the strategically important aspect that firms can influence the salience of certain product attributes without having to change the underlying utility. For practice, our results imply that firms facing consumers who are salient thinkers can rely on framing and presentation effects to affect purchase decisions in their favor. This allows firms to deliberately direct attention to specific attributes of the products via clever marketing but without actually having to change the utility-relevant features of the product itself. Hence, our results contribute to a better understanding of how consumers are influenced by such (sometimes exploitative) marketing practices which can also help in guiding regulators and other policy makers to decide whether appropriate measures are necessary to constrain certain firm behaviors.

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Online Appendix

A Additional Tables

	(w_l, e_l)	(w_h, e_h)	
P-5	63 (51.2%)	60 (48.8%)	123
P-105	45 (35.2%)	83 (64.8%)	128
	108 (43.0%)	143 (57.0%)	251

$p = 0.010$

Table A1: Choice Frequencies (Participants who recall number of presolved tasks correctly)

	(w_l, e_l)	(w_h, e_h)	
P-5	67 (48.6%)	71 (51.5%)	123
P-105	45 (32.9%)	83 (67.2%)	128
	108 (40.7%)	143 (59.3%)	275

$p = 0.008$

Table A2: Choice Frequencies (Participants who recall wages correctly)

	(w_l, e_l)	(w_h, e_h)	
P-5	66 (49.6%)	60 (50.4%)	133
P-105	44 (36.4%)	83 (63.6%)	121
	110 (43.3%)	144 (56.7%)	254

$p = 0.033$

Table A3: Choice Frequencies (Participants who recall number of tasks correctly)

	Recall Presolved		Recall Wages		Recall Tasks	
	(1)	(2)	(3)	(4)	(5)	(6)
P-105	0.157	0.148	0.156	0.143	0.124	0.104
	(0.0609)	(0.0610)	(0.0573)	(0.0567)	(0.0605)	(0.0601)
	[$p = 0.010$]	[$p = 0.015$]	[$p = 0.007$]	[$p = 0.012$]	[$p = 0.040$]	[$p = 0.085$]
Observations	251	251	275	275	254	254
Session Dummies	YES	YES	YES	YES	YES	YES
Additional Controls	NO	YES	NO	YES	NO	YES

Note: The table reports the average marginal effects from a Logit regression with the dependent variable equal to one if the high wage/ high effort contract is chosen. P-105 is a dummy variable equal to 1 for participants in treatment P-105. Columns (1) and (2) exclude all subjects that did not recall the number of presolved tasks correctly. Columns (3) and (4) exclude all subjects that did not recall the wages in both contracts correctly. Columns (5) and (6) exclude all subjects that did not recall the number of tasks in both contracts correctly. The additional control variables used in columns (2), (4) and (6) are *Age, Age*^{2}, *Female, Field of Study* (classified according to the faculty of their degree). Standard errors in parentheses and p-values in square brackets.

Table A4: Treatment Differences in Choice Behavior

item	mean	p-value of paired t-test against:			
		$\hat{e}_l$	$\hat{e}_h$	w_l	w_h
$\hat{e}_l$	0.902				
$\hat{e}_h$	0.965	< 0.001			
w_l	0.975	< 0.001	< 0.001		
w_h	0.965	< 0.001	0.249	0.706	
z	0.881	0.387	< 0.001	< 0.001	< 0.001

Table A5: Recall rates by item

B Experimental Instructions

[Translated from German]

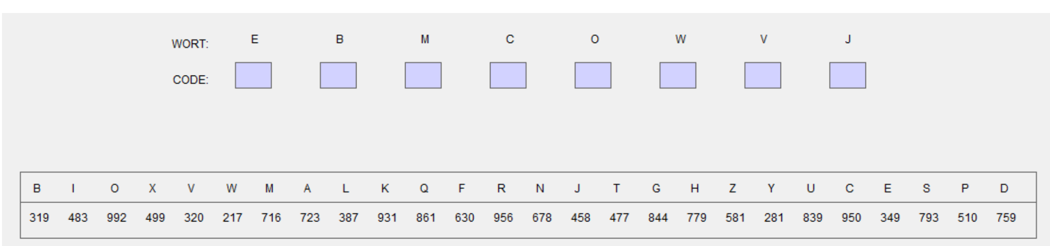
Information about the experiment

Welcome to this experimental study. Please note that from now on and during the whole experiment, you are neither allowed to use your mobile phone nor talk to the other participants.

Please read the following instructions carefully. For a successful execution of the experiment, it is important that you have really understood them. Should you have a question at any time during the experiment, pleas raise your hand. An experimenter will then answer your question individually at your desk.

In this experiment, you will once make a choice between two work assignments. In the context of these assignments, you will complete a number of coding tasks which we will explain in more detail in what follows. In return, you will receive a certain wage. In addition, you will receive 4 Euro for participation in this experiment.

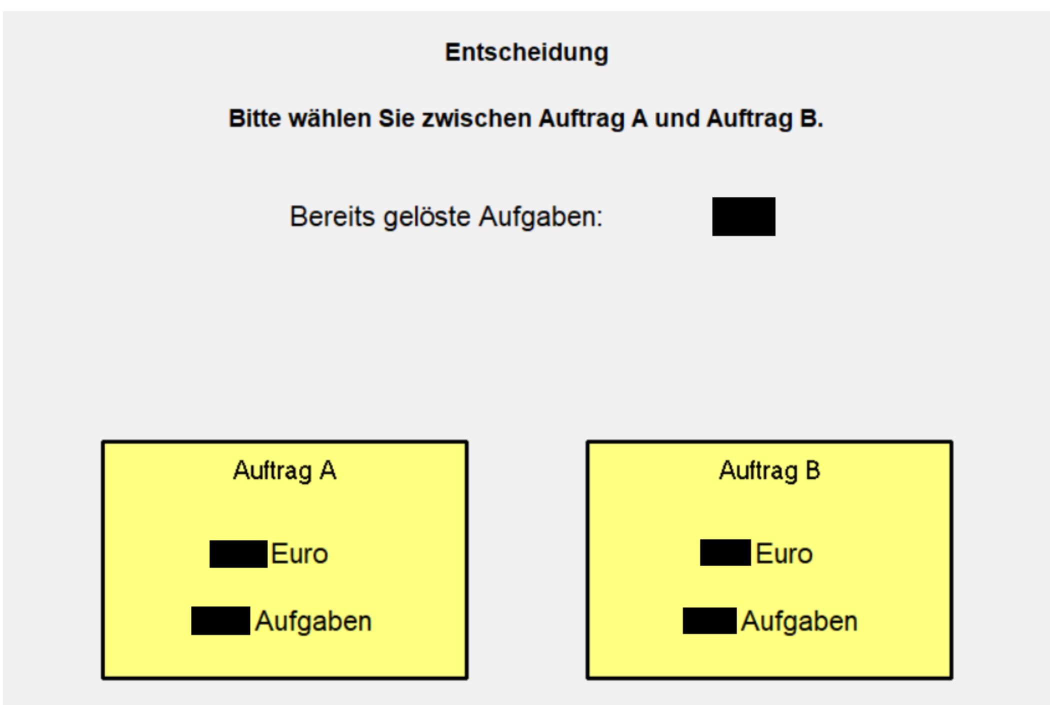
Example: The picture below shows such a coding task. At the top, you can see a sequence of letters and below them input boxes, as well as a table in which each letter has been allocated a three-digit number. Your task is to enter for each letter the corresponding number into the respective box. In this example, you have to enter the number 349 in the box below the letter E, in the box below the letter B the number 319, and so on. Once you have entered all numbers, please press "OK".



At the beginning of the experiment, you will solve two coding tasks in order to practice the task.

Afterwards, you will choose between two work assignments which we will call "assignment A" and "assignment B". To this end, you will see on the screen how many tasks have to be solved for the respective assignment and which amount of money you will receive if you solve the corresponding number of tasks.

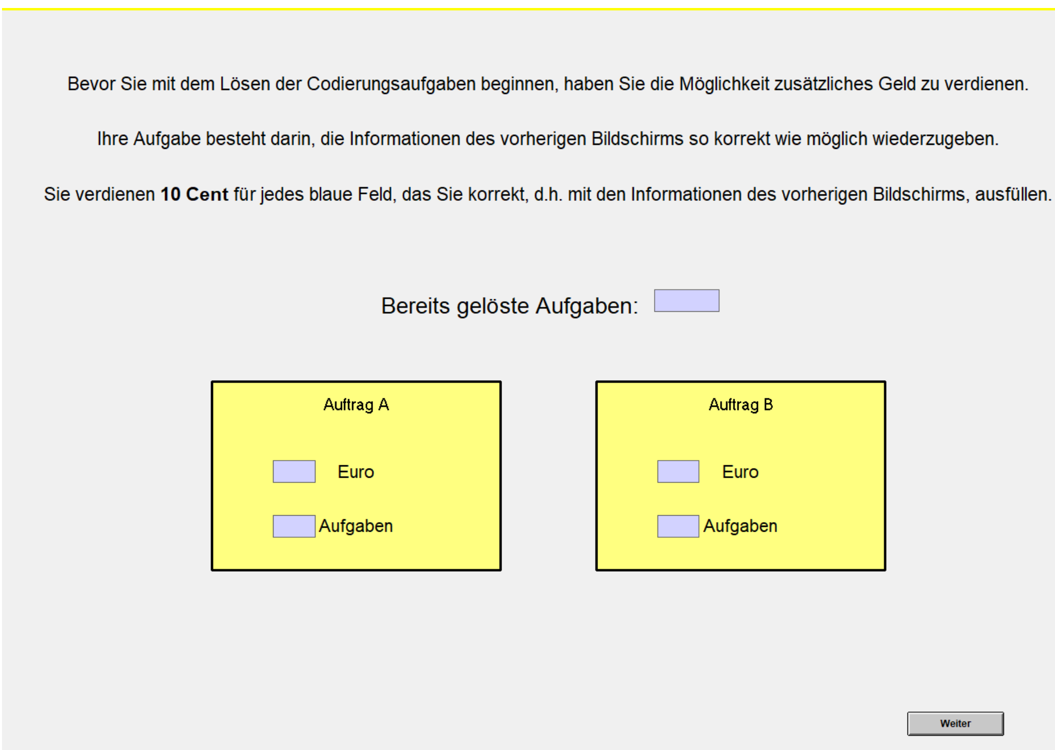
Important: Each assignment requires that you solve a specific number of tasks. The assignments A and B always indicate the **total number** of tasks which need to be solved. It his the case, however, that a specific number of tasks have already been solved. How many tasks have already been solved for you, can be seen on the upper part of your decision screen. What exactly this screen looks like can be seen on the screenshot below. There you can see for assignment A and assignment B the corresponding wage and the total number of tasks that need to be solved. In the experiment, you will see the concrete values instead of the black boxes.
The number of tasks which you have to solve is therefore determined by the **difference** between the total number of tasks and the tasks which have already been solved. Put differently: the number of tasks that you have to solve if you choose a specific assignment, is reduced by the stated number of tasks that have already been solved.



After you have chosen your assignment, you will solve the corresponding number of tasks and receive the corresponding wage. More precisely: when you have solved the specified number of tasks, an experimenter will come to your desk and will hand over the amount of money plus the 4 Euro which we pay you additionally for participating in the experiment. After that, you may leave the lab. Hence, you do not have to wait for the other participants to solve their tasks.

——————— *end of paper instructions*———————

After participants made their choice, they saw the following screen for the (surprise) memory task:



The English translation reads as follows:

> Before you start with solving the coding tasks, you have the opportunity to earn some extra money.
>
> Your tasks is to reproduce the information from the previous screen as accurately as possible.

You can earn **10 cents** for each blue box which you enter correctly, i.e., with the information from the previous screen.

After solving the coding tasks, we asked participants for the following information:

Please state your gender: male ☐ ☐ female

Please state your subject of study:
- ☐ Faculty of Mathematics and Natural Sciences
- ☐ Faculty of Management and Economics
- ☐ Faculty of Management and Economics
- ☐ Faculty of Law
- ☐ Faculty of Arts and Humanities
- ☐ Other

Please state your age: ____________________