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ORIGINAL ARTICLE

Cost–benefit and distributional analyses of accessory stimuli

James A. Grange · Andrew Lody · Sophie Bratt

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Abstract Accessory stimuli (AS) are task-irrelevant events (typically an auditory tone) that speed reaction time (RT). With two conditions (AS-present, AS-absent) it is unclear whether AS-presence causes benefits or AS-absence causes costs, possibly due to the expectancy violations. The current study added a third condition where AS were absent in blocks and not expected (pure blocks); in other blocks, AS occurred with a probability of 0.5 (mixed blocks), allowing cost–benefit analysis comparing AS-absent RTs in pure and mixed blocks. Results demonstrated RTs were slower when AS were absent, regardless of whether the absence occurred in a mixed block or a pure block, suggesting AS do provide a benefit to RT. Additionally, AS-facilitation across the RT distribution was analysed using cumulative distribution frequencies and ex-Gaussian parameter estimation. Both provided converging evidence that AS-facilitation increases towards the slower end of the RT distribution. The implications for the utility of AS paradigms are discussed.

Introduction

It has been known for some time that task-irrelevant stimuli presented in a different modality to that of a primary task—so-called accessory stimuli (AS)—can speed reaction time (RT; Bernstein, Clark, & Edelstein, 1969a, b; Bernstein & Edelstein, 1971; Todd, 1912). This effect is interesting as the facilitation occurs even when the AS are presented before stimulus presentation; as the AS carry no task-specific information, the speed of responding cannot be explained by task-specific preparation. AS not only passively speed RT, they have also been shown to improve spatial and temporal visual search (Dalton & Spence, 2007; Van der Burg, Olivers, Bronkhorst, & Theeuwes, 2008). AS have also been used to investigate the emergence of conflict in selective attention tasks (e.g. Böckler, Alpay, & Stürmer, 2011). Thus interest in AS is widespread in cognitive psychology.

There are several theoretical interpretations of accessory stimuli, recently reviewed by Jepma, Wagenmakers, Band, and Nieuwenhuis (2009). To contrast between these, Jepma et al. performed diffusion-model analysis of AS (Ratcliff, 1979)—which models the components of RTs, such as evidence accumulation from the stimulus, response caution, and non-decisional components—and found that AS affect non-decisional components of RT. In conjunction with electrophysiological evidence, the authors concluded that AS speed stimulus encoding and increase motor activation. That AS speed stimulus encoding makes AS attractive as a tool to speed such processes in conjunction with other experimental manipulations (for example if one wanted to manipulate encoding speed whilst holding decisional-process speed constant).

Despite the attractiveness of AS, caution must be employed when analysing costs and benefits with just two conditions (i.e. AS-present and AS-absent). Indeed, when measuring the benefits of one condition over the other, the question arises whether the benefit in one condition is actually caused by a cost in the other condition (Jonides & Mack, 1984); hence, what may appear to be a benefit is really a consequence of perspective, and a change of perspective can challenge theoretical interpretations that were

J. A. Grange (✉) · A. Lody · S. Bratt
School of Psychology, Keele University,
Dorothy Hodgkin Building, Keele,
Staffordshire ST5 5BG, UK
e-mail: j.a.grange@psy.keele.ac.uk
URL: http://www.cognitivecontrol.co.uk

constructed to explain the benefit. The question addressed in the present study is whether AS lead to a benefit in performance, or whether the absence of AS lead to a cost. We argue that—to date—this question has remained unanswered as only two conditions exist in AS research (AS-present and AS-absent).

On costs and benefits

The question of costs and benefits of AS was born from anecdotal reports from participants in a pilot study in our laboratory investigating the effects of AS on task-switching performance. When questioned as to the purpose of the AS, many participants reported that they were distracted when the AS was absent. Several participants reported that due to the startling nature of the AS when present, they came to prepare themselves for its presence on more trials than it actually occurred; therefore, AS-absence may have lead to some form of expectancy violation, which could well induce a RT cost. From this perspective, AS-presence does not cause a benefit; rather AS-absence causes a cost. This is important as the theoretical conclusions of Jepma et al. (2009) could be reversed: it could be that AS-absence slows stimulus encoding and other non-decisional components. Thus, at stake are the theoretical conclusions which hinge on whether AS-presence causes a benefit or AS-absence causes a cost. We note that expectancy is just one of many possibilities that could lead to cost in AS-absent trials, and thus question the AS-absent RTs as a suitable baseline; thus the question of the present research is not necessarily focussed on the role of expectancy, but more the suitability of AS-absent trials as a neutral condition with which to compare AS-present RTs.

To address this issue, pure blocks were introduced wherein AS did not occur and were not expected to occur (i.e. no violation of expectancy). This was paired with a mixed block, wherein AS occurred with a 0.5 probability, as per standard AS manipulations. The contrasting predictions for this procedure are demonstrated in Fig. 1. Figure 1a shows the standard AS effect, with AS-present producing faster RTs than AS-absent trials when both are in a mixed block. Figure 1b depicts the prediction whether AS produce a benefit to RT performance, as is the general consensus in the literature; specifically, AS-present RT should be faster than AS-absent trials, regardless of whether the AS-absence occurs in a mixed block or a pure block. If this pattern of results emerges, the role of expectancy suggested from our pilot study can be discounted, and suggests that AS-absent (mixed) trials are a suitable control condition for comparison of AS-present performance. If expectancy-violations do slow AS-absent (mixed) trials, then the pattern depicted in Fig. 1c should emerge. In this instance, AS-absent (pure) RT is equivalent to AS-present RTs, as in both cases no violations of expectancy have occurred. This pattern would demonstrate that AS-absence (mixed) induces a cost, rather than AS-present inducing a benefit. AS-absent (mixed) RTs are slower than AS-absent (pure) RTs because in the former

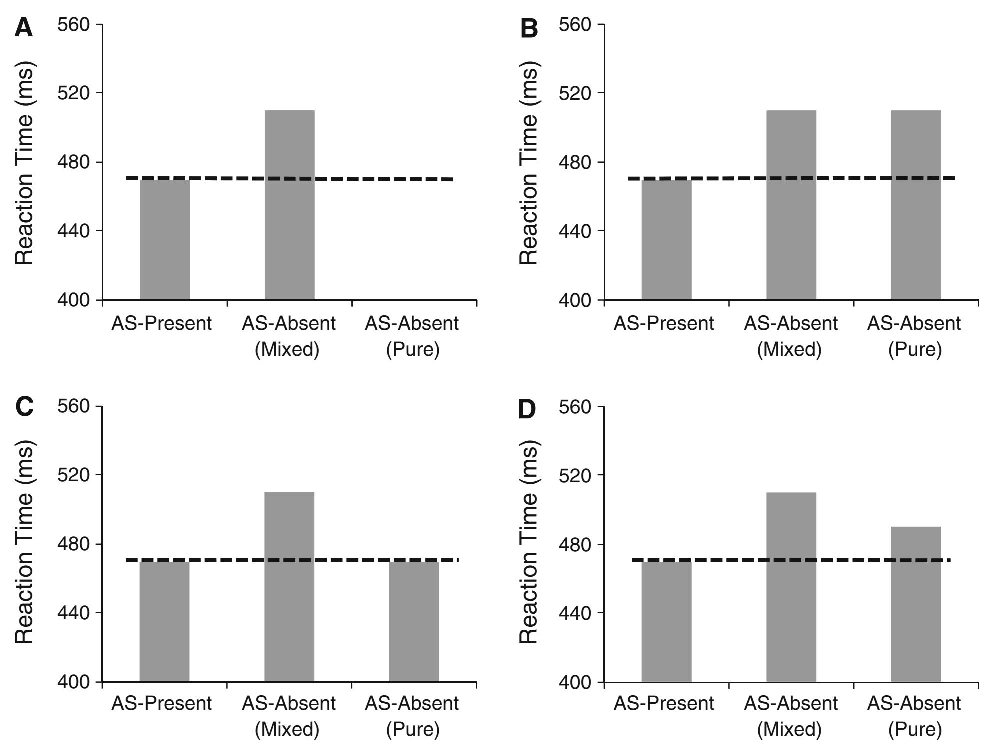

Fig. 1 Differing predictions of cost–benefit analysis from the present study. See the text for full details

case a held expectancy of AS-presence is violated; in the AS-absent (pure) condition, no expectancy of AS is held by the participant, so no costs emerge. Figure 1d depicts an intermediate stage between Fig. 1b, c, which represent a more realistic pattern if expectancy-violations do play some role in AS-performance; specifically, AS-presence may cause a benefit and AS-absence (mixed) may cause a cost relative to the neutral AS-absent (pure); such a pattern would suggest costs and benefits contribute to performance in AS paradigms. Finding a pattern of results depicted in Fig. 1c or 1d would call into question the benefit of accessory stimuli to RT performance.

A similar procedure of comparing mixed and pure block performance has previously been employed by Jaffard, Benraiss, Longcamp, Velay, and Boulinguez (2007), who investigated the effects of a neutral visual cue on choice RT. Previous evidence had shown that RT is speeded when a neutral visual cue is presented prior to stimulus onset compared to conditions where no cue was presented. This finding has informed theoretical models of attention that includes an alerting process, which provides non task-specific preparation (Posner & Peterson, 1990). Comparing cued and non-cued performance in mixed and pure blocks, Jaffard et al. found that the cueing advantage was only evident in mixed blocks: although speed of responding to cued-trials did not differ between mixed and pure blocks, non-cued trials were significantly slower in the mixed block than in the pure block. Thus, in mixed blocks, there seemed to be a cost of not having a cue which was absent when a proper baseline was introduced (i.e. pure blocks).

Distribution analyses

Additionally, this study sought to investigate the dynamics of AS effects across the whole RT distribution. Distributional analysis is important as sometimes experimental manipulations may affect components of the RT distribution whilst leaving the mean for each condition equivalent. Thus, experimental effects on RT can go unnoticed if relying purely on mean RT analysis (see e.g. Heathcote, Popiel, & Mewhort, 1991).

For the purpose of RT distribution analysis, we utilised cumulative distribution frequency plots (CDFs; Ratcliff, 1979) and ex-Gaussian parameter estimation. CDFs are constructed by ordering all RTs for each condition of each participant from quickest to slowest; quantile cut-off points are then calculated for each of these sets of data. Then, the RTs that constitute such quantile cut-off points are averaged across each participant and plotted (see Fig. 2 of the current paper for an example from the current study). CDFs are useful as they allow examination of differences between conditions across the whole distribution, rather than just at the mean-RT level (see Grange & Houghton, 2011; Houghton & Grange, 2011, for examples as to the utility of CDF examination). CDFs are descriptive plots of RT distributions (Balota & Yap, 2011), which are relatively uninformative as to the shape of the underlying distribution. To seek converging evidence as to the effect of AS on RT distributions, we also fitted explicit statistical models to the data in the form of ex-Gaussian distributions, which have been shown to fit RT very well (Van Zandt, 2000). The ex-Gaussian distribution is a convolution of a Gaussian (i.e. normal) component (typically the body of the RT distribution) and an exponential component (reflecting the slow tail-end of an RT distribution). Ex-Gaussian analysis involves estimation of three parameters which describes the positively-skewed distribution: Mu, which reflects the mean of the Gaussian component; Sigma, which reflects the standard deviation of the Gaussian component; and Tau, which reflects the mean of the exponential component. A change in the Mu parameter moves the whole distribution, whereas a change in the Tau parameter alters the spread of data towards the tail end of the distribution.

We are aware of only one other study which examined the effects of AS on the whole RT distribution. Jepma et al. (2009) constructed delta plots of the AS effect—similar to CDF analysis but plotting only the difference score as a function of reaction time—using the 0.1, 0.3, 0.5, 0.7, and 0.9 quantiles. They reported a relatively consistent AS benefit from quantiles 0.1–0.7, but an increase in the effect at the final quantile. The authors proposed that this pattern of results was consistent with the results of their diffusion analysis, as an influence of AS on non-decisional components of RT predicts no overall increase in the AS benefit across the RT distribution. We therefore wished to add to the as yet minimal information available on the dynamics of accessory stimuli across the RT distribution in a descriptive (CDF) and explicit (ex-Gaussian) manner.

Method

Participants

Twenty-eight participants—19 female—were recruited from the participant panel run by the School of Psychology at Keele University in exchange for partial course credit. Their mean age was 19.43 years (SD = 2.44). All participants were naïve as to the study's purpose.

Stimuli and apparatus

Stimuli were presented on a 17-in. monitor connected to a PC running E-Prime 2.0 software. Responses were collected on a standard QWERTY keyboard. Stimuli were the numbers 1–9, excluding 5, presented in white on a black background in size 24 Courier New font. Stimulus size was approximately 1 cm in height and width. Stimuli were presented within a square frame, measuring 7 cm in height and width; the square frame was white. The accessory stimulus was presented though Sony Dynamic stereo headphones (model MDR-V150), which were adjusted for comfort of the participant during the practice session. The accessory stimulus was an 80 dB 150 ms bleep played through the headphones.

Procedure

The experiment consisted of 8 experimental blocks of 96 trials, preceded by a small practice block of 24 trials. Each experimental block was followed by a rest screen, which lasted as long as the participant wished. The task was to judge whether the presented number was odd or even. Each experimental block instructed the participant whether to expect an AS (a mixed block) or not (a pure block); mixed blocks and pure blocks alternated predictably (i.e. mixed–pure–mixed–pure etc.). The expectancy on the first block was counterbalanced across participants. The practice block was a mixed block.

During pure blocks, the instructions informed participants that no bleep would occur. A trial started with the presentation of the blank square frame centred on the screen for 1,000 ms. After this time, the stimulus appeared centred within the square frame, and remained visible until a response was made by the participant. Participants were required to respond as quickly and as accurately as possible to the number stimulus by making a key-press: if the stimulus was odd, participants were required to press the "C" key; if the stimulus was even, the "B" key served as the response. Participants were instructed to use the index finger of each hand for responding, and to keep the fingers rested on the keys at all times. Once a response was registered, the frame went blank and the next trial started immediately. No stimulus repetitions were allowed for pure or mixed blocks.

During mixed blocks, the instructions informed participants to expect a bleep in their headphones with p (beep) $= 0.5$. The trial structure was identical to the pure block, with the exception that of those trials in which AS occurred. During these trials, the AS occurred 30 ms before stimulus onset (i.e. the AS overlapped temporally with the visual stimulus; Jepma et al., 2009). Participants were instructed to ignore the bleeps and to continue responding as quickly and accurately as possible.

Design

The experiment manipulated one factor in a repeated measures design. The independent variable was the presence of AS [AS-present vs. AS-absent (mixed) vs. AS-absent (pure)]. The dependent variables were reaction time (RT in milliseconds, ms) and error rate (%).

Results

Standard analysis

The first trial from each experimental block was removed, as were error trials. As the focus of the latter analysis is on RT distributions, no trimming of correct data was conducted so as to preserve the tail of the RT distribution. It should be noted though that an equivalent analysis with RTs 2.5 standard deviations from each participant's mean removed—a standard trimming procedure—produced qualitatively identical results as that without trimming. RTs and errors were analysed in separate one-way ANOVAs with the levels as described in Design. The error rates did not produce any significant effects, so we focus on RTs exclusively (Table 1).

Reaction times

RTs were faster to AS-present trials compared to AS-absent (mixed) and AS-absent (pure) trials. This was reflected in a significant main effect of accessory stimulus, $F(2,54) = 10.27$, $p < 0.01$, $\eta_p^2 = 0.28$. Planned contrasts showed that the 25 ms facilitation when the AS was present compared to when it was absent in the mixed block was highly significant, $F(1,27) = 21.61$, $p < 0.001$, $\eta_p^2 = 0.45$. The difference in RTs when the AS was absent between the mixed and the pure block was not significant, $F(1,27) = 0.85$, $p > 0.36$, $\eta_p^2 = 0.03$.

Distributional analysis

In this section the distributional analysis of the RTs are described. The analysis followed two stages: in the initial stage, simple CDF analysis was performed; after this, ex-Gaussian parameters were estimated.

Table 1 Mean reaction times (RT) in milliseconds (ms), standard errors (SE), and error rates (%) for all conditions of accessory stimuli

Accessory stimulus	Mean RT	SE	Error rate
Present	564	14.97	6.01
Absent (mixed)	589	19.08	5.91
Absent (pure)	595	22.05	5.84

Cumulative distribution analysis

CDF analysis was conducted using CDF–XL (Houghton & Grange, 2011), an Excel macro that computes quantile cut-off values for each participant for each condition. The quantiles used were 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9. The 1.0 quantile merely returns the slowest RT for each condition and is therefore of little interest. Quantiles were estimated for each participant for each of the three levels of the factor AS. The RTs at each of the quantiles were then averaged across all participants and plotted in Fig. 2.

As can be seen in Fig. 2, there was practically no difference between AS-absent (mixed) and AS-absent (pure) across the whole distribution; the largest difference was at the 0.9 quantile, where the AS-absent (mixed) was 7 ms faster than AS-absent (pure).

Focussing on the difference between AS-absent (mixed) and AS-present, it was smallest at the fastest quantile (12 ms), increasing to 35 ms at the slowest quantile. The linear trend of this comparison (with quantile as an additional factor) was significant, $F(1,27) = 4.74$, $p < 0.05$, $\eta_p^2 = 0.15$. It should be noted that the difference between AS-present and AS-absent (mixed) was significant across all quantiles (smallest $t(27) = 3.55$, all *p*s < 0.01).

The increase of the AS effect towards the slower end of the distribution is noteworthy because it suggests that the effect is minimal when participants are responding quickly. However, it could be that the difference between AS-present and AS-absent (mixed) is a constant proportion of overall RT, and that the effect of AS increases merely because overall RT increases. To test this, proportional scores were calculated by dividing the AS effect for each participant by the overall RT for AS-present trials. Thus, the proportion scores for AS were calculated by:

$$\text{Proportion (AS)} = \frac{(\text{RT[AS Absent(Mixed)]} - \text{RT [AS Present]})}{\text{RT[AS Present]}} \quad (1)$$

Proportion scores were calculated for each participant for each quantile; quantile values were then averaged across all participants, and are plotted in Fig. 3. Even when the AS-effect is calculated as a proportion score, it still increases towards the slower end of the RT distribution. The linear regression provided a good fit to the data explaining 64% of the variance ($p < 0.01$). Taken together, the results suggest that the facilitation of AS increases towards the slower end of the RT distribution.

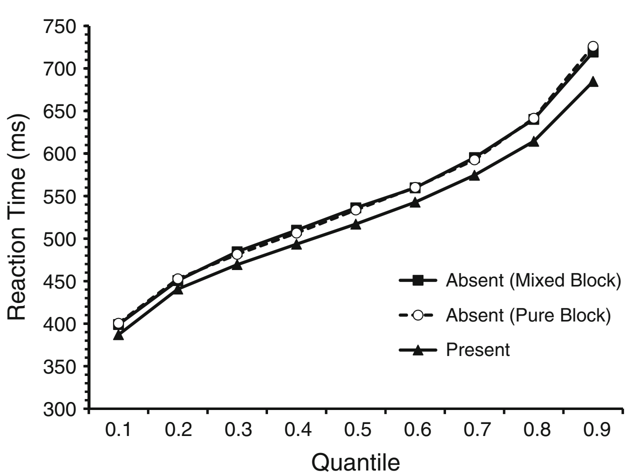

Fig. 2 Cumulative distribution frequency (CDF) plot of reaction times for AS-absent (mixed), AS-absent (pure), and AS-present trials

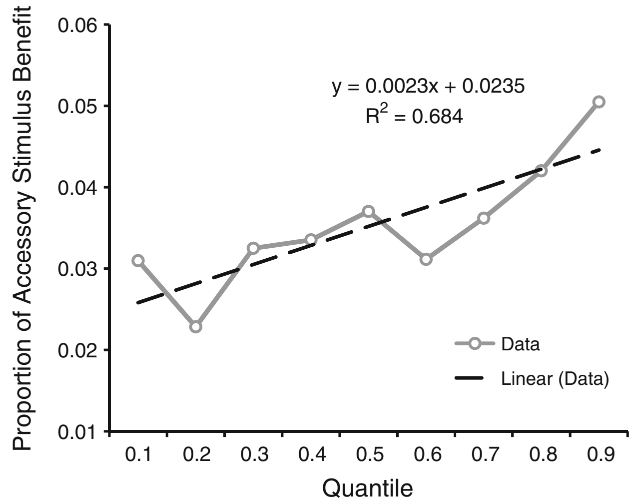

Fig. 3 Magnitude of proportional scores of the accessory stimulus benefit (see Eq. 1) across the RT distribution. The *dotted line* represents the linear regression, with the regression equation embedded within the figure

Ex-Gaussian distribution analysis

Correct RTs for each condition and for each participant were used to estimate ex-Gaussian parameters Mu, Sigma, and Tau. Parameter estimation was achieved by adapting source code utilising the distibv2.3 toolbox in MatLab (Lacouture & Cousineau, 2008). For analysis purposes, the factor accessory stimulus was analysed for each of the three parameters separately, resulting in three one-way ANOVAs. Averaged estimates for each condition and each parameter can be found in Fig. 4.

The effect of accessory stimulus was not significant for the Mu parameter [$F(2,54) = 1.72$, $p > 0.18$, $\eta_p^2 = 0.06$] or for the Sigma parameter [$F(2,54) = 0.32$, $p > 0.72$, $\eta_p^2 = 0.01$]. However, there was a significant effect of accessory stimulus on the Tau parameter [$F(2,54) = 4.56$,

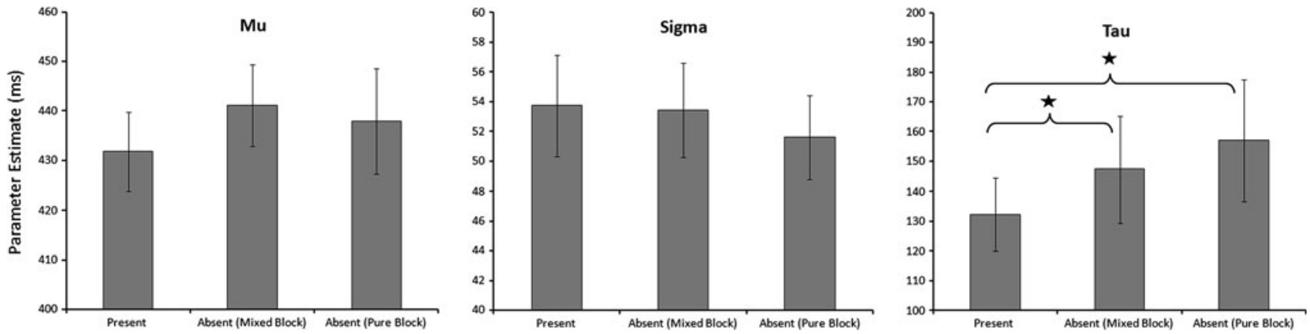

Fig. 4 Ex-Gaussian parameter estimations (in ms) for all AS conditions. *Error bars* represent ±1 standard error around each parameter estimate's mean. *$p < 0.05$

$p < 0.05$, $\eta_p^2 = 0.15$]. Planned contrasts showed that this was driven by a significant difference between the Tau parameter estimate for when the AS was present ($M = 132$ ms) than when it was absent in the mixed block ($M = 147$ ms), $F(1,27) = 4.73$, $p < 0.05$, $\eta_p^2 = 0.15$. There was no difference between the two AS-absent conditions, $F(1,27) = 2.01$, $p > 0.17$, $\eta_p^2 = 0.07$.

Discussion

The present study sought to investigate whether AS-absent (mixed) were a suitable neutral condition with which to compare AS-present performance; with just two conditions it is difficult to ascertain whether facilitation of AS-present trials was due to a benefit or a cost of AS-absent trials. One possibility for a cost in AS-absent trials was anecdotal reports from subjects that they expected AS on more trials than in which they occurred; thus the possibility existed that AS-absent trials lead to a cost due to violations of expectancy.

Addition of a third condition—AS-absent (pure)—controlled for expectancy, and is thus a more suitable neutral condition from which to perform cost–benefit analysis (c.f. Fig. 1). The results were clear: AS-present lead to facilitation of RT compared to AS-absence regardless of whether the absence occurred in a mixed block or a pure block (Jonides & Mack, 1984). To our knowledge, this is the first time AS can be unequivocally considered to lead to a benefit in performance. On the basis of these results, researchers can continue to use AS to speed performance with little concern about their costs and benefits.

In addition to analysing mean RT, distributional analysis was also presented. Descriptive CDF analysis (Houghton & Grange, 2011) and more formal ex-Gaussian parameter estimation (Balota & Yap, 2011) provided converging evidence as to the dynamics of the AS-benefit across the distribution. CDF analysis showed that the facilitation increased toward the slower end of the distribution, even when the facilitation was calculated as a proportion of overall RT. Ex-Gaussian analysis showed AS selectively affected the Tau parameter, which reflects a shift in the tail (slower) end of the RT distribution. Prima facie these results stand contra to those of Jepma et al. (2009) who found AS-facilitation did not increase across the RT distribution. Jepma et al. used this as converging evidence that AS affect non-decisional components of RT according to their diffusion model (Ratcliff, 1979)—the parameter associated with non-decisional components predicts no increase in AS facilitation across the distribution. To address these differences, we note three points. First, there is a shortage of distributional analysis of AS-facilitation in the literature, so a coherent pattern of results is yet to emerge. The present paper adds to the literature, but much work is needed in order to find converging evidence supporting the present findings, or those of Jepma and colleagues. Second, there were vast procedural differences between our study and Jepma et al.'s; our study required parity judgements of number stimuli, whereas Jepma et al. used lexical decisions on word stimuli. Thus procedural differences may have exacerbated differing results. Finally, we did not perform full diffusion analysis on our data due to the low error rates of several participants (some had 100% accuracy for some conditions). As diffusion analysis requires estimation of error- as well as correct-RTs, researchers have estimated that at least 5% errors are required to perform the analysis in an experiment with at least 200 trials per condition (Wagenmakers, 2007).

However, we did perform some preliminary investigations using EZ-diffusion analysis (Wagenmakers, van der Maas, & Grasman, 2007),[1] a simplified version of the full diffusion model which only estimates three parameters: drift rate (the rate of information-accumulation from the stimulus), response caution, and non-decision time. The EZ diffusion model is ideal for data-sparse situations (as is the

[1] We thank Marieke Jepma for suggesting we use the EZ diffusion model.

Table 2 Mean EZ-diffusion model parameter estimates for two conditions of accessory stimuli

Accessory stimulus	Drift rate	Response caution	Non-decision time
Present	0.256 (0.01)	0.114 (0.005)	0.34 (0.01)
Absent (mixed)	0.254 (0.01)	0.120 (0.006)	0.34 (0.02)

Standard errors of parameter estimates are in parentheses

case with the low error rate in the present study) due to its simplified approach, but the results should be considered preliminary. As the EZ diffusion model demands equal trial numbers for conditions of comparison, we only analyzed mixed-conditions (AS-present vs. AS-absent). Additionally, three participants were not included in the EZ-analysis;[2] two had perfect accuracy in at least one condition (making parameter estimation impossible), and one obtained negative EZ parameter estimations for non-decision time, which is not plausible. Parameter estimates averaged across subjects are shown in Table 2.

The analysis showed no difference between AS-present and AS-absent (mixed) trials, either for drift rate [$t(25) = 0.24$, $p > 0.8$], response caution [$t(25) = -1.5$, $p > 0.14$], or non-decision time [$t(25) = -0.23$, $p > 0.8$]. The lack of any effect in the EZ diffusion parameters (contrary to the differences found with the full diffusion model by Jepma et al., 2009) likely reflects the loss of sensitivity having used a reduced version of the diffusion model, rather than an absence of an effect altogether. It is likely that a more sensitive analysis using the full diffusion model may expose effects of AS on different diffusion parameters.

An additional note of caution is that although some authors have found relations between ex-Gaussian parameters and parameters of the diffusion model, it is a debated issue whether ex-Gaussian parameters uniquely map on to parameters in the diffusion model (Matzke & Wagenmakers, 2009), thus it is difficult to ascertain whether the present study provides evidence against the conclusion of Jepma et al. (2009) that AS uniquely affect non-decisional components of RT (although it should be noted that an effect of AS exclusively on the Tau parameter cannot be explained by modulation of the non-decisional component of the diffusion model on its own; Matzke & Wagenmakers, 2009). Indeed, focussing exclusively on distributional patterns (CDFs and ex-Gaussian) provides relatively little information as to what cognitive processes are affected by AS, so future research adopting the full diffusion model analysis seems imperative.

It should also be noted that the present results appear to stand contra to those of Jaffard et al. (2007), who reported speed of overall RTs for non-cued (i.e. AS-absent) in pure blocks compared to mixed blocks. Jaffard et al. explained their results by proposing an inhibitory mechanism in mixed blocks that suppresses movement triggering, which may fire erroneously in response to a neutral visual cue rather than the target itself. This inhibition is necessary due to the uncertainty of the cueing condition on the current trial, and can only be overcome when the visual display presents a target. Thus, in no-cue (mixed) conditions, target identification requires overcoming this inhibition, which is not required in the pure blocks; due to the lack of uncertainty in the pure blocks, no inhibition is required as the next visual input will always be a target. In the present study, RTs when AS was absent were identical, regardless of whether they were in a mixed or a pure block. Methodological differences likely explain this discrepancy; specifically, as the AS and the visual target were presented in different modalities in the present study, inhibition of visual input after the appearance of the AS may not be required, as a visual input will always be a target. A replication of the current study in which the AS and the targets share the same input modality may shed more light on the differences between the present study and that of Jaffard et al.

A further avenue of potentially fruitful research may be the investigation of sequential effects on AS-facilitation.[3] The question of whether AS-presence and absence is influenced by the nature of the AS condition on the previous trial is unaddressed in extant research. For example, is AS-present RT speeded if the previous trial was also an AS-present trial compared to if the previous trial was an AS-absent trial? Investigation of behavioural sequential effects have highlighted interesting phenomena in the cognitive control literature (Gratton, Coles, & Donchin, 1992), leading to influential computational models (Botvinick, Braver, Barch, Carter, & Cohen, 2001). Although not the purpose of our study, our data allowed a preliminary investigation of sequential effects. For mixed-blocks only, trials were classified according to the present trial (AS-present vs. AS-absent) and the previous trial (AS-present vs. AS-absent). This classification resulted in a factorial manipulation of AS on the previous trial and AS on the current trial (previous trial–current trial): present–present; absent–present; present–absent; and absent–absent. A two-factor ANOVA showed a main effect of Current trial, with faster RTs if the present trial was an AS-present trial [$F(1,27) = 20.85$, $p < 0.001$, $\eta_p^2 = 0.44$]. The main effect of Previous trial was not significant

[2] Removal of these subjects did not alter the pattern of results in either the mean RT or error analysis.

[3] We are grateful to Sander Los for suggesting this possibility, and for suggesting the subsequent analysis.

[F(1,27) = 2.20, p = 0.15, $\eta_p^2 = 0.08$] but the interaction of the two factors was significant, [F(1,27) = 12.60, $p < 0.01$, $\eta_p^2 = 0.32$]. Planned comparison t tests showed that present–present RTs (562 ms) did not differ from absent–present RTs (565 ms), $t(27) = -0.49$, $p > 0.6$; however, present–absent RTs (600 ms) were significantly slower than absent–absent RTs (578 ms), $t(27) = 2.44$, $p < 0.05$. It is important to note that in this latter case, the present trial did not have an AS present in either condition, and was thus modulated by the presence/absence of AS on the previous trial. It is not clear from the present data what is driving this difference. One possibility is that when an AS occurs, there is heightened expectancy of an AS to occur on the next trial; when this does not transpire (as is the case on present–absent trials), there may be a RT cost due to expectancy violations. Although the present study investigated—and found no evidence for—expectancy violations in the AS paradigm, trial-to-trial variations in expectancy are short-lived in comparison to the block-wise manipulation of expectancy reported here. If these sequential effects on AS are replicable in future research, they may prove important in explaining just what is driving the observed AS-facilitation.

Conclusion

To summarize, the present study has provided evidence in the form of cost–benefit analysis that accessory stimuli do facilitate RT performance, and that AS-absent (mixed) trials are a suitable neutral condition with which to calculate this facilitation (Jonides & Mack, 1984). It is imperative for future research to analyse whole RT distributions in order to obtain a clearer picture of the dynamics of this facilitation across the whole range of response times, supplemented by fitting explicit cognitive models to data to infer what cognitive processes are facilitated by AS presence.

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