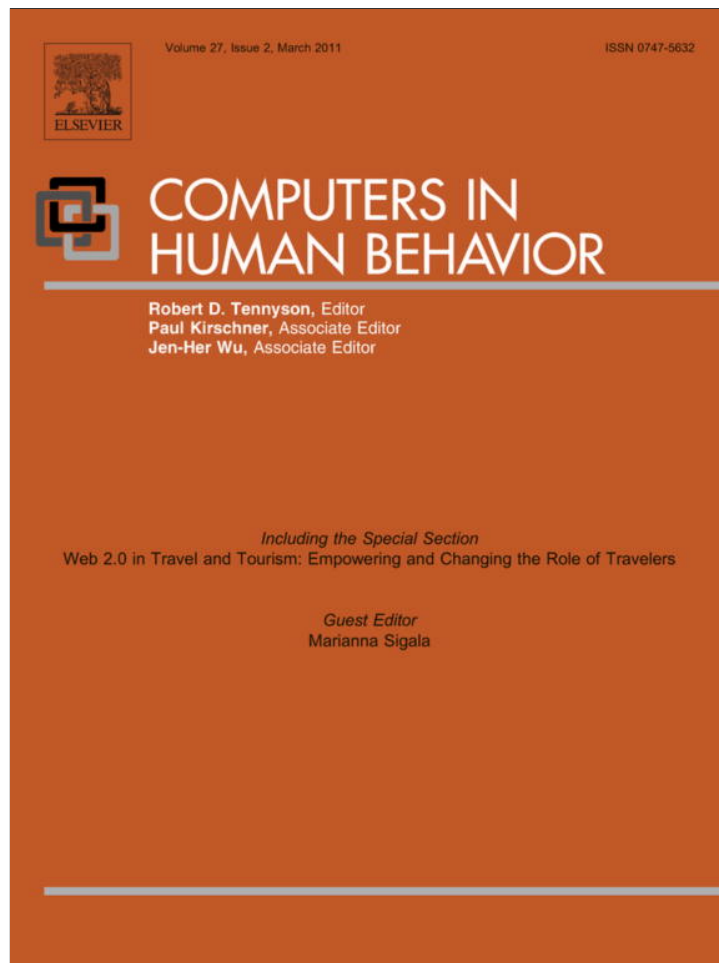


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## Further evidence on the validity of web-based research on associative learning: Augmentation in a predictive learning task

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### ABSTRACT

Most demonstrations of the validity of Internet-based research methods are based on replications of well-known experimental phenomena on the Internet. However, in order to test whether the lack of control over the experimental conditions usually found in Internet studies has an effect on the quality of data, it would be more interesting to show that the Internet cannot only be used to replicate common and well-documented effects, but also less-known experimental findings or elusive phenomena that tend to occur only in very specific conditions. The present experiment explores one such effect, namely augmentation in associative learning, and shows that it can be readily found in the laboratory and on the Internet.

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### 1. Introduction

During the last two decades, computers have become the most widely used experimental devices in the study of human associative learning. Since the seminal studies conducted in the 80s (Dickinson, Shanks, & Evenden, 1984), almost all experiments have been conducted by asking participants to interact with a computer program in which they have to learn predictive relations between cues and outcomes. In fact, the development of new and better experimental tasks for the study of associative learning has become a major goal of methodologists in recent years (Arcediano, Ortega, & Matute, 1996; Costa & Boakes, *in press*; Franssen, Clarisse, Beckers, van Vooren, & Baeyens, 2010; Matute, Vadillo, & Bárcena, 2007; Molet, Leconte, & Rosas, 2006).

During all these years, experimenters were obliged to bring participants to the laboratory, where already setup computers were awaiting for the participants to take part in the study. However, with the recent development in information technologies and the wide-spread access to the Internet, it is becoming possible to send the experimental program right to the participants' computers, so that they can perform the experiment wherever they want to, instead of having to attend the experimenter's facilities. Researchers can now implement their software in open-access websites, so that anyone interested in participating in the experiment can enter the virtual laboratory, perform the experimental task and send his or her data to the experimenter (Birnbaum, 2000; Gosling, Vazire, Srivastava, & John, 2004; Kraut et al., 2004; McGraw, Tew, & Williams, 2000).

The main advantage of this modality of research is that it provides an easy, fast, and nonexpensive access to much larger and more heterogeneous samples (Reips, 2002). However, this methodology is not without its risks: the experimenter usually lacks any control over the conditions on which the experiment takes place. For instance, participants can perform the experiment in noisy environments, while they are distracted by other activities, or even in the presence of observers who might perhaps alter their behavior. Additionally, they can decide to participate several times in the same experiment and submit more than one data file to the experimenter. Usually, these potential problems are overcome by the huge sample sizes that can be gathered in online experiments, which minimize the final impact of the low quality data submissions. Additionally, researchers can sometimes reduce the impact of these problems by taking some measures, such as using carefully chosen data selection criteria (in order to remove participants who might not have paid enough attention to the experimental task) or by registering the IP of each participant's computer (so that multiple submissions from a single computer can be detected; see Reips, 2002). However, in the end, the only way of making sure that the experiments conducted over the Internet are trustworthy is to replicate these experiments in the traditional laboratory. Identifying the general conditions under which the results of laboratory and Internet experiments tend to converge or diverge is the first step that must be taken before the use of the Internet in psychological research can be generalized.

Extant studies have explored the similarities and divergences of laboratory and Internet data in a wide variety of research procedures and designs. For example, it has been shown that the results of Internet studies tend to match those of the laboratory in personality research (Buchanan & Smith, 1999), probability learning

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(Birbaum & Wakcher, 2002), causal reasoning (Steyvers, Tenenbaum, Wagenmakers, & Blum, 2003), or problem solving (Dandurand, Shultz, & Onishi, 2008), among others. Experiments conducted within the area of associative learning research, which is the focus of the present research, also confirm the validity of online research (e.g., Matute, Vadillo, Vegas, & Blanco, 2007; Vadillo, Bárcena, & Matute, 2006; Vadillo & Matute, 2009).

Many of these previous studies aimed at replicating well-known associative learning effects as a means to test the validity of online research methods. However, the fact that these methodological tests have focused on widely reported phenomena somewhat reduces their face value: the associative learning effects that have been replicated so far (such as overshadowing or discrimination reversal) are so general and reliable that any success at replicating them is hardly surprising. A much more convincing test of the validity of online research methods could perhaps be achieved by replicating relatively unknown experimental effects or elusive phenomena that tend to appear only in certain, well-controlled conditions. The present study aims at providing a stronger test of the validity of Internet-based research methods by exploring a relatively undocumented associative learning effect, augmentation, both in the laboratory and on the Internet.

In the following experiment, participants were exposed to the sequence of trials shown in Table 1. During the first phase, they were exposed to pairings of a colored figure in the screen (i.e., cue A) with the possibility of earning points (i.e., Outcome1). During the second phase, the same cue was presented together with a novel colored figure, X, also followed by Outcome1. The usual result of experiments performed with this design is that the association between cue X and Outcome1 tends to be poorly learned, relative to its control cue, Y: Given that during AX–Outcome1 trials the outcome can be easily predicted by paying attention only to A, people either tend to ignore X or fail to correctly encode its relationship with the outcome. This detrimental effect of A–Outcome1 trials upon learning of the X–Outcome1 association is called *blocking* and is probably one of the best documented effects in the associative learning literature due to its deep implications for several theories of learning and memory (for reviews, see Mitchell, De Houwer, & Lovibond, 2009; Shanks, 2010). However, under certain conditions, it has been observed that previous learning of the A–Outcome1 association can enhance, rather than reduce, subsequent learning of the X–Outcome1 association. A similar effect has sometimes been observed with rats under conditions in which A and X are different conditioned stimuli and the outcome is an unconditioned stimulus. Although the mechanisms underlying this *augmentation* effect have received some attention in the animal conditioning literature (Batsell & Batson, 1999; Batson & Batsell, 2000), it is a relatively infrequent result in human learning experiments (Beesley & Shanks, submitted for publication; Mitchell, Lovibond, & Gan, 2005). Thus, simultaneous replication of augmentation in the laboratory and on the Internet would provide stronger support to the validity of Internet-based research than our previous studies on more solid and reliable learning effects. A recent experiment conducted by Vadillo and Matute (2010) showed that augmentation can be found in web-based studies. However, that experiment did not include a traditional laboratory sample and, therefore, did not allow a comparison of the relative effect sizes

of the augmentation effect under both locations. The present experiment sought to provide such a comparison.

One of the main disadvantages of Internet-based research methods is that the lack of control over the conditions in which participants perform the task usually adds some noise and variance to the target dependent measures. However, this noise might perhaps be reduced by using restrictive data selection criteria and by computing alternative measures of learning that take into account the general level of performance of each participant. Therefore, a secondary goal of the present experiment is to assess the relative adequacy of alternative dependent variables that can be used to measure associative learning effects in behavioral tasks such as the one described here.

## 2. Methods

### 2.1. Participants and apparatus

Fifty-eight undergraduate students from Deusto University and 73 anonymous visitors of our virtual laboratory ([www.labpsico.com](http://www.labpsico.com)) volunteered to take part in the experiment. The former sample performed the experiment in a large computer room, with each participant at least 1.5 m apart from the adjacent participant. The conditions in which the Internet participants performed the experiment are completely unknown to us. No attempt was made to control for multiple resubmissions in Internet participants.<sup>1</sup>

All the materials were presented in a HTML document which included JavaScript functions to manage the presentation of the stimuli on the screen and to collect participants' responses. All the stimuli involved in the experiment were preloaded in the computer's memory before participants could start the experiment, so that differences in the connection speed did not influence the pace of the experiment.

### 2.2. Procedure and design

The experiment was conducted with a preparation and cover story that has already been used in several experiments (e.g., see Escobar, Pineño, & Matute, 2002; Pineño & Matute, 2000) and that provides the conditions necessary for augmentation to occur (e.g., certain level of time pressure and a predictive, non-causal cover story; see Vadillo & Matute, 2010). Participants were asked to imagine that they were soldiers whose task was to rescue some refugees that were hidden in a ramshackle building. On each trial, participants were given the opportunity to place a number of people in a truck and to take them to a safe place. Participants could enter people into the truck by pressing the space bar repeatedly. Participants could also enter larger numbers of people into the truck by keeping the space bar pressed instead of pressing it repeatedly. However, the refugees placed into the truck did not always arrive safely at their destination. In some trials, the road the truck had to move through contained mines that could explode. Participants could predict whether or not the road would be mined on a given trial by paying attention to a spy-radio installed in the truck. Certain colors in the spy-radio predicted that the road would be safe (and, therefore, that participants should place as many refugees as possible into the truck), whereas other colors predicted that the road would be mined (and, therefore, that participants

**Table 1**  
Design summary of the experiment.

Condition	Phase 1	Phase 2	Test
Exp.	16 A–Outcome1	4 AX–Outcome1	X?
Ctrl.	–	4 BY–Outcome1	Y?
Filler	8 C–Outcome2	8 C–Outcome2	

<sup>1</sup> The main reason for doing so is that all the techniques available for reducing the impact of multiple resubmission have some disadvantages (e.g., they all involve some risk of eliminating data which were not actually resubmissions). However, previous studies conducted in our virtual laboratory suggest that the frequency of multiple submissions from a single IP address is rather negligible. This is consistent with previous research showing that multiple submissions pose no or little threat to the reliability of Internet-based studies (see Reips, 2002).

should avoid placing refugees into the truck during those trials). Participants were not told which lights predicted which outcome but they could learn this throughout the learning phase by paying attention to what happened after the presentation of each color. Thus, the number of refugees placed in the truck on each trial when the light was on was taken as an index of the extent to which participants had learned that the cue (i.e., the color light) presented in that trial predicted that the road would be safe. Participants earned one point for each refugee placed in the truck in the trials in which the road was safe and lost one point for each refugee placed in the truck in the trials in which the road was mined. Participants could only decide whether or not to put people in the truck and enter their responses during the 3-s interval in which the color lights were present on each trial.

The blue, yellow, red, and green colors in the spy-radio (counterbalanced) played the roles of cues A, B, X, and Y of the experimental design shown in Table 1. Outcome1 was the opportunity to gain points by pressing the space bar in the presence of these colors (i.e., these colors predicted that the road would be safe). For all participants, cue C was represented by the purple color and this cue always predicted that the road would be mined and that any response to it would produce a loss of points (Outcome2). The number of trials of each type presented to participants throughout the experiment is shown in Table 1. Within each training phase, the different types of trials were presented in a pseudo-random order. In both phases the inter-trial interval was random, ranging from 3 to 7 s. After the second sequence of training trials, cues X and Y were presented in two test trials (counterbalanced for order) in which participants were given no feedback. More responding at test to cue X (whose associated cue, A, had already been paired with Outcome1 in Phase 1) than to cue Y (whose associated cue, B, had never been paired with Outcome1 before compound training) was taken as indicative of augmentation.

### 3. Results

As is usually done in this type of experiments, and in order to assure that participants were paying attention to the experimental task, two data selection criteria were used. First, we removed from the sample the data from participants who responded less on the last A–Outcome1 trial than in the last C–Outcome2 trial of Phase 1, which was indicative of poor or null learning of the target contingencies. Second, for the same reason we also removed the data from participants who responded less on the last AX–Outcome1 trial or BY–Outcome1 trial than in the last C–Outcome2 trial of Phase 2. Following these two criteria, data from 3 participants in the laboratory sample and 12 participants in the Internet sample were removed from the subsequent analyses. Inferential analyses confirmed that the proportion of participants who did not meet these selection criteria was larger in the Internet sample than in the laboratory one,  $\chi^2(1) = 4.05, p < .05$ . This suggests that Internet subjects are more likely to participate in the experiment without actually paying enough attention to the task or to the experimental contingencies.<sup>2</sup> The subsequent analyses were conducted with the remaining 55 laboratory participants and 61 Internet participants.

Mean responses at test to cues X and Y, both in the laboratory and the Internet samples are shown in Fig. 1. As can be seen, mean responses to X were consistently higher than mean responses to Y

both in the laboratory sample,  $t(54) = 2.54, p < .05$ , and in the Internet sample,  $t(60) = 2.33, p < .05$ . Thus, these results show a significant augmentation effect regardless of the location in which the experiment was performed. Visual inspection of Fig. 1 suggests that the size of the augmentation effect is comparable in both locations. Accordingly, a 2 (cue: X vs. Y)  $\times$  2 (location: Laboratory vs. Internet) analysis of variance (ANOVA) performed on the number of responses at test yielded a main effect of cue,  $F(1, 114) = 11.35, p < .005$ , but the main effect of Location and the cue  $\times$  Location interaction were far from statistical significance, both  $F_s(1, 114) < 1$ .

In spite of this lack of differences between the results observed in the laboratory and Internet samples, it is still possible that the highly variable dependent measure used in our analyses (the absolute number of responses at test) is somehow masking latent differences that could arise with more fine-grained measures of learning. The following analyses were conducted with two alternative dependent variables that aimed at reducing the impact of between-subject variability in responding.

The dependent variable R/A16 was computed by dividing the absolute level of responses to X and Y at test by the number of responses given by each participant in the last A–Outcome1 trial in Phase 1. Given that by the end of Phase 1 participants were responding at a relatively high and stable rate, these responses can be taken as a good baseline that can be used as a reference point on which to assess the number of responses at test. This dependent variable had already been analyzed in previous demonstrations of augmentation (Vadillo & Matute, 2010). The other dependent variable, R/Mean was computed by dividing the absolute level of responses to X and Y at test by the mean number of responses given during all training trials with Outcome1. As shown in Fig. 2 the pattern of results observed with both of these dependent variables closely mirrors those reported in Fig. 1. Paired-samples *t* tests conducted on the R/A16 measure confirm that the augmentation effect was significant in the laboratory,  $t(54) = 2.46, p < .05$ , and on the Internet,  $t(60) = 2.40, p < .05$ . The same analyses conducted on the R/Mean measure also yielded significant augmentation effects in the laboratory,  $t(54) = 2.52, p < .05$ , and on the Internet,  $t(60) = 2.69, p < .01$ .

Fig. 3 depicts the effect size of the augmentation effect with each of the previous dependent variables in both locations. As can be seen, overall, the effect size of augmentation tended to be somewhat larger in the laboratory than in the Internet condition. Although all the dependent measures yielded similar effect sizes in the laboratory, in the Internet sample the R/Mean measure yielded better results than the other two dependent variables, especially when compared to the R/A16 measure.

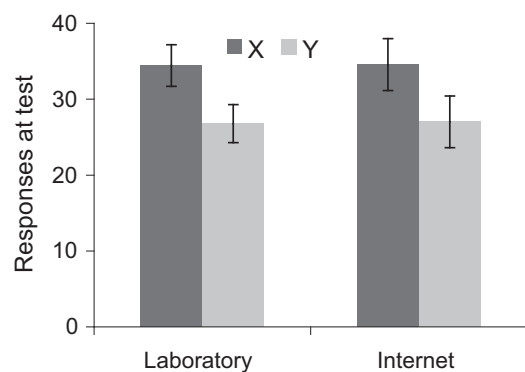


Fig. 1. Mean absolute number of responses to cues X and Y at test for participants in the Laboratory condition and in the Internet condition. Error bars denote standard errors of the means.

<sup>2</sup> This finding might seem at first glance contradictory with previous research showing that volunteer subjects tend to be more intelligent and better educated than non-volunteers (Callahan, Hojat, & Gonnella, 2007; Rosenthal & Rosnow, 1975). Note, however, that our laboratory participants were also volunteers (they did not participate in exchange for course credit) and that our experimental task is relatively simple, so that differences in general intelligence or education are unlikely to have an appreciable impact on the results.

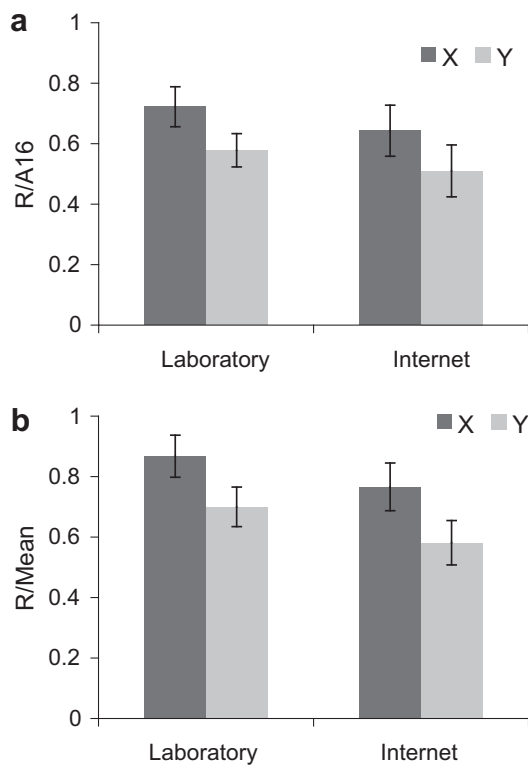


Fig. 2. Mean number of responses to cues X and Y at test measured by means of the R/A16 and R/Mean indexes (top and bottom panels, respectively). Error bars denote standard errors of the means.

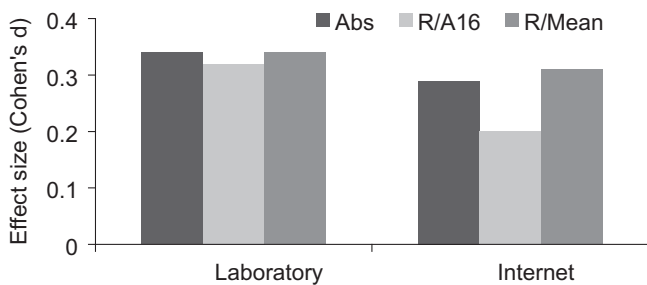


Fig. 3. Effect size of the augmentation effect observed in the laboratory and in the Internet conditions as measured with the absolute, R/A16, and R/Mean indexes.

#### 4. Discussion

The present experiment provides strong support for the claim that Internet-based research methods can be successfully used in the area of associative learning, as it shows that not only common and well-known effects, but also relatively specific and unexplored phenomena, can be replicated on the Internet. Traditionally, web-based research has been criticized because of the lack of experimental control over the conditions in which the experiment is conducted. If this lack of control had a significant effect on associative learning experiments, one would expect that learning phenomena that are only observed in very specific conditions would vanish, or at least would be dramatically reduced, when the experiment is conducted over the Internet. Therefore, the fact that we observed comparable augmentation effects in both conditions strongly suggests that the lack of experimental control associated to Internet-based research methods does not undermine the results of experiments conducted within this particular paradigm.

The analysis of the number of participants removed from the sample by virtue of the data selection criteria showed that a significantly higher proportion of participants failed to meet one or more criteria in the Internet sample than in the laboratory one. This suggests that a higher proportion of participants performing the experiment over the Internet paid little attention to the experimental contingencies. In light of this, it seems especially important to use carefully chosen data selection criteria before conducting an experiment over the Internet. Additionally, it would be advisable to conduct the experiments over the Internet with relatively large numbers of participants, so that the impact of the data from volunteers not paying attention can be diminished.

This experiment also suggests that in spite of its being relatively unknown in the literature, the augmentation effect is a solid result: augmentation was found both in a standard laboratory experiment and in an Internet-based study. The effect sizes depicted in Fig. 3 suggest that, as could be expected, the effect might be somewhat larger in the laboratory sample than in the Internet sample. However, statistical analyses failed to show any significant effect of Location or a Location  $\times$  cue interaction. Moreover, augmentation was significant also when alternative measures of responding at test were considered, suggesting that the effect is robust. Given that the most popular theories of associative learning are unable to account for augmentation (Dickinson & Burke, 1996; Rescorla & Wagner, 1972; Van Hamme & Wasserman, 1994), the reliability of this effect has important implications for the future theoretical development of this research area.

Before concluding, we would like to remark a number of limitations of the present study that should be considered in future work. First, unlike other experiments conducted on the Internet, our experiment included no measure of the impact of multiple data submissions. Although extant evidence suggests that this methodological problem has little impact on data (Reips, 2002), the role it might play in the specific case of associative learning studies remains unexplored. Second, following the standard procedures and analyses used in associative learning research, we did not collect socio-demographic data from participants, as it is usually assumed that these variables have no influence over such basic learning processes. However, these variables could be useful to predict other outcomes such as, for example, the failure or success to meet the data selection criteria. Finally, augmentation in human contingency learning has been observed only in a limited set of experimental tasks (Beesley & Shanks, submitted for publication; Mitchell et al., 2005; Vadillo & Matute, 2010). In order to better assess the reliability of the effect it would be necessary to prove not only that it can be observed under less controlled conditions (as shown by the present study), but also in completely different experimental settings.

In spite of these shortcomings, the present study is an important contribution for researchers interested in conducting learning experiments over the Internet and for scholars involved in the development of e-Learning systems. Together with previous studies (e.g., Matute et al., 2007; Vadillo & Matute, 2009; Vadillo et al., 2006), the present experiment confirms that all the evidence on human associative learning gathered during the last decades can be generalizable to Internet settings. This, in turn, suggests that current attempts to develop efficient and evidence-based e-Learning systems can benefit from the extensive research on associative learning conducted from the 80s on (for a recent review, see Shanks, 2010). Moreover, on the basis of this vast literature, it is possible to make a large number of predictions that can be tested over the Internet as a means to validate e-Learning techniques.

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