Outcome predictability and learned helplessness:

Through the lens of motivation

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Marburg an der Lahn, 10. August 2021

Genisius Hartanto

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Summary

Learning bias has been prominently studied in the past few decades. The relationship between the *cue* and *outcome* in learning, and the nature of their properties have been observed to have an impact on future learning. One example is the *outcome predictability effect*. Outcome predictability effects describe better learning about outcomes with a history of greater predictability in a similar but unrelated task compared to outcomes with a history of unpredictability. It was first described in Griffiths et al. (2015) using an allergy task. Despite the prominent observation in various studies, questions about how this effect could be brought about remain open. One of the possible hypotheses states that the outcome predictability effect is driven by a change of motivation. This hypothesis puts the outcome predictability effect to a similar category as the *learned helplessness effect*, which is also a certain type of learning bias using an instrumental learning paradigm. The present thesis aims to investigate the connection between outcome predictability effect and motivation, and how it is related to learned helplessness. Three studies are presented in this thesis. Study I investigated whether learning about unpredictability decreases outcome-specific motivation to learn. A modified version of the allergy task involving an active learning paradigm was used as a tool to measure participants' motivation to learn about a certain outcome. Study II also utilized the allergy task to investigate the connection between outcome predictability and motivation. Specifically, Study II investigated whether manipulating extrinsic rewards for a correct prediction could affect subsequent learning and whether it counteract or diminish the outcome predictability effect. Study III investigated this hypothesis in instrumental learning, expecting to find both learned helplessness and outcome predictability effects in the same experiment. We created a new computer-based task in which the participants had to stop several tones.

The results from Study I confirmed the hypothesis that outcome unpredictability indeed decreased the motivation to learn about that specific outcome in a new situation. Furthermore, the effect of extrinsic rewards indeed affects subsequent learning. Both the results from Study I and II showed the relationship between outcome predictability effect and motivation. However, this reward effect also appeared to have a significant impact on the outcome predictability effect itself. Using the instrumental task in Study III, we indeed observed a learning bias in a new situation. Implications of the present thesis to learning and motivation, as well as clinical implications, are discussed.

Zusammenfassung

Verzerrungen in Lernprozessen wurden in den letzten Jahrzehnten ausgiebig untersucht. Es wurde beobachtet, dass sowohl die Beziehung zwischen dem *Cue* und dem *Outcome* als auch ihre spezifischen Eigenschaften Einfluss auf zukünftiges Lernen nehmen. Ein Beispiel hierfür ist der *Outcome Predictability Effect.* Outcome Predictability Effekte beschreiben einen Lernvorteil für Outcomes, die in vorherigen ähnlichen aber nicht verwandten Aufgaben eine höhere Vorhersagbarkeit besitzen, im Vergleich zu Outcomes, die hier bisher nicht vorhersagbar waren. Dieser Effekt wurde erstmals von Griffiths et al. (2015) mittels einer Allergieaufgabe beschrieben. Obwohl der Outcome Predictability Effekt in vielen Studien repliziert wurde, ist immer noch unklar, wie er zustande kommt. Eine mögliche Hypothese besagt, dass hinter dem Outcome Predictability Effekt eine Veränderung in der Motivation liegt. Diese Hypothese ordnet dem Outcome Predictability Effekt einer ähnlichen Kategorie wie dem *Erlernte Hilfslosigkeit Effekt* zu, der ebenfalls eine bestimmte Art von Lernverzerrung mit Hilfe des Instrumentellen Lernparadigmas darstellt.

Die vorliegende Arbeit zielt darauf ab, den Zusammenhang zwischen dem Outcome Predictability Effekt und der Motivation zu untersuchen, und wie dieser mit der erlernten Hilflosigkeit zusammenhängt. Drei Studien werden vorgestellt. In Studie I wurde untersucht, ob das Erlernen von Unvorhersagbarkeit die ergebnisspezifische Lernmotivation verringert. Eine modifizierte Version der Allergieaufgabe mit einem aktiven Lernparadigma wurde als Instrument zur Messung der Motivation verwendet, über einen bestimmten Outcome zu lernen. In Studie II wurde ebenfalls die Allergieaufgabe verwendet, um den Zusammenhang zwischen Vorhersagbarkeit und Motivation zu untersuchen. Insbesondere wurde in Studie II untersucht, ob die Manipulation extrinsischer Belohnung für eine korrekte Vorhersage das anschließende Lernen beeinflusst und ob dies dem Outcome Predictability Effekt entgegenwirkt oder abschwächt. Studie III untersucht diese Hypothese in Bezug auf instrumentelles Lernen, in der

Erwartung, sowohl Erlernte Hilfslosigkeit Effekte als auch Outcome Predictability Effekte im Experiment zu finden. Wir erstellten eine neue computerbasierte Aufgabe, bei der die Versuchspersonen mehrere Töne anhalten mussten.

Die Ergebnisse aus Studie I bestätigen die Hypothese, dass Nicht-Vorhersagbarkeit des Outcomes in der Tat die Motivation verringert in einer neuen Situation über dieses spezifische Ergebnis zu lernen. Darüber hinaus beeinflusst der Effekt von extrinsischen Belohnungen tatsächlich das spätere Lernen. Sowohl die Ergebnisse aus Studie I als auch aus Studie II zeigen den Zusammenhang zwischen dem Outcome Predictability Effekt und der Motivation. Allerdings scheint dieser Belohnungseffekt auch einen signifikanten Einfluss auf den Outcome Predictability Effekt selbst zu haben. In der instrumentellen Aufgabe in Studie III, beobachteten wir tatsächlich eine Lernverzerrung in einer neuen Situation. Implikationen der vorliegenden Arbeit auf Lernen und Motivation sowie klinische Implikationen werden diskutiert.

Proposed Manuscripts

I. Hartanto, G., Livesey, E., Griffiths, O., Lachnit, H., & Thorwart, A. (2021). Outcome unpredictability affects outcome-specific motivation to learn. *Psychonomic Bulletin & Review*. https://doi.org/10.3758/s13423-021-01932-x

II. Thorwart, A., Hartanto, G., Lachnit, H., Griffiths, O., Livesey, E. (2021). Effects of Prior Outcome Reward and Predictability on Subsequent Learning. *Learning & Behavior, under review*

III. Hartanto, G., Thorwart, A. (2021). The influence of outcome unpredictability and uncontrollability on subsequent learning in an instrumental task. *Learning and Motivation, under review*

Introduction

Learning is a never-ending process throughout one's lifespan. It refers to a change of behavior after being exposed to stimuli that have been encountered in the past. A little boy, for instance, would not understand the point of waiting for the traffic light until he learns that green means "go" and red means "no-go". After learning, his behavior would change when he stands by a traffic light: to stop on the red light and to go on the green. Such ability to learn as an organism is one of the most basic processes that are necessary for survival. Humans and non-human animals have evolved this capability because knowledge about such relationships allows them to predict (and thereby control) both appetitive and aversive consequences of other events or their behaviors. Many of these behaviors rely on the association of two events. One event, a *cue*, that precedes another, an *outcome*, allows one to make the prediction and then change their behavior accordingly. For instance, someone learned that eating shrimp (*cue*) could make them suffer from a skin rash as an allergy reaction (*outcome*). Then, they will be able to predict the allergy reaction after eating shrimps and avoid eating them in the future. However, the relationship between a cue and an outcome is not always that perfect in nature (see e.g., Mackintosh, 1975; Rescorla & Wagner, 1972). Using the example of allergic reactions, one may experience few different allergic reactions by eating the same food. Eating peanuts, for example, could sometimes cause one to suffer from stomach bloating and some other times stomach cramps. Therefore, the patient could not perfectly predict the exact allergic reaction that would occur after eating peanuts. Both stomach bloating and stomach cramps would be referred to as unpredictable outcomes[1], whereas the skin rash would be referred to as a predictable outcome. Equivalently, shrimps and peanuts would be referred to as predictive and unpredictive cues, respectively.

[1] For simplicity's sake, we refer to "unpredictable outcomes" or "unpredictability", even when the outcomes are not completely unpredictable but only less predictable compared to the fully predictable outcomes.

Learning bias due to predictiveness and predictability

Both predictiveness of the cue and predictability of an outcome could affect future learning. Previous studies proved that the changes of behavior on learning in a new situation could be affected by the properties of the cues (Le Pelley & McLaren, 2003; Lochmann & Wills, 2003). One common task that was used to investigate this effect was a two-phase allergy task with human participants. In this task, participants assumed their role as an allergist and try to predict the allergy reaction (outcome) a fictitious patient would have after eating some foods (cue). During Phase 1, participants were exposed to different cues with two different properties: predictive cues, which perfectly predicted the outcomes, and unpredictive cues, which did not reliably predict the outcomes. In Phase 2, a new set of outcomes were introduced while the cues from Phase 1 remain the same. In addition, all cues were fully predictive in Phase 2. This means, participants should not carry over the information about the cues from the previous phase to the next phase, since the relationship between the cues and the outcomes in Phase 1 was irrelevant in Phase 2. Yet, the participants learned better about the previously predictive cues than the previously unpredictive cues. This was then referred to as the learned predictiveness effect.

The question is now whether the same principle would apply to the outcome. If learning can be biased by the nature of the cue, can it also be biased by the nature of the outcome? This was firstly investigated by Griffiths et al. (2015) using the allergy task. The task was modified to investigate the effect of the predictability of the outcomes, similar to the one used to investigate learned predictiveness. Here, in Phase 1, some outcomes could be perfectly predicted by the cues, and some outcomes could not be predicted by the cues. In Phase 2, a new set of cues were introduced, but the outcomes remained the same and they were fully predictable. Even though the association between the new cues and the outcomes was completely irrelevant to the ones in Phase 1, participants learned better about the previously predictable outcome than the previously unpredictable outcome. This biased learning towards the previously predictable outcome was then referred to as the *outcome predictability effect*.

These two different effects originating from the different properties of the stimuli have been investigated further by Thorwart et al. (2017). They hypothesized that both learned predictiveness and outcome predictability effects may be two manifestations of the same phenomenon. Four experiments manipulating the relationships and functional properties of the stimuli were conducted. Even though the authors observed the outcome predictability effect like the one observed in Griffiths et al. (2015), no effect was found when the role and function of the stimuli were switched. This study showed that learned predictiveness and outcome predictability effects are rather independent.

This thesis focuses on the outcome predictability effect and how it can be brought about. To this date, this effect has been investigated using four different paradigms (Griffiths et al., 2018, 2015; Liu et al., 2020; Quigley et al., 2017; Thorwart et al., 2017). A meta-analysis proved that the outcome predictability effect was robust across multiple studies (Griffiths et al., 2019). However, questions about the nature of the outcome predictability effect remain open.

Motivational accounts of outcome predictability effect

One possible explanation of the mechanism of outcome predictability effect is that outcome predictability causes motivational changes in subsequent learning. Hall and Rodríguez (2017) defined an outcome as an event of motivational significance. This motivational significance can be seen from a practical point-of-view of the outcome predictability task. In the allergy task, for instance, the outcomes are highly relevant and significant for the participants because they were told explicitly to predict Mr. X’s allergy reactions as their main task. Predicting the outcome correctly would be their main motivation for learning. Failing to correctly predict the outcome then leads to demotivation for learning, which ultimately causes the subsequent learning bias.

Expectancy-value theories (Atkinson, 1957; Eccles & Wigfield, 2002) provided a further explanation on this. They explained that motivation was based on the individual's expectancies of how probable a result can be achieved and the value that the individual places on the desired result. These expectancies are influenced by task-specific beliefs, such as perceptions of the controllability of the task. From the example of the allergy task, the knowledge and perception of unpredictability over an outcome may form an expectancy that the prediction will not create the desired result, and therefore, may decrease one's motivation for further engagement in future tasks and hence the learning bias. The values, then, can be based on the individual's intrinsic appraisal of being correct in the task. The more value the individual gets from being correct, the more likely the subsequent performance to be better. From this perspective, the outcome predictability effect might come from the interplay between the two components in this theory: expectancy and value.

Outcome predictability and learned helplessness

This idea that outcome predictability could have a strong motivational effect on subsequent learning shows a remarkable connection with the learned helplessness effect. The learned helplessness effect was described as subsequent learning bias due to the exposure to uncontrollable outcomes in the previous learning phase (Maier & Seligman, 2016; Seligman, 1972). An outcome in learned helplessness refers to a stimulus that can or cannot be altered by a response of the learner. In a procedure that involves stopping different tones, for example, a stoppable tone makes the tone a controllable outcome, while an unstoppable tone makes the tone an uncontrollable outcome.

Few similarities connect the outcome predictability effect to the learned helplessness effect. Firstly, both effects involve learning bias that is observed in subsequent learning and behavior. Despite the difference in the generalizability of these two effects – learned helplessness effect appears to transfer to vastly different tasks that involve new learning materials, while the outcome predictability effect involves learning about the same outcome in two different situations – in both cases, initial learning results in a relative deficit in later learning and performance. Secondly, outcome predictability is a major factor in determining both effects. Using the tone stopping task as an example, when participants can successfully stop a tone, then it is also naturally predictable as the tone can be predictably stopped. On the other hand, uncontrollable tones are also unpredictable as the stopping of the tones is controlled by some hidden processes, like a computer algorithm to stop the tone after reaching a certain duration, for instance. Some studies have investigated the role of both predictability and controllability in the learned helplessness effect. Burger and Arkin (1980), for instance, investigated the roles of perceived predictability and perceived controllability of the outcome by using a "noise pollution" experiment and manipulating the perceived control and noise exposure duration. They showed that both uncontrollability and unpredictability of the outcome must present for a learned helplessness effect to occur, which was then interpreted as essential for the motivational change in these tasks. Lastly, both effects have the element of failure in the first situation of their tasks. In the anagram task by Hiroto and Seligman (1975), for instance, participants "failed" to solve the anagrams in the first situation. Similarly, participants "fail" to make correct predictions of an outcome in the first situation of outcome predictability paradigms.

Even though these two effects are similar as described above, they still have some procedural differences. Firstly, outcome predictability tasks are based on classical conditioning (cue-outcome relationships). Almost all learned helplessness paradigms, from electric shock tasks (Houston, 1972), tone-stopping tasks (Burger & Arkin, 1980; Hiroto, 1974; Tiggemann & Winefield, 1978, 1987), anagram tasks (Gatchel et al., 1977; Miller & Seligman, 1975), and even across tasks (Hiroto & Seligman, 1975) used instrumental conditioning (reaction-outcome relationships). Secondly, the outcome predictability effect so far has been investigated with within-subject designs only. Surprisingly, little is known about the learned helplessness effect in within-subject designs, most likely due to the methodological difficulties in realizing a design with within-subjects yoking of the exposure of the controllable and uncontrollable outcomes (see, for instance, Winefield, 1982). Due to this use of different experimental designs, all outcome predictability experiments have shown biased learning specific only to certain outcomes as they learn about those outcomes that participants had experienced as unpredictable, as compared to learning about those outcomes that they had experienced as predictable. The learned helplessness effect, on the other hand, is known to generalize. Hiroto and Seligman (1975), for example, investigated the induction of the learned helplessness effect using both, a tone-stopping task, and an anagram task in two learning phases of the same experiment. They showed that the learned helplessness effect could even transfer from one learning situation to another. Griffiths et al. (2019) discussed these differences between the two effects, concluding that outcome predictability could be a "qualitative distinct sub-process of the more widely studied and prototypical form of learned helplessness effect." (p. 6)

Taken together, outcome predictability and the learned helplessness effect are related to some degree. We would argue that based on the similarities with the learned helplessness effect, the change of motivation is the underlying principle of the learning bias in outcome predictability. This thesis aimed to investigate if the outcome predictability effect is brought about by a change of motivation and if changes to external attributes associated with the outcomes could affect motivation. This thesis also further investigated the relationship between outcome predictability and learned helplessness effects using an instrumental task.

Outline of Present Thesis

This thesis consists of one manuscript that was published in *Psychonomic Bulletin and Review*, and two manuscripts that were submitted for peer-review. The first study investigated the effect of outcome unpredictability on motivation to learn about a specific outcome. The second study investigated the effect of extrinsic reward and outcome predictability on subsequent learning and motivation. The third study investigated both the learned helplessness effect and outcome predictability effect using an instrumental task. The following sections provide summaries of the studies.

Study I: Outcome unpredictability affects outcome-specific motivation to learn

We conducted Study I to investigate if the outcome predictability effect was related to motivation to learn about a specific outcome. We designed an experiment using a modified version of the two-phase allergy task. In the first phase, participants had to learn about different cue-outcome contingencies by choosing which allergy reactions (skin-related reactions or stomach-related reactions) an imaginary patient would suffer from after eating certain vegetables. One outcome category was predictable, and the other was unpredictable. In the second phase, we implemented an active learning method. Active learning was defined by Kruschke (2008) as a procedure where participants can actively seek information. In our case, participants should choose at the beginning of each trial about which outcome category they want to learn. Their choices, therefore, represented their motivation to learn about a specific outcome. We hypothesized that if the unpredictability of an outcome in the first phase leads to a motivational deficit, participants would be more eager to learn about the previously predictable outcomes in the second phase.

During the first phase, participants learned better to predict the allergic reactions (the outcomes) from the predictable category than the unpredictable outcome category. Then, as we expected, at the beginning of the second phase, participants' choice of learning was biased significantly towards the previously predictable category. This showed that they were more motivated to learn about one specific outcome category which had previously been learned as predictable. This change in participants' motivation could be explained as the change of expectancy. By the end of the first phase, participants had the expectancy to successfully predict the predictable outcomes, but not the unpredictable ones. As elaborated above, expectancy-value theory predicted that expectancy affects the motivation to further engage in the task. Learning about the unpredictable outcome affected their expectancy to successfully predict that outcome and therefore also changed their motivation to learn about it in the second phase.

Interestingly, after choosing to learn about the predictable outcome, their learning shifted towards the previously unpredictable category. This behavior supported the notion that participants' choice was based on their motivation to learn, instead of just making the correct prediction in each trial. Such behavior could also relate to curiosity, the trait, or a state of a person, leading to a general desire to learn about the world (see Marvin et al., 2020).

However, the outcome predictability effect was not visible in Study 1. One simple explanation would be that the choices of the outcome category in the second phase were easier compared to the previous studies involving similar tasks (Griffiths et al., 2015; Thorwart et al., 2017). In our experiment, participants were only exposed to one outcome category in each trial in the second phase, which then seemed overall easier for the participants to learn about the cue-outcome relationship. Moreover, participants had to make an overt choice which might increase their overall motivation to learn about the chosen category. Thus, any possible differences in learning about the two outcome categories could not be visible anymore by the end of the second phase.

Study II: Effect of Prior Outcome Reward and Predictability on Subsequent Learning

As aforementioned, motivation to learn is not only based on the expectancies but also based on the value that individuals assign to the desired result. Like Study I, Study II was performed to investigate motivation in the learning bias caused by outcome predictability, by using an extrinsic reward for correct predictions as an explicit assignment of value to the outcomes and thereby manipulated their motivation to learn using the point/incentive rewards. Study II used an allergy task, similar to the task described in Griffiths et al. (2015) and Thorwart et al. (2017). Two experiments were conducted on this matter.

Experiment 1 aimed to test whether the rewards that the participants received after making correct predictions would affect learning about that outcome in the next phase. Participants experienced two outcome categories in the first phase. After making correct predictions, one outcome category would reward them with a higher point (value) than the other. In the second phase, no reward was given to the participants. Outcome predictability was not manipulated in this experiment; all outcomes in both phases were equally predictable. The results showed that participants had higher accuracy at the beginning of the second phase for the outcome category that had been rewarded with higher reward in the first phase than the lower reward category, proving that prior reward influenced future learning. The differing prediction accuracies in the second phase indicated that participants were motivated by the goal of making correct predictions in the predictive learning task. It also indicated that one could bias their motivation and learning in subsequent tasks by manipulating the attributes of the learning goal. According to expectancy-value theories, the two attributes of expectancy and value are connected in a multiplicative manner so that their effects will amplify or diminish each other. An increase in the reward for unpredictable outcomes, for instance, ought to offset any deteriorating effects of unpredictability on learning and performance. Similarly, a reduced reward for the predictable outcomes ought to diminish any advantage due to the high predictability. Manipulating both predictability and reward, however, may intensify the observable differences between the outcomes.

Therefore, we conducted Experiment 2 to test these hypotheses by manipulating both the rewards and predictability using the same allergy task. Here, participants were separated into two different groups: Group Same (high reward for correctly predicting the predictable outcome, low reward for correctly predicting the unpredictable outcome) and Group Different (high reward for correctly predicting the unpredictable outcome, low reward for correctly predicting the predictable outcome). We expected that in Group Same, participants would be motivated to learn about the outcome category, which was both predictable and highly rewarded, and demotivated to learn about the other category, which was unpredictable and lowly rewarded. In Group Different, we expected that the increase in rewards should counteract any loss in motivation due to the unpredictability and therefore lead to a diminished effect of prior predictability in the second phase. Even though the participants correctly identified the predictability and the associated reward for each category during the manipulation check, participants did not show any significant learning bias in the second phase. Nevertheless, the pattern of the results was in line with the prediction that participants in Group Same showed a greater difference of learning accuracy between the outcome categories than the participants in Group Different. Furthermore, we found an effect of predictability on response preferences, which were independent of the rewards. Our results supported the idea that making correct predictions for an outcome is one of the motivations in simple predictive learning tasks, as the likelihood and the reward associated with correct predictions affect behavior in future situations.

Study III: The influence of outcome unpredictability and uncontrollability on subsequent learning in an instrumental task

Study I proved that learning about unpredictable outcomes caused demotivation in subsequent learning. As described above, such demotivation and subsequent learning bias have been observed in the learned helplessness effect (Maier & Seligman, 1976, 2016; M. E. Seligman & Maier, 1967). The question was whether the outcome predictability effect was a different manifestation of learned helplessness. If this was true, an outcome-specific effect of uncontrollability might also be observable in a within-subject design using an instrumental task, in which the learned helplessness effect has been found using between-subject designs. In Study III, we designed a newly developed computer-based task, which was inspired by the tone-stopping task described in Tiggemann and Winefield (1987). Participants had to find a way to stop the tone using the virtual buttons presented on the screen. We manipulated the controllability of the tones so that some tones were fully stoppable, some were partially stoppable, and some were unstoppable. Two experiments were conducted in this study.

Experiment 1 converged the procedures of outcome predictability effect and learned helplessness effect. Participants were separated into three different groups: the controllable group (C Group), the uncontrollable group (U Group), and the within-subject group (WS Group). In the Training Phase, participants in the C Group experienced three completely stoppable tones, while participants in the U Group experienced completely unstoppable tones. Both the trial orders and tone durations of participants in the U Group were yoked to their counterparts in the C Group. Participants in the WS Group experienced one stoppable tone (CP Tone), one partially stoppable tone (CUP Tone), and one completely unstoppable tone (UCUP Tone). The CUP tone was stoppable by pressing a certain button, which was randomly determined for each trial. Participants therefore could control the tone, but they could not predict by which button they could do so in a certain trial. The durations of the CUP and UCUP tones were yoked between blocks to the CP tone duration in the previous block. In the Test Phase, all participants in all groups were presented with a new set of eight buttons and each tone was stoppable by pressing one of them. We introduced a stoppable new tone in the Test Phase (Control Tone) to evaluate if any learning bias would affect learning about this tone as well. We expected to find a general learned helplessness effect between C Group and U Group, where U Group would take longer to learn to stop the previously exposed tones in the Test Phase. In the WS Group, if learned helplessness effects could become outcome specific, we expected participants to take longer to learn to stop the previously uncontrollable tone (UCUP) than the previously stoppable tone (CP). Furthermore, we expected the performance for the CUP tone to be worse than the performance of the CP tone, but better than the UCUP tone.

Despite participants' correct perception of the controllability of the tones in the manipulation check, we did not find any significant difference in learning performance between the C Group and U Group, as the learned helplessness would manifest. Also, in the WS Group, we did not see any differences in participants' learning about the different tones. One reason that could explain this is participants' perception of predictability. Participants in the U Group, for instance, might have perceived the tones as rather predictable due to the consistent behavior of their counterparts in the C Group. Similarly, participants in the WS Group might have perceived the UCUP tones as rather predictable due to the consistent learning about the CP Tone. Therefore, we conducted Experiment 2 to test this hypothesis between the C and U groups by increasing both the randomness and range of the tone durations for the uncontrollable tones in the Training Phase and thereby focusing only on the between-subject learning bias.

Participants in Experiment 2 were separated into three different groups: a controllable group (C Group), an uncontrollable group with a yoked mean (U-YM Group), and an uncontrollable group with high variance (U-HV Group). In the Training Phase, participants in the C Group experienced three completely stoppable tones, while participants from both the U-

YM Group and U-HV Group experienced three completely unstoppable tones. The tone durations in Training Phase for the U-YM Group were taken from a uniform distribution around the overall mean of all participants in the C Group with a 2000 millisecond range. For the U-HV Group, the tone durations were not yoked. Instead, they were randomly generated from a uniform distribution between 500 and 5000 milliseconds throughout the Training Phase, which made the overall exposure higher than the other groups.

The results from Experiment 2 showed that manipulating controllability and predictability with enough variance on the exposure could bias subsequent learning, similar to the learned helplessness effect. This result confirmed that participants from Experiment 1 experienced the uncontrollable tones as rather predictable during the Training Phase and could have been the reason for the absence of learning bias in the first experiment. This is also in line with the conclusion of Burger and Arkin (1980). Furthermore, participants indeed showed better learning towards the control tone in the Test Phase. However, this performance did not neutralize the effect of unpredictability and uncontrollability as the groups still differed. This supports the global effect of unpredictability and uncontrollability in instrumental learning design.

Contribution of Present Thesis

This thesis provided insight on one of many facets of the outcome predictability effect, particularly from the motivational point of view using three studies. Both Study I and Study II investigated the relationship between the outcome predictability effect and motivation. Study I showed a causal relationship between outcome predictability and outcome-specific motivation to learn. Study II showed that participants were motivated to make correct predictions in predictive learning tasks. Based on the similarities between outcome predictability and learned helplessness effects in the motivational perspective, Study III investigated the relationship between these two effects using an instrumental task.

Study I revealed that motivation played a crucial role in the outcome predictability effect. Participants' choice to learn about the predictable outcome category first showed that their motivation was biased by the manipulation of predictability in the first phase. Furthermore, their decision to learn about the unpredictable category by the end of the second phase showed their curiosity and motivation to learn about the unpredictable outcome category, instead of their desire to be correct. Study I, therefore, confirmed the hypothesis outcome unpredictability affects motivation to learn. The motivational aspect of outcome predictability was also investigated in Study II using extrinsic rewards. The results supported the idea that people in such predictive learning tasks are motivated by making correct predictions. Also, both prior reward and prior predictability of correct predictions influenced people's subsequent learning performance. Taken together from both studies, both the motivation to learn and motivation to be correct were observed to play crucial roles in driving subsequent learning. Motivation to learn causes participants to behave curiously and acquire information when they have the chance (Marvin et al., 2020), while motivation to be correct allows them to be more eager to get higher rewards. In short, learning bias in these tasks stemmed generally from a change in motivation.

With the relationship between outcome predictability and learned helplessness effects, Study III proved that subsequent learning could be influenced by learning about both uncontrollability and unpredictability in an instrumental task. Although the connection between outcome predictability and learned helplessness effects was not revealed in Study III, the effect we found from this study was remarkably similar to the learned helplessness effect. However, we still could not say that this replicated the learned helplessness effect for two reasons. One, unlike the original studies, our yoking was not performed trial-by-trial, and two, our study design was not a triadic group design: we did not have a control group (see, e.g., Hiroto & Seligman, 1975). Nevertheless, the observed learning bias confirmed the effect of uncontrollability and unpredictability on subsequent learning.

The present thesis gave insight not only on predictive and causal learning but also shed some light on clinical applications. The change of motivation and learning bias after learning about unpredictable and uncontrollable outcomes relate closely to the depression model developed based on the learned helplessness effect (Alloy & Abramson, 1982; Depue & Monroe, 1978; Forgeard et al., 2011; Gatchel et al., 1977; Miller & Seligman, 1975, 1976). Mental health disorders like major depressive disorder and post-traumatic stress disorder have indeed been described using learned helplessness as a model (Abramson et al., 1989; Alloy et al., 1992). Since our results suggested that demotivation could also be affected by learning about an outcome’s unpredictability, they could provide a certain basic mechanism that would contribute to giving a better understanding and perhaps improving therapeutic approach on mental health disorders related to unpredictability such as anxiety disorders (Barlow, 2000; Grillon, 2002; Veltman et al., 1998). Although this thesis contributed in such ways as described above, further research on the outcome predictability effect, motivation, and its relationship with learned helplessness is still required. For instance, experiments investigating the generalizability versus specificity of the learned helplessness effect should be conducted to define the relationship between the two effects.

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Appendix A: Curriculum Vitae

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GENISIUS HARTANTO

EDUCATION

Jul 2018 – Jul 2021
Doctoral degree: Dr. rer. nat. (Supervisor: Dr. Anna Thorwart)
Phillips-Universität Marburg
Focus: Associative learning, behavioral psychology

Oct 2015 – Oct 2017
Master of Science: M. Sc. (Elite Network Program)
Julius-Maximillians Universität Würzburg
Major: Translational Neuroscience (GPA: 2.2/1.0)
Focus: functional neuroimaging, nuclear medicine

Aug 2011 – Aug 2015
Bachelor of Engineering: S.T., B. Eng. (Double Degree)
Swiss German University, Tangerang, Indonesia, and Fachhochschule Südwestfalen, Soest
Major: Biomedical Engineering (GPA: 3.73/4.0)
Focus: biomedical instrumentation, programming, electronics

PROFESSIONAL EXPERIENCE

Jul 2018 – Jul 2021
Research Scientist
Fachbereich Psychologie, Philipps-Universität-Marburg
- Empirical and experimental development and analysis of scientific questions in the field of associative learning.
- Working in a multidisciplinary and international research group (i.e., student assistants, professors, PhD candidates, post-docs).

Feb – Aug 2017
Working Student under Prof. Dr. Dr. Ioannis Isaias
Neurologische Klinik und Poliklinik, Universitätsklinikum Würzburg
- Conducted functional neuroimaging (PET and MRI) analysis of patient data.
- Involved in clinical research on Parkinson's Disease.

Feb – Aug 2014
Research Project under Dr. Anna Popova
Institut für Toxikologie und Genetik, Karlsruher Institute für Technologie, KIT Campus Nord (Forschungszentrum)
Topic: "*Optimization of a novel system for ultra-high-throughput screening of stem cells using superhydrophilic microarrays.*"
- Experimented on the newly developed microarrays by culturing cell lines (e.g., HeLa, HEK293), in a wet lab.

PRACTICAL EXPERIENCE

Feb – Jul 2015
Bachelor's Thesis (Research) under Dr. Anto Satriyo Nugroho
Swiss German University, Tangerang, Indonesia
- Designed an electronic/integrated system for microscope automation.
- Developed a customized GUI for malaria detection automation software with QtCreator.

Jan – Feb 2013	**Voluntary Side Project: Instrumentation of an automated fermenter** *Swiss German University, Tangerang, Indonesia* • Developed a program using NI LabView to stabilize temperature of liquid inside a fermenter.
Oct – Nov 2012	**Bachelor Internship** *Medical device calibration division, PT Global Promedika Service, Jakarta, Indonesia* • Involved in on-site medical device calibration in hospitals and companies.
Sep – Oct 2012	**Bachelor Internship** *Radiology Division, and Anatomical Pathology Division, Dharmais National Cancer Hospital, Indonesia.* • Learned and observed PET contrast manufacture, medical imaging devices, and clinical lab tests.
Jul – Aug 2012	**Voluntary Side Project: Implementation of Digital sphygmomanometer with LED lights** *Swiss German University, Tangerang, Indonesia* • Designing, evaluating, and troubleshooting electrical circuits.

TRAININGS

Jul 2020	**“How to Design Scientific Figures” Workshop** *Philipps-Universität Marburg*
Sep 2020	**“Get that Job After Your Doctorate” Workshop** *Philipps-Universität Marburg*
Sep 2019	**Internet-based Data Collection and Analysis in Decision Making** *Universität Konstanz (Summer School)*
May 2017	**Statistical Parametric Mapping (SPM) Starter Course** *Medizinische Hochschule Hannover*
Jul 2013	**Short Management Training (Project Management)** *Healthcare Division PT. Siemens Indonesia*

COMPUTER SKILLS

Microsoft Office	Advanced
JavaScript & HTML	Advanced
Statistical Parametric Mapping (SPM)	Advanced
Arduino IDE	Advanced
IBM SPSS	Advanced
C/C++	Good
MATLAB	Good
Qt Creator	Good
Adobe Premiere Pro and Audition	Good
UNIX (Linux)	Good
R	Basic knowledge
NI LabView, GUI-Programming	Basic knowledge

LANGUAGE SKILLS

English	Expert
German	Advanced (Level: C1)
Indonesian	Mother tongue
Mandarin	Heritage speaker

Appendix B: REPRINTS

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BRIEF REPORT

Outcome unpredictability affects outcome-specific motivation to learn

Genisius Hartanto[1] · Evan Livesey[2] · Oren Griffiths[3] · Harald Lachnit[1] · Anna Thorwart[1]

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Abstract
Outcome predictability effects in associative learning paradigms describe better learning about outcomes with a history of greater predictability in a similar but unrelated task compared with outcomes with a history of unpredictability. Inspired by the similarities between this phenomenon and the effect of uncontrollability in learned helplessness paradigms, here, we investigate whether learning about unpredictability decreases outcome-specific motivation to learn. We used a modified version of the allergy task, in which participants first observe the foods eaten by a fictitious patient, followed by allergic reactions that he subsequently suffers, some of which are perfectly predictable and others unpredictable. We then implemented an active learning method in a second task in which participants could only learn about either the previously predictable or unpredictable outcomes on each trial. At the beginning of each trial, participants had to decide whether they wanted to learn about one outcome category or the other. Participants at the beginning of the second task chose to learn about the previously predictable outcomes first and to learn about the previously unpredictable outcomes in later trials. This showed that unpredictability affects future motivation to learn in other circumstances. Interestingly, we did not find any sign of outcome predictability effect at the end of the second phase, suggesting that participants compensate for biased outcome sampling when making overt choices in ways that they may not when learning about both outcome categories simultaneously.

Keywords Outcome predictability · Outcome-specific motivation · Active learning · Predictive learning · Learned helplessness

The outcome predictability (OP) effect refers to the tendency to learn better about an outcome that has a history of predictability than about an outcome with a history of unpredictability, even if both are encountered in new situations where all outcomes are predictable. For instance, take a commonly used causal learning task (the allergy task) in which the learner is presented with a fictitious patient, Mr. Y, suffering from food allergies. When Mr. Y eats shrimp, he always suffers from skin itchiness. The learner can then use eating shrimp as a cue to predict skin itchiness, a thereby predictable outcome. In contrast, Mr. Y eating peanuts sometimes results in stomach bloating and sometimes stomach cramps. This makes both stomach bloating and stomach cramps unpredictable outcomes. In a new situation, even if these allergic reactions are fully predictable, the learner would learn better to predict skin itchiness than stomach bloating or cramps.[1]

Four different predictive learning protocols have investigated the OP effect (Griffiths et al., 2015; Griffiths et al., 2018; Liu et al., 2020; Quigley et al., 2017; Thorwart et al., 2017), and a meta-analysis reported that the OP effect is significantly evident across these protocols (Griffiths et al., 2019). The OP effect was reported only recently and has been documented in relatively few studies to date. Naturally, questions about the characteristics and underlying mechanism of the OP effect remain. The current experiment investigated whether the OP effect is due to changes to outcome-specific motivation to learn by outcomes' prior predictability.

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[1] For simplicity's sake, we will refer to "unpredictable outcomes" or "unpredictability" even when the outcomes are not completely unpredictable, but only less predictable compared with the fully predictable outcomes.

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This hypothesis is based on the similarities between the OP effect and the learned helplessness (LH) effect (Maier & Seligman, 1976, 2016). The LH effect describes the tendency to learn better about an outcome that has a history of controllability than an outcome that has a history of uncontrollability, even if both outcomes are encountered in a new situation where all outcomes are controllable. The outcome in LH tasks refers to a stimulus that can or cannot be altered by a response of the learner. For example, an LH procedure in which a tone can be stopped by pressing a button makes the tone controllable, while a tone that cannot be stopped is uncontrollable. Several features of LH and the OP effect are similar. First, learning in an initial phase establishes a bias that is observed in subsequent learning and behavior. Although they differ in terms of generalizability—LH appears to transfer to very different tasks that involve new learning materials, whereas the OP effect involves learning about the same outcome in two different situations—in both cases, initial learning results in a relative deficit in later learning and performance. Second, outcome predictability is a major component of both manipulations. Using the previous example, when participants can successfully stop a tone, it is also naturally predictable as it can be predictably stopped. In contrast, uncontrollable tones are also unpredictable as the stopping of the tones in each trial is controlled by some hidden process. Some studies have investigated the role of both predictability and uncontrollability in the LH effect. Burger and Arkin (1980) investigated the roles of perceived predictability and perceived controllability by separating the two properties of the outcomes to some degree. Only participants who were exposed to both uncontrollable and unpredictable tones showed a sign of LH effect in a new situation. They, therefore, concluded that not only the perceived controllability but also perceived predictability is crucially involved in determining LH effects, thereby linking the LH effect directly to the outcome unpredictability in OP protocols. Third, both effects have the element of failure in the first of their tasks. In the anagram LH task by Hiroto and Seligman (1975), for example, participants "fail" to solve the anagrams in the first situation. Similarly, participants "fail" to make correct predictions of an outcome in the first situation of OP effect protocols.

Given the similarities, we argue that both the OP effect and the LH effect share an underlying principle: demotivation to learn as a result of exposure to unpredictability. According to accounts of the LH effect, the learning bias is mainly based on the changes to the motivation to learn (Burger & Cooper, 1979; Miller & Seligman, 1976). Expectancy-value theory (EVT) (Eccles & Wigfield, 2002) explains that motivation is based on the individual's expectancies of how probable a result can be achieved and the value that the individual places on the desired result. These expectancies are influenced by task-specific beliefs, such as perceptions of the controllability of the task. In LH tasks, the perception of uncontrollability over one outcome like an aversive tone will form an expectancy that the responses will not create the desired result of stopping the tone (Miller & Seligman, 1973), and this may decrease one's motivation for further engagement in future tasks involving similar outcomes and situations (Alloy & Abramson, 1982).

However, despite these links between controllability and predictability, there is relatively little known about the relationship between the unpredictability of a specific outcome and motivation to engage and learn about that particular outcome in OP tasks. In OP tasks, the perception of unpredictability will form an expectancy that predictive responses will not create the desired result of correct predictions, and this may decrease one's motivation for further engagement in future situations involving that particular outcome.

Based on this argument, we investigated the relationship between outcome-specific motivation and OP using an active learning method. Active learning refers to learning procedures in which learners can actively seek information (Kruschke, 2008). Kruschke (2008) described an example procedure that lets the participants choose at the beginning of each trial which cues would be more informative to learn about. Their choices, therefore, represent their motivation to learn about that specific cue. In our task, we were interested in measuring the motivation to learn about a specific outcome category instead. Therefore, we adapted the active learning procedure by having participants choose which specific outcome category they wanted to learn in each trial of the second learning situation. If the unpredictability of an outcome in the first situation leads to a motivational deficit, we expect that participants are more eager to learn first about the previously predictable outcomes in the second situation.

Methods

Design

The design of the experiment is summarized in Table 1. Our behavioral experiment used a modified version of the allergy task described by Griffiths et al. (2015). In this two-phase learning task, participants were shown either one or two vegetables or fruits (cues) and were told about the allergic reactions Mr. X suffered (outcomes) when he ate those foods. The first phase familiarized the participants with the two outcome categories: predictable (p) and unpredictable (u), represented as either skin-related or stomach-related allergic reactions. As shown in Table 1, Outcome p1 would always occur when cue Vegetable A was presented. Similarly, p2 would always occur when cue Vegetable B was presented. A third vegetable (X)

Table 1 Experimental design

Phase 1	Phase 2	Test
A → p1, u0	EY → p1 or u2	E?
B → p2, u0	FY → p2 or u1	F?
X → u1, p0	GY → p1 or u1	G?
X → u2, p0	HY → p2 or u2	H?
AX → p1, u1 AX → p1, u2		Y?
BX → p2, u1		
BX → p2, u2		

Note. Letters A–Y represent foods (A, B, and X: vegetables; E, F, G H, and Y: fruits), and the symbols [p0, p1, p2, u0, u1, u2] represent allergic reactions. The letters "p" and "u" represent the predictable category and the unpredictable category, respectively. For instance, if skin-related reactions are the predictable category, then p0 would refer to "no skin reaction," p1 to "skin swelling," and p2 to "skin itchiness." For the unpredictable outcome category, u0 would refer to "no stomach reaction," u1 to "stomach bloating," and u2 to "stomach cramps."

preceded unpredictable outcomes. For half of the trials, Outcome u1 would occur when cue X was presented, and the other half u2. In the second phase, a new set of cues (fruits) was introduced: E, F, G, and H, but the outcomes remained the same as Phase 1. Each cue in Phase 2 was predictive of one outcome in each category. Crucially, at the beginning of each trial in this second phase, and before participants saw which fruits Mr. X had eaten in this trial, participants had to choose which outcome category they would like to learn. If they chose, for example, skin reactions, they would only receive information about the skin-related reaction Mr. X suffered after eating one of the fruits. The same rule was applied for stomach-related reactions.

Participants

Twenty undergraduate students of the Philipps-Universität Marburg completed the experiment. The sample consisted of 17 identifying as female, two identifying as male, and one did not specify their gender. Age data were collected for 11 participants (the age of the remaining participants was lost due to technical problems). The age of the collected participants ranged from 18 to 30 years (M = 23.27, SD = 3.66). They were paid with money or received course credit.

Using G*Power (Faul et al., 2007), a sensitivity analysis (two-sided, $\alpha = .05$, power = 80%) for a one-way analysis of variance (ANOVA) of the choices in Phase 2 revealed a minimal detectable effect (MDE) of $f = .19$, an effect of medium size. (As we report contrasts, the actual power was higher or the actual MDE was lower; see Lazic, 2018). A sensitivity analysis for the follow-up t tests resulted in an MDE of d =.66. Therefore, given the sample size of 20 participants, we were able to detect medium to large effects.

Apparatus and stimuli

This experiment was developed using JavaScript and HTML language, and the JsPsych plugin (https://www.jspsych.org/; de Leeuw, 2015). Five vegetables served as cues during the first phase: broccoli, carrots, mushrooms, corn, and green peas. The assignments of these vegetables to the cues A, B, or X were randomized for each participant. In the second phase, five fruits were randomly assigned to the five cues E, F, G, H, and Y: apple, apricots, banana, grapes, and strawberries. Two outcome categories with three choices each were presented on the screen as six rectangles in the middle of the screen, with different colors for each button. The six possible outcome buttons were labeled as: "no skin reaction," "skin swelling," "skin itchiness," "no stomach reaction," "stomach bloating," and "stomach cramps." The allocation of the outcome categories was counterbalanced across participants. Half of the participants experienced skin reactions as predictable and stomach reactions as unpredictable. The other half experienced skin reactions as unpredictable and stomach reactions as predictable.

Procedure

In the instructions, the participants were told to assume the role of an allergist examining the allergic reactions[2] of an imaginary patient, Mr. X, after he had eaten vegetables (Phase 1) or fruits (Phase 2).

Phase 1 The first phase consisted of 16 blocks of each trial mentioned in Table 1. These trials were randomized within each block. The positions of the cues in each trial on the screen were counterbalanced. When the participants were told that Mr. X had eaten the corresponding vegetable(s), they were asked which allergic reactions Mr. X would have. They did it by clicking two buttons, one button from each outcome category. For example, when Mr. X ate carrots, they may have guessed that he had experienced no skin reaction and stomach bloating by pressing the "no skin reaction" button and the "stomach bloating" button. As soon as they clicked both buttons, they received feedback on whether their predictions were correct or incorrect for each outcome category separately and which two allergic reactions Mr. X suffered.

[2] One might think of these allergic reactions as more aversive than rewarding. However, since the aversiveness of the allergic reactions suffered by the fictional patient is independent of the choices that the participant made (correct or incorrect), we did not consider the aversiveness of the allergic outcomes as relevant in this experiment (unlike the relevance of losses vs. gains in reinforcement learning, for instance). In another study, we have investigated the effect of reward (i.e., points won for a correct choice) in the allergy task, which showed that points rewarded in this type of task can also bias learning in future situations (Thorwart et al., 2021).

Phase 2 Participants were instructed that they would now learn about the allergic reaction Mr. X suffers when eating fruits, and that they would have to choose which symptom category they would like to learn about. Phase 2 consisted of 12 blocks of each trial type shown in Table 1. The positions of the cues were counterbalanced, and trials were randomized within each block. Before each trial, a question appeared asking the participant, "Which symptoms/reactions do you want to learn more about?" Then the participants had to choose one out of two options: skin-related or stomach-related reactions. Only the three buttons of the chosen category were then presented on the screen together with the cues, and participants were asked to make a prediction by clicking on one of them. They then received feedback about this prediction and the correct allergic reactions of the chosen outcome category.

Test phase After Phase 2, participants were instructed to rate the likelihood of each cue presented in Phase 2 (E, F, G, H, and Y) to cause each allergic reaction (p0, p1, p2, u0, u1, and u2).

Manipulation check At the end of the experiment, the participants were asked to give a rating between 0 and 100 on how confident they were to predict the allergic reactions of Mr. X after eating vegetables (i.e., in Phase 1). This was performed to see if the experimental conditions established in the first phase had worked as expected.

Data analysis

In the result figures, data normalization based on Cousineau (2005) was performed for the standard error of means (*SEM*s) to better reflect the within-subject design. Significance levels after Greenhouse–Geisser correction of the degree of freedom were reported.

Results

Phase 1

The mean prediction accuracy, calculated as the proportion of correct predictions, increased according to the outcomes' predictability (see Fig. 1). A repeated-measures ANOVA, with two within-subject factors, Predictability (Predictable and Unpredictable) and Blocks (1–16), confirmed significant main effects, Predictability: $F(1, 19) = 246.390$, $p < .001$, $\eta_p^2 = .928$; Blocks: $F(1, 19) = 13.217$, $p < .001$, $\eta_p^2 = .410$, and a significant interaction: $F(15, 285) = 3.268$, $p = .002$, $\eta_p^2 = .147$.

Phase 2

Figure 2a shows the mean proportion of choices of the previously unpredictable outcome across the four trials in each block. Values below 0.5 indicate that the previously predictable outcome category was chosen more often. Using a one-way ANOVA, with repeated-measure factor Blocks (1–12) and polynomial contrasts, we found a significant linear trend across blocks, $F(1, 19) = 5.618$, $p = .029$, $\eta_p^2 = .228$. Follow-up one-sample *t* tests compared the proportion of unpredictable choices to 0.5 for each block. The first block was found to be significantly lower than 0.5, $t(19) = -3.111$, $p = .006$; the remaining blocks did not differ significantly from .5 ($ts < 1.308$, $ps > .206$). This result demonstrates that the participants' choice was biased towards the previously predictable outcome category at the beginning of Phase 2 (Block 1), with a linear trend shifting towards the other category later. By the end of Phase 2 (Block 12), the participants chose to learn about both categories equally often.

We also checked the average number of trials that were experienced per cue per outcome category (previously predictable versus previously unpredictable) across the entire Phase 2. Because participants could choose which outcome category to learn about on each trial, we could not force equivalence of exposure between outcome categories. A repeated-measures ANOVA, with factors Cue and Outcome Category, found neither a main effect of Outcome Category, $F(1, 19) < 1$, $p = .786$, $\eta_p^2 = .004$, nor a significant interaction between Outcome Category and Cues, $F(3, 57) < 1$, $p = .523$, $\eta_p^2 = .037$. There was no evidence that participants saw more trials of one cue–outcome category combination than of the others during Phase 2.

Figure 2b shows the corresponding mean prediction accuracy per block during Phase 2. No differences in accuracy were observed between the previously predictable and unpredictable outcome categories. However, the mean prediction accuracy is not as representative for learning about each outcome as it may seem, as it neglects the participants' choices for each outcome category. The block-by-block data shown in Fig. 2b can only show the prediction accuracy of trials in which participants chose that outcome category. As the number of participants who chose each outcome category differed, each data point is based on a different number of predictions. Secondly, two participants might choose the previously predictable outcome category in Block 3 but differ concerning what they chose in Blocks 1 and 2. They would therefore differ concerning the opportunity to learn before making their predictions in this block. Moreover, these differences were systematic, rather than random; people had more opportunities to learn about predictable outcomes than the unpredictable outcomes in the first block as their choice was biased at the beginning of Phase 2.

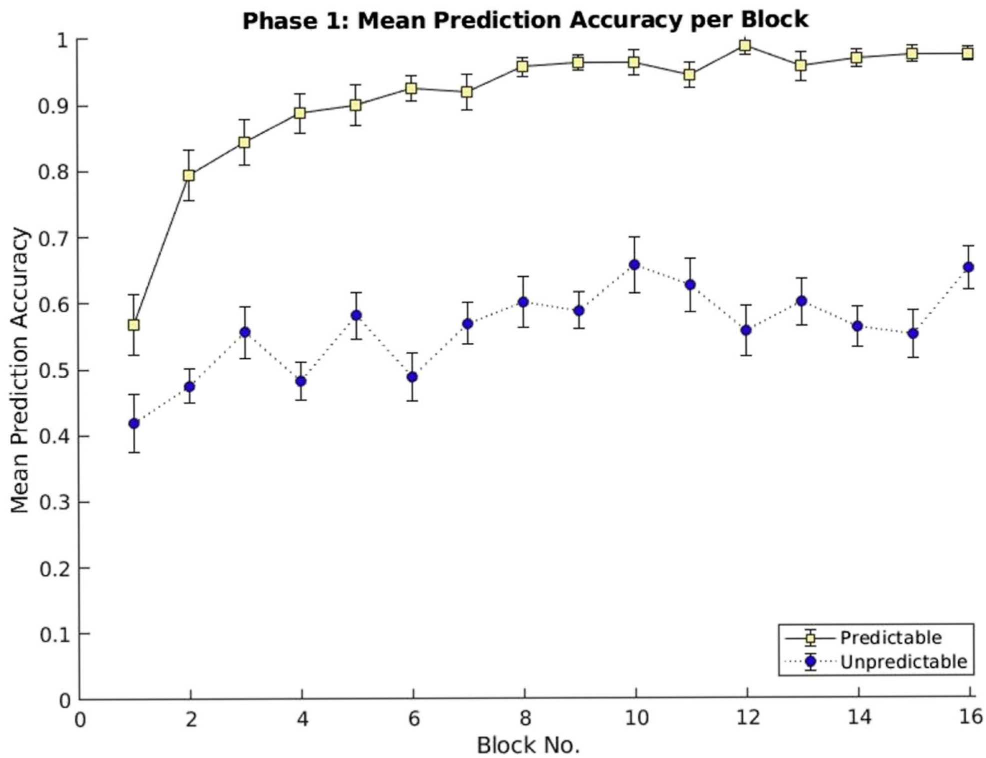

Fig. 1 Mean prediction accuracy of Phase 1 averaged across all trials of each block. The black line with light-yellow data points represents the predictable outcome category, and the dotted line with blue data points represents the unpredictable outcome category. Error bars indicate the *SEM* of the normalized data. (Color figure online)

To address these limitations, we reanalyzed the predictions. We compared the accuracy for predictable and unpredictable outcomes on each trial based on the number of previous encounters with each outcome category that had been experienced before that trial, rather than on the block in which that trial chronologically occurred. To make sure that there were enough encounters with each category to meaningfully analyze the data in this manner, Fig. 2c plots the number of participants who had *N* fewer encounters with each outcome category. The inflection point is approximately 25 encounters, suggesting that across Phase 2 most participants had between 24 and 27 encounters with each outcome category. Figure 2d confirmed the previous impression that prediction accuracy in both categories over these encounters increased equally. As the analyses neglect both the varying number of participants, how many previous trials they received, or when the predictions were made, no further statistical tests were conducted.

Test phase

A repeated-measures ANOVA was performed with two factors, Prior Predictability (Predictable and Unpredictable) and Correctness (Nil, Correct, or Incorrect). A typical OP effect would manifest as an interaction between these factors (a greater difference between the correct and other outcome ratings for the predictable outcome category than for the unpredictable outcome category). We found a significant main effect of Correctness, $F(2, 38) = 43.995$, $p < .001$, $\eta_p^2 = .698$, but no significant interaction, $F(2, 38) < 1$, $p = .754$, $\eta_p^2 = .013$.

Manipulation check

Participants correctly perceived the predictability of the two outcome categories during the first phase. A paired-samples *t* test resulted in a significant difference between the ratings, as participants gave a higher rating on the predictable category than the unpredictable category ($M_{predictable} = 90.55$, $M_{unpredictable} = 45.55$), $t(19) = 5.432$, $p < .001$. Individual data points of the manipulation check are shown in Fig. 3.

Discussion

We investigated whether learning about unpredictability decreases outcome-specific motivation to learn about an outcome. During Phase 1, people learned to better predict the symptoms from the predictable outcome category than the unpredictable outcome category and later reported the difference in predictability correctly. In Phase 2, participants were asked about which outcome category they would like to learn. Participants were more eager to learn about the predictable outcome first, before learning about the other category in later

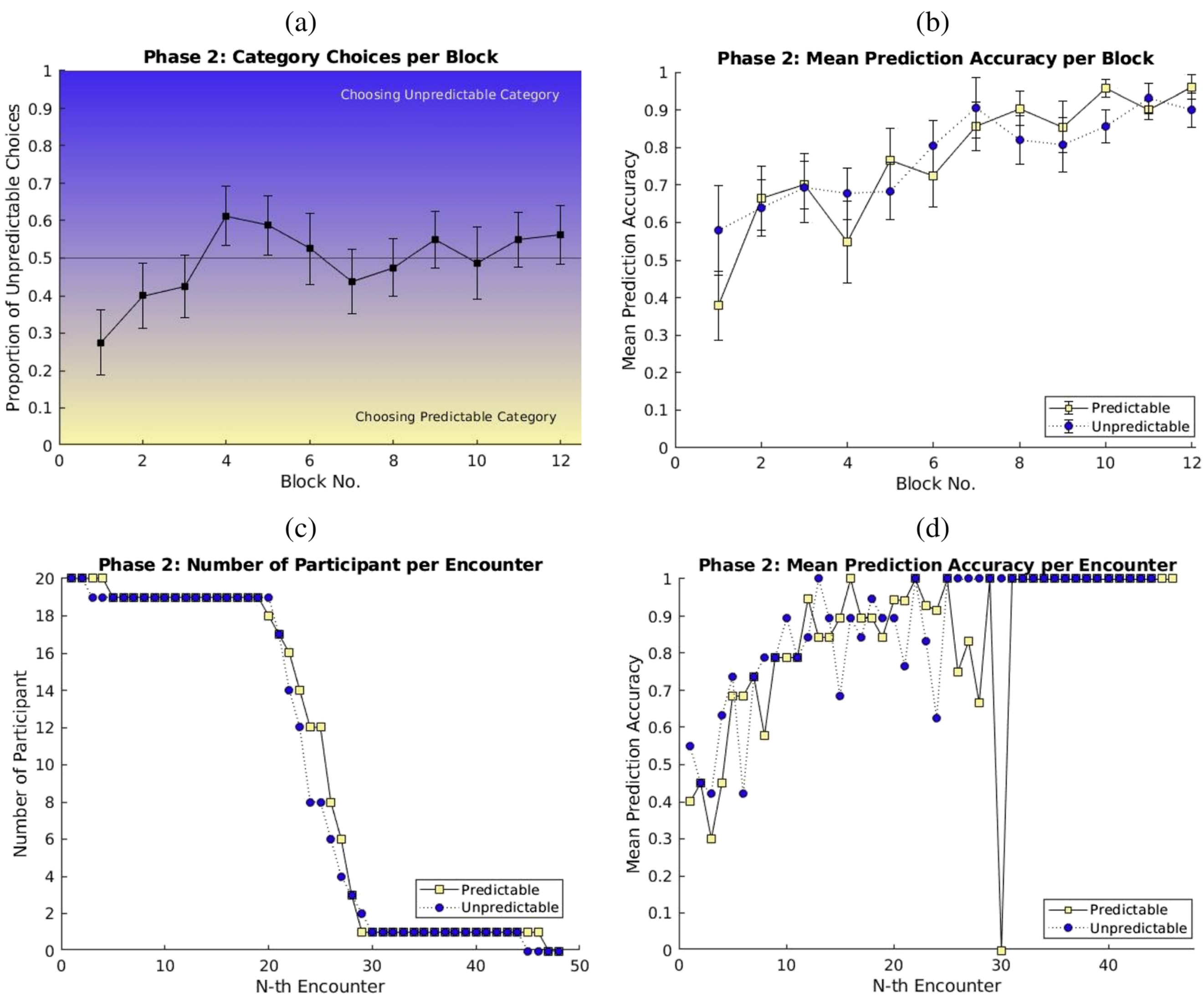

Fig. 2 **a** The proportion of unpredictable choice for each block. The line at 0.5 indicates the mid-point between the choices. The blue shade represents the choice of unpredictable category, and the yellow shade represents the choice of predictable category. **b** Mean prediction accuracy of Phase 2 averaged across all trials of each block. **c** The number of participants at the *Nth* outcome encounter (outcome category that had been experienced). **d** Mean prediction accuracy of Phase 2 averaged across the *Nth* outcome encounter. In Panels **b–d**, the black lines with light-yellow data points represent the previously predictable outcome category, and the dotted lines with blue data points represent the previously unpredictable outcome category. Error bars indicate the *SEM* of the normalized data. (Color figure online)

trials. The motivation to engage with a specific outcome category was therefore affected by its prior predictability. Note that this difference was not a product of that outcome's current predictability, as all outcomes were equally and perfectly predictable during Phase 2.

This change of outcome-specific motivation to learn could be explained as a result of a change in participants' expectancy. By the end of Phase 1, participants had the expectancy that they can achieve a successful prediction about the predictable category, but not the unpredictable category. EVT models predict that the expectancy influences motivation to engage. The unpredictability of an outcome during Phase 1 thereby affects the participants' motivation to learn about that outcome, and therefore their choices in Phase 2. This demotivation to learn could also be a product of frustration felt by being unable to predict correctly, as similar motivational factors have been considered important in animal learning (Amsel, 1962, 1992; Stout et al., 2003). Furthermore, it confirms the similarities with the demotivation caused by the LH effect (Maier & Seligman, 2016). Therefore, this effect could be relevant to a range of mental health disorders such as major depressive disorder (Abramson et al., 1989; Alloy et al., 1992).

Another way to understand these results is through the lens of decision-making processes, particularly risk-taking behavior, and opportunity costs. Risk-taking behavior refers to the preference to take the chances to gain from a choice or an action with an unpredictable outcome (Kacelnik & Bateson, 1996; Platt & Huettel, 2008). In our experiment, a risk-taking

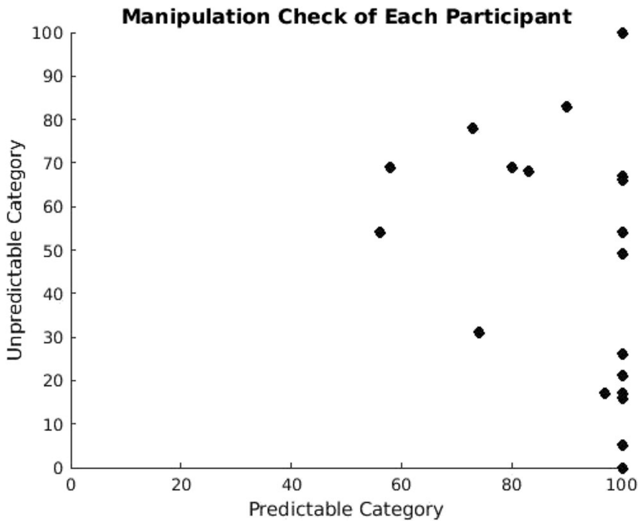

Fig. 3 Participants' ratings during the manipulation check. At the end of the experiment, participants were asked to give a rating between 0 and 100 on how confident they were to predict the allergic reactions of Mr. X in Phase 1. The *x*-axis represents their confidence to predict the predictable category, and the *y*-axis represents their confidence to predict the unpredictable category (0 being the lowest and 100 being the highest level of confidence). The black dots represent each participant's data point

behavior would involve choosing to learn about the unpredictable outcome first in Phase 2. However, participants first chose what they had previously known as predictable, even though this behavior creates opportunity costs (i.e., losing a chance to get more information from the other alternative; Anselme, 2015; Kurzban et al., 2013). Participants chose what they knew was predictable and sacrificed the opportunity to learn about the unpredictable category. Once they learned about the previously predictable outcomes and therefore started to make more correct predictions, they increased their risk-taking behavior by choosing the previously unpredictable category. This shifting behavior could be interpreted as a tendency to learn about the other given "opportunity" after learning enough about the firstly chosen one. It indicates that participants changed their evaluation of the opportunity cost they would have to pay when choosing the predictable outcome category again.

This shifting behavior also supports the notion that participants' choices were more about learning and not about making a correct prediction in each trial. As participants could not make more than one prediction in each trial, they only sacrificed the opportunity to learn about the unpredictable outcomes, but not the opportunity of making more correct predictions when choosing the previously predictable category. Indeed, the best strategy for making the most correct predictions would have been to choose the same category for the entire second phase. Participants nevertheless shifted their choice towards the other category supports the notion that their choice reflects their motivation to learn about an outcome category. This behavior could be related to curiosity. Curiosity is conceptualized as a trait or state of a person, leading to a general desire to learn about the world (see, e.g., Marvin et al., 2020). This desire has two sides: (1) a desire to learn to "know now" and (2) the patience to "wait for later." One might speculate that the OP, a property of a part of the world, fits the desire to "know now," and therefore our participants were more eager to learn about the predictable outcome first because they assume that doing so will allow them to acquire information about the new cue–outcome relationships faster.

The results support the proposed link between unpredictability and outcome-specific motivation and offer an account for the OP effect. When participants are confronted with previously unpredictable outcome categories, the reduced outcome-specific motivation might lead to a decreased allocation of cognitive resources for learning about this outcome in new situations, particularly when simultaneously learning about other previously predictable outcomes. In Griffiths et al. (2015) and Thorwart et al. (2017) for example, if participants had the same preference during Phase 2, then despite receiving feedback about both outcome categories, they might devote more resources to using the feedback from the previously predictable outcome. But also when there is only one outcome per trial as in Griffiths et al. (2018), the information about the unpredictable outcomes might be disregarded while prioritized information about predictable outcomes is still processed.

Then why was there no OP effect visible in the test phase of the current experiment? This cannot be due to participants' opportunity to learn about each cue's relationship with each outcome category, as the accumulated number of trials at the end of Phase 2 was the same for each cue–outcome combination. However, and in contrast to previous OP experiments using the allergy task (Griffiths et al., 2015; Thorwart et al., 2017), participants were only presented one outcome category in each trial, and it seemed overall easier for the participants to learn about the cue–outcome relationship in the current experiment. Indeed, participants reached about 90% accuracy at the end of Phase 2, which is at least descriptively higher than in previously reported experiments (~80%). Furthermore, as participants had to make an overt choice, this might increase their overall motivation to learn about the chosen outcome category. Therefore, any possible difference in learning about the two outcome categories might not be visible anymore in the test phase.

Some questions exist about whether associative learning is consciously controlled or unconscious and relatively automatic (Frensch & Rünger, 2003; Newell & Shanks, 2014). Since this task is explicit and transparent regarding the goal of making correct predictions, we cannot say with certainty whether participants' preference for predictable outcomes is driven by a strategic consideration of their goals or a more habitual tendency to choose the more appealing option (the one that has met with the reward of being correct more often). Understanding the locus of these effects is an important consideration for future research.

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Effects of Prior Outcome Reward and Predictability on Subsequent Learning

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Abstract

When human learners encounter several cue-outcome relationships at the same time, learning is often biased towards certain outcomes in subsequent experiences. Such an bias might be caused by participants' diminished motivation to engage with and learn about a certain outcome due to past experiences with this outcome. To test this motivational account of learning biases in simple predictive learning tasks, we manipulated reward for an outcome's correct prediction in an initial training phase – participants received points for correct responses. Experiment 1 demonstrated that this prior reward biased learning but not response preferences when the outcomes were encountered in a new learning task, in which no reward was given. Experiment 2 additionally introduced a manipulation of outcome predictability. It is known that human participants learn more about an outcome that has a history of high predictability and therefore high likelihood of correct predictions, than about an outcome with a history of low predictability. Experiment 2 investigated whether the effects of prior reward would counteract and diminish these effects of prior unpredictability. However, no direct effect of prior unpredictability or reward on subsequnt learning was observed. Instead, predictability affected response preferences independently of reward. An interaction between the reward and predictability was furthermore obtained for the perceived predictability. The results of the two experiments together support the general idea that making correct predictions for an outcome is a key motivation in human predictive learning tasks, as the likelihood and the reward associated with correct predictions affected behavior in future situations.

Keywords: predictive learning, outcome predictability, motivation, reward

Effects of Prior Outcome Reward and Predictability on Subsequent Learning

In a classical experimental paradigm of human predictive learning, participants learn to predict which allergic reactions (the *outcome*s) a fictitious patient, Mr. X, will suffer if he eats certain foods (the *cues*). They do this naturally, successfully, with little effort, and without receiving any additional explicit reinforcement for correct predictions. However, when learners encounter several cue-outcome relationships at the same time, learning is often biased based on different characteristics of the the cues, or the outcomes or the relationships between the cues and outcomes (e.g. Le Pelley, 2004; Griffiths et al., 2019). The current experiments follow the idea that such biases in human predictive learning can be based on biased motivation to learn (in contrast to, for example, biased ability to learn).

This idea might seem trivial but there is surprisingly little research on motivational processes during simple predictive learning tasks. In contrast to reinforcement learning paradigms, in predictive learning tasks participants often learn about abstract and affectively neutral stimulus events, over which they have no control and which only receive significance due to their task- and situation-specific role. Hartanto et al. (2021) demonstrated that prior predictability of an outcome affects participants’ motivation to learn about this outcome in subsequent tasks. Using a modified version of the allergy task, participants had to learn to predict both stomach- and skin-related allergic reactions of the fictitious patient Mr. X. In a first learning phase, the predictability of the skin-related and stomach-related outcome categories was manipulated. For instance, stomach bloating and cramps were perfectly predictable by eating mushrooms and eating broccoli respectively, but either skin itchiness or rash could (or could not) occur after eating mushrooms or broccoli. In a second learning phase, Hartanto et al. implemented an active learning method, in which participants could learn in each trial only about one of the outcome categories. At the beginning of each trial, participants had to decide whether they wanted to learn about skin-related or stomach-related allergic reactions. The results showed that participants at the beginning of the second task chose to learn about the previously predictable outcomes first and to learn about the previously unpredictable outcomes in later trials. This showed that unpredictability affects future motivation to learn in other circumstances.

According to expectancy-value theories of motivation (e.g., Atkinson, 1957), the overall motivation to work for a goal depends on the product of the expectancy to achieve a goal and its value. The results of Hartanto et al. suggest that participants' goal in such predictive learning tasks is simply to be correct as unpredictability directly affects the likelihood of being correct. The experimental designs used by Hartanto et al. (see also Griffiths et al., 2015) ensured that participants at the end of the first learning phase achieved nearly 100% correct predictions of the predictable allergic reactions but only 60% for the unpredictable outcome category. Unpredictability and the repeated experience of failures therefore directly decrease the likelihood and expectancy to achieve the goal of making correct predictions. Participants should then indeed become less motivated to learn about the unpredictable outcome. This bias in motivation could in turn result in a bias in learning itself. Even though not observed by Hartanto et al., the Outcome Predictability effect demonstrates such biased learning towards previously predictable outcomes and away from previously unpredictable outcomes (Griffiths et al., 2015; Griffiths et al., 2018; Griffiths et al., 2019; Liu et al., 2020; Quigley et al., 2018; Thorwart et al., 2017).

The first experiment of this paper explored the hypothesis that participants in a predictive learning task are motivated by the goal of being correct and that by manipulating attributes of this goal, one can bias their motivation and learning in subsequent tasks. The second parameter of expectancy-value theories is the value the learner attaches to the goal. As participants received no explicit rewards in previous experiments, this value had to be based on participants' intrinsic appraisal of being correct. We predicted that, if participants received some additional extrinsic reward for making correct predictions and this reward differed between outcomes, they should learn and perform better for the highly rewarded outcomes. Furthermore, and in line with the effect of prior predictability, any bias ought to continue to influence subsequent learning and performance even if no explicit reward is given anymore. As far as we are aware, no study has systematically investigated whether differently rewarding a correct prediction in human predictive learning tasks has such effects on participants' motivation and learning.

As in previous studies using the allergy task, learning was measured both as an increase in *prediction accuracy* in training trials and in a final test phase. We additionally inspected the response times for the predictions in each training trial as a measure of both learning and motivation in the allergy task. In the current version of the task, participants had to make two predictions in each trial, one for each of the two outcome categories. Comparing the response times for both these predictions indicates whether participants had a systematic preference for responding first to one of the outcome categories, even when there is no time pressure and there is no benefit or cost in doing so. In line with other learning paradigms using response time (cued search tasks, e.g., Griffiths et al., 2018; serial letter-prediction task, e.g., Quigley et al., 2018), we expected participants to respond faster and therefore first to the outcome category about which they had already learned more. In addition, we reasoned that participants respond first to the outcome category they are more motivated to engage. That is, even when people learn equally well about which cues predict which outcomes, they respond first to those outcomes with a higher motivational status. The response times as a measure for *response preference* might therefore be more sensitive to motivational biases than prediction accuracy alone.

Experiment 1

The aim of Experiment 1 was to test whether the rewards that participants received for making a correct prediction about an outcome affect the current and subsequent learning about that outcome. The design of Experiment 1 is shown in Table 1. It is based on the experimental design for the Outcome Predictability effect, developed by Griffiths et al. (2015) and used by Hartanto et al. (2021). The design was adopted so that the two outcome categories did not differ in predictability anymore but in the reward participants received for correct predictions in each outcome category.

In Phase 1, four cues, A, B, X, and Z, were presented either in single cue or compound trials. They preceded a compound of two outcomes, one each of two independent outcome categories. Each outcome category had two positive values (h1, h2, and l1, l2) and a “no outcome” value (h0, l0; i.e. Mr. X did not suffer an allergic response of this category). Cue A and B predicted the outcomes of the high reward category (h1, h2) whereas X and Z predicted the outcomes of the low reward category (l1, l2). Participants received three points for correct predictions in the high reward category but only one point for correct predictions in the low reward category.

Table 1. Experimental Design for Experiment 1

Phase 1	Phase 2	Test
A → h1, l0	EY → h1, l2	E?
B → h2, l0	FY → h2, l1	F?
X → h0, l1	GY → h1, l1	G?
Z → h0, l2	HY → h2, l2	H?
AX → h1, l1		Y?
AZ → h1, l2		
BX → h2, l1		
BZ → h2, l2		

Note. Letters A – Z represent foods (A, B, X and Z: vegetables; E, F, G H, and Y: fruits), and the letter-number combinations [h0, h1, h2, l0, l1, l2] represent allergic reactions. The letters “h” and “l” represent the high and the low reward category, respectively.

In the second phase, a new set of cues was introduced but the outcomes remained the same as in Phase 1. Cues E to H predicted one outcome from each category, e.g. cue E was predictive for outcomes h1 and l2. Another cue, Y, was shown on every trial in Phase 2 and was presented to ensure comparability with previous experiments (Griffiths et al., 2015, Thorwart et al., 2017) as well as Experiment 2 of the current study. In contrast to Phase 1, no explicit reward was given anymore. Any differences in learning between the outcome categories in Phase 2 thereby would be a result of the previous differences in reward in Phase 1.

In the test phase, the participants were required to rate the likelihood of every outcome separately, given each cue from Phase 2. We predicted that motivation and learning would be biased toward the high reward category in both Phase 1 and Phase 2. This bias should affect both the accuracy of the predictions as well as the response preferences. We included also a manipulation check at the end of the experiment that measured how participants had perceived and remembered the prior predictability and prior reward of each outcome category.

Methods

Participants. Thirty undergraduate students of the Philipps-Universität Marburg completed the experiment in exchange for course credit or payment (EUR 9 per hour). The final sample consisted of 17 females and 13 males, ranging from 18 to 34 years old of age (*M* = 23.63, *SD* = 3.30). Data of one participant for each manipulation check is missing as he or she exited the experiment prematurely. All participants received a complete description of the experiment and signed a written informed consent form prior to data collection. The studies were approved by the local ethics committee of the department of psychology, Philipps-Universität Marburg.

Apparatus. The experiment took place in a small lab at the Department of Psychology in Marburg. In this lab, a Tobii Eyetracker TX300 was mounted on a 21” monitor display and recorded the eye-movements at a rate of 300 Hz. After an initial inspection of the raw data, it became clear that the 5-point calibration procedure had unreliable and invalid results due to changes to the hardware set-up. Further analyses of the gaze data were therefore abandoned. The raw data is available under https://osf.io/djqyr/.

A chin rest was used to make the participants feel more comfortable during the experiment and to increase the reliability of the eye-tracking. Behavioral responses to the experiment were given using a standard optical mouse. The experiment was written in MATLAB, using the Psychtoolbox library (Kleiner et al., 2007), as well as the code provided by Tobii with the SDK 3.0.

Stimuli. Four vegetables served as cues during the first phase: broccoli, carrots, mushrooms, and tomatoes. The assignments of these vegetables to the cues (A, B, X, or Z) were randomized for each participant. In the second phase, five of the following six fruits were randomly assigned to the cues E, F, G, H, and Y: apple, apricots, banana, grapes, lemons, and strawberries.

Skin- and stomach-related allergic reactions represented the two outcome categories, counterbalanced across participants. If the high reward outcome category were the skin-related reactions, the symptoms “skin swelling” and “skin itchiness” served as h1 and h2, respectively, and “stomach cramps” and “stomach bloating” as l1 and l2. The same rule was applied if the category was swapped (i. e. when stomach reaction was the high reward category and skin reaction was the low reward category). An additional outcome in each category was labeled as “no skin/stomach reaction” to represent h0 and l0.

Procedure. Instruction told participants to assume the role of an allergist, examining an imaginary patient, Mr. X. Their task was to predict the allergic reaction Mr. X had after eating certain foods. They were also told they would receive points for correct predictions. Furthermore, their goal should be to make as many points as possible, achieved by making as many correct predictions as possible.

Phase 1. The first phase consisted of 16 blocks of each trial mentioned in Table 1. These trials were randomized within each block. Trials began with the presentation of the vegetable(s) to the participant in two positions on the left side of the screen. The positions of the foods were randomly determined on trials where two were shown. When only one vegetable was presented, the top position was used. Participants were told that Mr. X had eaten the corresponding vegetable(s) on a certain day, and they were supposed to make two predictions by clicking one button from each outcome category (i. e. skin-related and stomach-related symptoms). The six possible outcomes were presented as different colored response buttons. Skin-related outcomes were colored blue and presented slightly left of the middle of the screen. Stomach-related outcomes were indicated as green buttons on the right side of the screen. As soon as they had chosen an outcome in each category, they were informed for each category separately about the correctness of their prediction, the actual correct symptom, and their currently accumulated points for this category. Below the buttons of each category, text feedback informed them whether their prediction was correct (”RICHTIG!” in green) or incorrect (“Falsch.” in red) and how many points they had accumulated (“Punkte: XX”). The button of the correct symptom was then marked by a red frame. In addition, a comic depicting Mr. X having the symptom appeared underneath the response buttons. The next trial started after participants clicked on a “next” button, which was placed in the middle between both outcome categories.

Phase 2. The end of Phase 1 led the participant to the second instruction, telling them again their current points for each category and that they would now investigate Mr. X’s allergies with respect to fruits. Furthermore, even though the goal was still to make as many correct predictions as possible, they would receive no points anymore. Phase 2 consisted of six blocks of each trial type shown in Table 1, and two cues were presented in each trial. These trials followed the same procedure as Phase 1.

Test Phase. After Phase 2, participants were instructed to rate the likelihood that Mr. X would experience an allergy response after eating a certain fruit. Ratings were collected in separate trials for every single fruit of Phase 2. Vertical rating scales appeared below the response button of each symptom. The ratings were between 1 (highly unlikely) and 100 (highly likely) and could be adjusted independently of each other. Participants had to rate all the six possible outcomes before they could move to the next page with the next cue by pressing the “next” button.

Manipulation Checks. Manipulation checks were presented on one final screen, which was similar to the training and test screen, and showed the two outcome categories as well as the (now inactive) response buttons. On top of the screen, it said: “Lastly, a quick control: When Mr. X ate vegetables, ... “. Positioned below the three buttons of each outcome category, participants were then asked "… how well could you predict for skin-related/stomach-related symptoms, whether and which kind of allergic response he will have?". A horizontal slider below was labeled with "not at all" and "very well". Again below, the second question was presented "… how many points did you receive for a correct answer?", and participants had to choose between two possible answers buttons, "+1" and "+3".

Data Analysis.

Response times from the training phase were calculated as the difference in ms between the onset of the presentation of the stimuli and the first prediction in each category. This difference was then log-transformed and the median across all trials per training block was calculated, following procedures described by Le Pelley et al. (2013).

In the result figures, data normalization based on Cousineau (2005) was performed for the standard errors of the mean (*SEM*s) to better reflect the error terms used in the within-subject analyses. During repeated measures analysis of variances (ANOVAs), significance levels after Greenhouse-Geisser correction of the degrees of freedom are reported. We also calculated Bayesian repeated measurement ANOVA using JASP 0.11.1 (JASP Team, 2019), assuming uninformed and thus equal prior probabilities for all models. We report Bayes factors (*BF*) from the analyses of effects across matched models (also known as the Baws factor; Mathôt, 2017). This *BF* averages evidence across all models that include a specific effect but not higher-order interactions and compares their evidence to evidence for matched models stripped of this effect. *BFs* higher than 3 speak for the inclusion of the effect, *BFs* lower than .33 for its exclusion. We follow the classification scheme for the interpretation of Bayes factors in Wagenmakers et al. (2018) but replace the label "anecdotal evidence" for *BFs* between .33 and 3 with "inconclusive evidence". We think this is more in line with Wagenmakers' own and the general interpretation of these values.

Results

Manipulation Checks. Figure 1A displays the average points gained at the end of Phase 1. Participants accumulated more points for the high reward outcome category than the low reward outcome category ($t(29) = 67.01$, $p < .001$, $d = 12.24$; $BF_{10} > 100$). Furthermore, when asked about the points that they had received in Phase 1, 27 out of the 29 participants remembered them correctly for both categories. A single participant responded incorrectly in both outcome categories and another one in the high reward outcome category. As seen in Figure 1B and as expected, participants perceived both outcome categories as highly predictable in Phase 1 ($t(28) = 0.96$, $p > .34$, $d = -0.18$; $BF_{10} = .30$;).

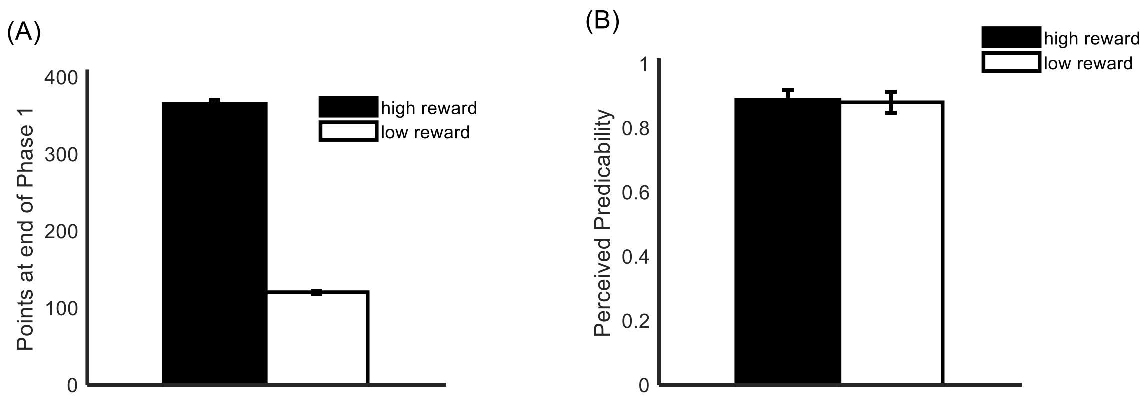

Figure 1. Manipulation checks of Experiment 1. (A) Accumulated points in Phase 1. (B) Mean perceived predictability of the high reward and low reward outcome categories in Phase 1.

Accuracy during training. Learning during Phase 1 (left panel in Figure 2) proceeded fast and at a similar pace for both outcome categories. Accordingly, an ANOVA with the two repeated measures factors Reward (High vs. Low) and Blocks (1 – 16) resulted only in a main effect of Block ($F(15,435) = 48.12$, $p < .001$, $\eta_p^2 = .62$) but no effect of Reward or an interaction (Fs < 2.03, ps > .16). The corresponding Bayesian ANOVA provided extreme evidence for the inclusion of the factor Block ($BF > 100$) and for the exclusion of the interaction of Reward and Block ($BF < 0.01$). The exclusion of the factor Reward was supported by moderate evidence ($BF = 0.3$).

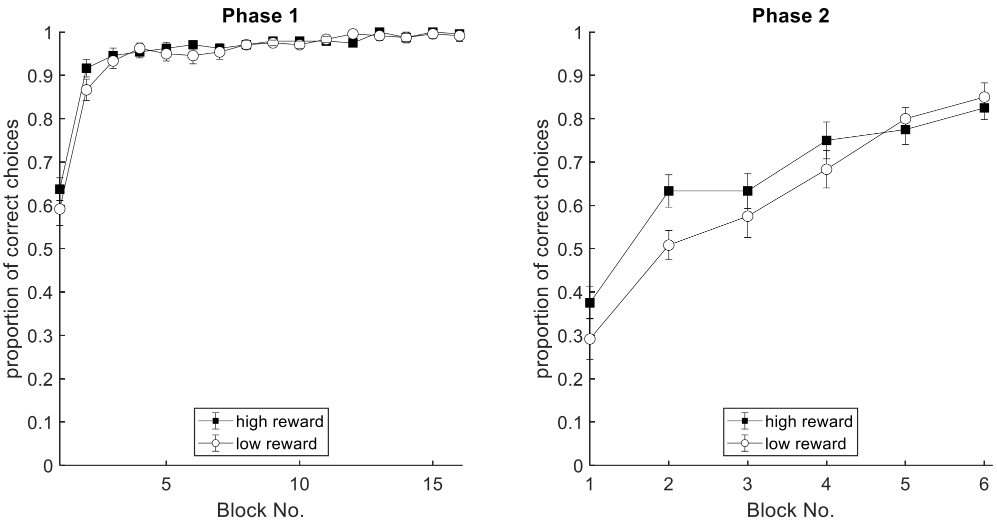

Figure 2. Mean prediction accuracy in both training Phase 1 and Phase 2 in Experiment 1. Black squares represent the high reward outcome category and white circles represent the low reward outcome category. Error bars indicate the SEM of the normalized data.

In Phase 2, participants showed better performance for the outcome category that was associated with a high reward in Phase 1. In the ANOVA with the two repeated measures factors Reward (High vs. Low) and Blocks (1 – 6), both main effects were significant. Although the difference between conditions all but disappeared by Block 5, there was no significant interaction with block (Reward: $F(1,29) = 4.48$, $p < .05$, $\eta_p^2 = .13$; Blocks: $F(1,145) = 31.96$, $p < .001$, $\eta_p^2 = .52$; Reward*Blocks: $F(5,145) = 1.62$, $p > .17$, $\eta_p^2 = .05$). The Bayesian ANOVA also provided support for the effect of Block ($BF > 100$) but was inconclusive with respect to the inclusion of Reward ($BF = 1.15$). Calculating post-hoc the Bayesian ANOVA for only the first half of Phase 2, where we expected the effect to be strongest, revealed moderate evidence for an effect of reward (BF=3.36). There was strong evidence for the exclusion of the interaction ($BF = 0.07$).

Ratings in Test Phase. Figure 3 shows the ratings for the outcomes in the test phase, averaged across the predictive cues E to H. Within each outcome category, the grey bars again present the averaged rating of the “no reaction” values, which were never correct and thus absent in the entire Phase 2. The correct outcomes of both outcome categories (white) were given higher ratings compared to the absent (grey) and incorrect (black) outcomes in both conditions. Furthermore, no difference between the two outcome categories is apparent. This pattern of results is in line with the results of the ANOVA with two repeated measures factors Reward (High vs. Low) and Correctness (Absent, Correct vs. Incorrect), in which only the main effect of Correctness reached significance ($F(2,58) = 20.43$, $p < .001$, $\eta_p^2 = .41$; other $Fs < 1.10$, $ps > .33$). This was also the only factor receiving extreme evidence for its inclusion ($BF > 100$) in the Bayesian ANOVA, whereas the exclusion of Reward ($BF = 0.16$) and Reward*Correctness ($BF = 0.2$) were both moderately supported.

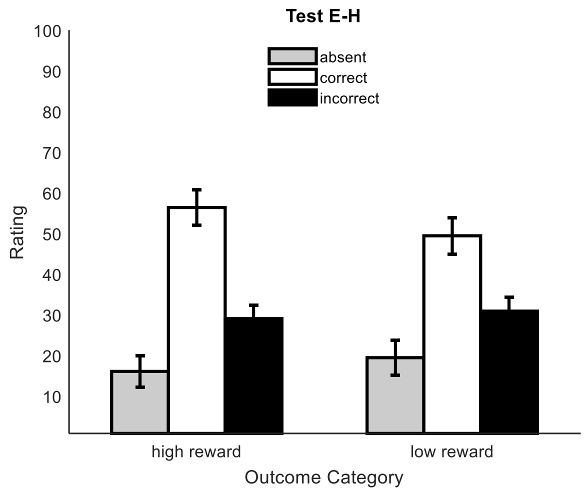

Figure 3. Mean likelihood ratings of all outcomes, averaged across the predictive cues E to H in Experiment 1. The grey bars labeled “absent” show the mean rating of the “no reaction” outcomes. The rating of the correct outcome for each cue is shown as white bars in the middle and the ratings of the incorrect outcomes are shown as black bars on the right. Error bars indicate SEM of normalized data.

Response Times during training. Figure 4 shows the median log-transformed response times of the first prediction for each outcome category, averaged across participants. In Phase 1, response time decreased for both outcome categories equally. This impression was confirmed in an ANOVA with the two repeated measures factors Reward (High vs. Low) and Blocks (1-16), in which only the main effect of Block was significant

($F(15,435) = 55.49$, $p < .001$, $\eta_p^2 = .66$; other $Fs < 1$). Likewise, the Bayesian ANOVA provided extreme support for the inclusion of Block ($BF > 100$) and the exclusion of the interaction between Block and Reward ($BF < 0.01$). It provided also very strong evidence for a missing effect of Reward itself ($BF = 0.05$).

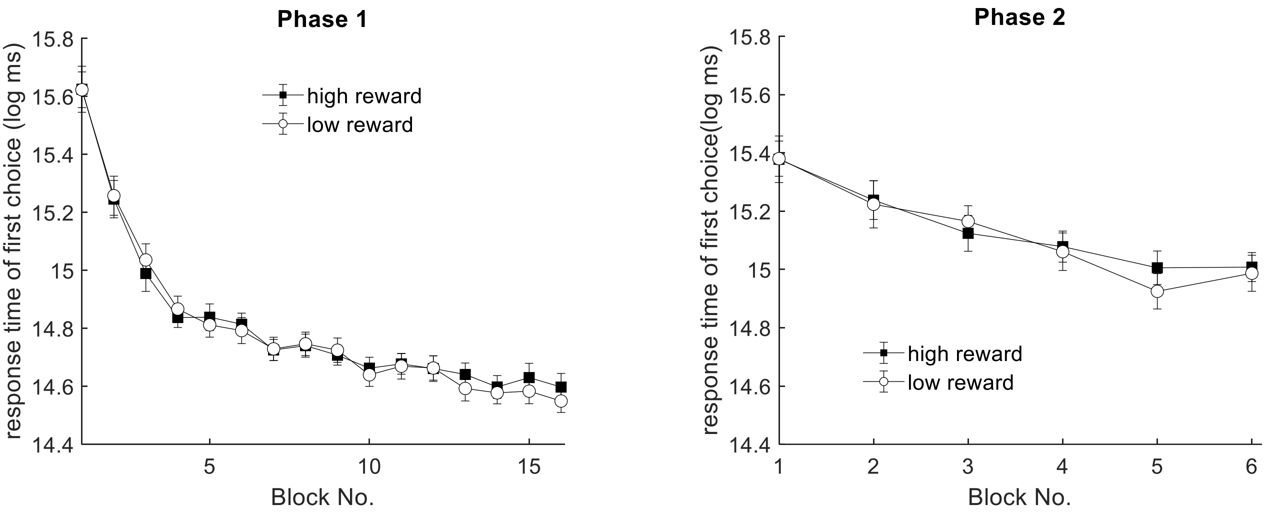

Figure 4. Mean median response times (log-transformed) in both training Phase 1 and Phase 2 in Experiment 1. Black squares represent the high reward outcome category and white circles represent the low reward outcome category. Error bars indicate the SEM of the normalized data.

The same was true for the second phase. The corresponding ANOVA with the two repeated measures factors Reward (High vs. Low) and Blocks (1-6) revealed again only a significant main effect of Blocks ($F(5,145) = 8.14$, $p < .001$, $\eta_p^2 = .29$; other $Fs < 1$). Extreme evidence was obtained in the Bayesian ANOVA for the inclusion of Block ($BF > 100$), moderate evidence for the exclusion of Reward ($BF = 0.17$), and very strong evidence for the exclusion of Reward*Block ($BF = 0.02$).

Discussion

Experiment 1 investigated whether receiving a different number of points as a reward for a correct response affects current and subsequent learning as well as response preferences in human predictive learning tasks. Both the final score and the manipulation check indicated that participants gained a different number of points for the two outcome categories and perceived this difference accordingly. In contrast to our predictions, no effect was visible in the initial training. However, an effect of prior reward on learning became visible at the beginning of Phase 2. Even though participants did not receive any points for their correct predictions in Phase 2, participants had higher accuracy for the outcome category that had been rewarded with three points in Phase 1 than for the outcome category that had been rewarded with only one point. The effect had vanished by the time participants were asked to give ratings in the test phase.

Crucially, learning about the two outcome categories should objectively be equally difficult in Phase 2 as each cue predicted one outcome of each category. Also, while learning about the two outcome categories occurred concurrently within the same trial, participants had no time pressure to distribute resources for learning between the two outcome categories. So there was no principled reason why participants could not sequentially deploy their full learning resources for each outcome within each trial. Nevertheless, previously increasing the reward for correct predictions for specific outcomes improved the performance for these outcomes. The results were in line with our hypothesis that participants in these tasks are motivated by the rewards associated with making a correct prediction and that outcomes, whose predictions had been highly rewarded, become more efficient in driving learning.

However, we would have also expected to see a similar effect in Phase 1, where the reward was explicitly given. The most obvious other difference in learning between the phases concerns the initial increase in prediction accuracy. Participants reached a high level of correct responses already in the second block of Phase 1, whereas accuracy increased slower in Phase 2. This could be based on an artefact of the experimental design. Due to the more complex design of Phase 1, each block averaged across three different encounters with each cue (e. g, A → h1, l0; AX → h1, l1; AZ → h1, l2). Each block in Phase 2 only comprises one encounter (EY → h1, l2). The analyses of Phase 2 were therefore more finegrained. However, the differences in Phase 2 were stable for several blocks and a similar effect in Phase 1 should therefore be detectable at least in the first block too. In addition to the reward being given or omitted, there are several other procedural differences between the two phases. For example, trials with single cues occur in Phase 1 but only pairs occur in Phase 2; the “no reaction” outcomes, h0 and l0, were correct and present in Phase 1 but were never correct and absent in Phase 2. Given that this is, as far as we are aware, the first study investigating the effect of reward on predictive learning, data and knowledge that might explain whether, why and how these differences might affect the impact of reward on learning are sparse. The fact that we did not observe the effect of current reward but in the same experiment and participants an effect of prior reward on learning demonstrates the need to further investigate the exact conditions.

The study additionally inspected the response times of the first prediction in each outcome category. As participants had to respond to both outcome categories in each trial, they were forced to choose between the two and systematic differences in the response times for the two outcome categories would indicate a systematic response preference for one of the categories. The idea was that this measure might be especially sensitive for effects on the motivation to engage with an outcome category and may even precede effects on learning. However, response times and therefore preferences in Phase 1 and Phase 2 were unaffected by the reward manipulation, suggesting that there was no systematic preference to engage with one outcome category before the other. There was therefore also no relationship between the response accuracy and response preference. Instead, participants were equally likely to respond first to the high or the low reward category, even when they showed better performance for the former in Phase 2.

The differing prediction accuracies in Phase 2 indicated that, in line with the results of Hartanto et al. (2021) and with the Outcome Predictability effect, participants in a predictive learning task are motivated by the goal of being correct and that one can bias their motivation and learning in subsequent tasks by manipulating attributes of this goal. According to expectancy-value theories, the two attributes of expectancy and value are connected in a multiplicative manner so that their effects will amplify or diminish each other. For example, an increase in the reward for unpredictable outcomes ought to offset any deteriorating effects of unpredictability on learning and performance. Similarly, a reduced reward for the predictable outcomes ought to diminish any advantage due to the high predictability. In contrast, reducing or increasing both predictability and reward in a congruent fashion should intensify the observable differences between outcomes. Experiment 2 combined the two manipulations of reward and predictability to see whether the two manipulations should offset or amplify each other in the predicted way.

Experiment 2

Based on the modified version of the allergy task of Experiment 1, participants were separated into two groups. Participants in Group “Same” received three points after predicting a predictable outcome correctly but only one point after predicting the unpredictable outcome correctly. At the end of the first phase, participants in this group not only should make many more correct predictions but also gain many more points for the predictable outcome category compared to the unpredictable outcome category. They ought then to be particularly motivated to learn about the outcome category that was both predictable and highly rewarded and particularly demotivated to learn about the unpredictable and low reward outcomes. The other group, “Different”, received three points for correctly predicting the unpredictable outcomes but only one point for correct predictions of the predictable outcomes. Therefore, even though participants should make fewer correct predictions for the unpredictable outcome category than for the predictable outcomes, the former outcome category is associated with gaining more points. This increase in rewards should counteract any loss in motivation due to the unpredictability and therefore lead to diminished effects of prior predictability in the following learning phase.

Table 2 describes the experimental design of the learning task. In Phase 1, again three cues, A, B, and X, were presented either in single cue or compound trials and preceded a compound of two outcomes, one each of two independent outcome categories. The two categories are named based on their predictability. Values from the category “p” were perfectly predictable as outcome p1 was always preceded by cue A and outcome p2 by cue B. In contrast, values on the outcome category "u" were less predictable by cue X as the outcome was just as likely to be u1 or u2. The two outcome categories also differed in the points participants received for correct predictions. Participants received three points for a correct prediction in the high reward category and one point for a correct prediction in the low reward category. Combining the manipulations of both predictability and rewards, one group of participants experienced one outcome category as both highly predictable and highly rewarded and the other as less predictable and less rewarded (Group "Same"). The other group of participants, Group "Different", experienced one category as highly predictable but less rewarded and the other category as less predictable but highly rewarded. Based on our hypotheses and the results of Experiment 1, differences in prediction accuracy between the two outcome categories should be larger in Group Same than in Group Different. As reward did not affect response preferences in Experiment 1, any differences in response preferences between the predictable and unpredictable outcome category might not be additionally modulated by reward and both groups might show similar response preferences.

Table 2. Experimental Design for Experiment 2.

Phase 1	Phase 2	Test
A - p1,u0	EY - p1,u2	E?
B - p2,u0	FY - p2,u1	F?
X – p0,u1	GY - p1,u1	G?
X – p0,u2	HY - p2,u2	H?
AX - p1,u1		Y?
AX - p1,u2		

BX - p2,u1
BX - p2,u2

Note. Letters A – Y represent foods (A, B and X: vegetables; E, F, G H, and Y: fruits), and the symbols [p0, p1, p2, u0, u1, u2] represent allergic reactions. The letters “p” and “u” represent the predictable category and the less predictable category, respectively.

Methods

Only differences to Experiment 1 are reported.

Participants. Forty undergraduate students of the Philipps-Universität Marburg completed the experiment. The final sample consisted of 31 females and 9 males, ranging from 19 to 32 years old of age (M = 22.33, SD = 2.79). Data for the manipulation checks of one participant in Group Same are missing as the participant exited the experiment prematurely.

Results

Manipulation Checks. The accumulated points of the participants for each outcome category after Phase 1 are plotted in Figure 5A. Group Same gained more points for the predictable outcomes whereas Group Different gained more points for the unpredictable outcomes. Therefore, both groups collected more points in the high reward category compared to the low reward category. An ANOVA with Predictability (Predictable vs. Unpredictable) as repeated measures factor and Group (Same vs. Different) as between-subject factor confirmed this result pattern with significant main effects of Predictability ($F(1, 38) = 664.93$, $p < .001$, $\eta_p^2 = .95$), Group ($F(1, 38) = 103.54$, $p < .001$, $\eta_p^2 = .99$), and a significant interaction ($F(1, 40) = 3166.01$, $p < .001$, $\eta_p^2 = .99$). Significantly more points were accumulated by the participants in Group Same on the predictable outcome category than the unpredictable outcome category ($F(1,38) = 3366.39$, $p < .001$, $\eta_p^2 = .99$). In contrast, participants in Group Different collected significantly more points on the unpredictable outcome category compared to the predictable outcome category (F(1,38) = 464.55, p < .001, η_p^2 = .93). The Bayesian ANOVA confirmed this pattern with extreme evidence for influences of Predictability and Predictability*Group on the points (BF > 100) but only inconclusive evidence for an effect of Group (BF = 1.28). In the manipulation checks, 35 of the 39 participants correctly remembered the points for correct responses for both outcome categories; the remaining participants (two in each group) gave one correct answer.

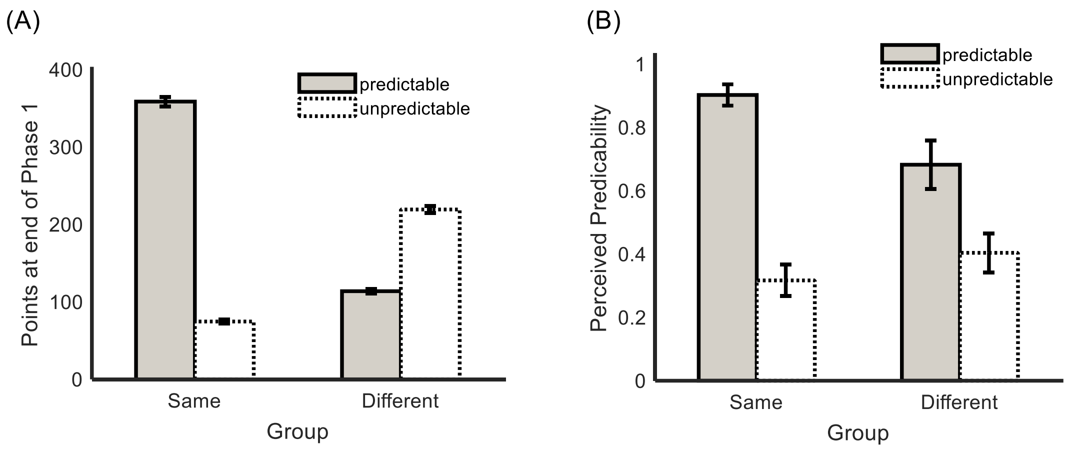

Figure 5. Manipulation checks of Experiment 2. (A) Accumulated points in Phase 1. (B) Mean perceived predictability of the predictable and unpredictable outcome categories in Phase 1.

Furthermore, participants in both groups gave higher ratings for the predictability of the predictable outcomes than the unpredictable outcome (Figure 5B). However, this difference was larger in Group Same than in Group Different. An ANOVA with repeated measures factor Predictability (Predictable vs. Unpredictable) and between-subject factor Group (Same vs. Different) confirmed this with a significant main effect of Predictability and interaction between Predictability and Group (Predictability: F(1,37) = 49.80, p < .001, η_p^2 = .57; Group: F(1,37) = 1.43, p > .24, η_p^2 = .04; Predictability*Group: F(1,37) = 6.31, p < .02, η_p^2 = .15). Analyses of simple main effects showed that both groups rated their predictive outcome category higher than the unpredictive one (Same: F(1,37) = 44.63, p < .001, η_p^2 = .55; Different: F(1,37) = 10.60, p < .003, η_p^2 = .22). However, Group Different rated their predictable outcome lower than Group Same ($F(1,37) = 6.60$, $p < .02$, $\eta_p^2 = .15$), whereas both groups gave equal ratings for the predictability of the unpredictable outcome ($F(1,37) = 1.20$, $p > .28$, $\eta_p^2 = .03$). The Bayesian ANOVA supported inclusion of the main factor Predictability (*BF* > 100). It also provided moderate support in favor of the interaction (*BF* = 6.23) but inconclusive evidence with respect to an effect of Group (*BF* = .47).

Accuracy during training. During Phase 1 (left panel in Figure 6), participants' learning curves developed according to the predictability properties (solid versus dashed lines). Furthermore, participants in Group Same seemed to learn faster for the predictable, high rewarded outcomes (solid line with black squares) than participants in Group Different for their predictable but low rewarded outcome (solid line with white circles). The asymptotic performance was similar. An ANOVA with the two repeated measures factors Predictability (Predictable vs. Unpredictable) and Blocks (1 – 16), and the between-subject factor Group (Same vs. Different) revealed a significant main effect of Predictability ($F(1, 38) = 537.11$, $p < .001$, $\eta_p^2 = .93$), confirming that participants tended to have a higher accuracy for the predictable outcome category compared to the unpredictable outcome category. A significant main effect of Blocks was also observed ($F(15, 570) = 31.51$, $p < .001$, $\eta_p^2 = .45$). However, and in contrast to the descriptive results, the main effect of Group and interactions between all these factors were non-significant (*Fs* < 1.78, *p*s > .19, $\eta_p^2 = .04$). In line with this, the Bayesian ANOVA found extreme evidence for the inclusion of the factors Predictability and Blocks (*BFs* > 100). Evidence for the in- or exclusion of the interaction Predictability*Group (*BF* = .78) was inconclusive. The remaining *BFs* provided moderate (Group: *BF* = .32) to extreme evidence for the exclusion of their effects (*BFs* < .03).

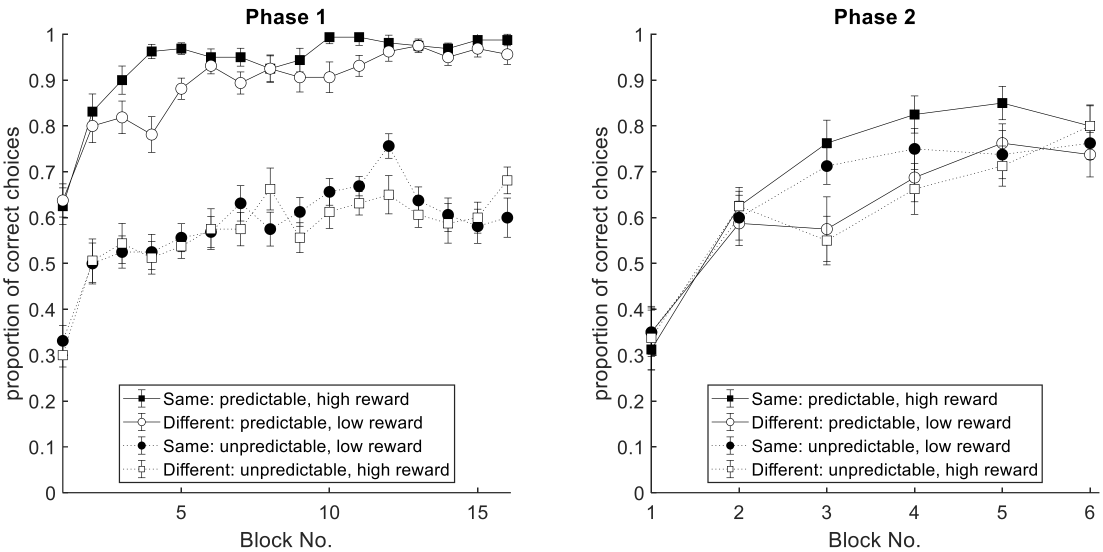

Figure 6. Mean prediction accuracy in both training Phase 1 and Phase 2 for Group Same (black) and Group Different (white) in Experiment 2. Solid lines represent the predictable outcomes and dashed lines represent the unpredictable outcomes. Squares represent the high rewarded outcome category, and circles represent the low rewarded outcome category. Error bars indicate the SEM of the normalized data.

Inspecting learning in Phase 2 (Figure 6, right panel), no clear difference in learning about predictable and unpredictable outcomes is obvious (the solid vs. the dashed line). Instead, Group Same (black) seemed to show overall better performance than Group Different (white) in the middle blocks of training. However, the ANOVA provided no support for the significance of this difference. There was a significant main effect of Blocks (F(5, 190) = 35.57, p < .001, η_p^2 = .50) but no significant main effect of Predictability (F(1, 38) < 1) or Group (F(1, 38) = 3.442, p > .07, η_p^2 = .08). All interactions failed to reach significance (Fs < 1.83, ps > .12). Similarly, the Bayesian ANOVA revealed only extreme support for the inclusion of Block (*BF* > 100). Evidence for effects of Group (*BF* = .59) and Block*Group (*BF* = .38) was inconclusive. The remaining *BFs* provided moderate to very strong evidence for the missing effects of the corresponding factors (*BFs* < .24).

Ratings in Test Phase. Figure 7 shows the ratings for the outcomes in the test phase, averaged across the predictive cues E to H. The correct outcomes of both outcome categories (white) were given higher ratings compared to the absent (grey) and incorrect (black) outcomes in both groups. An Outcome Predictability effect, which is a greater difference in the predictable than unpredictable outcome category, is apparent in neither Group Same nor Group Different.

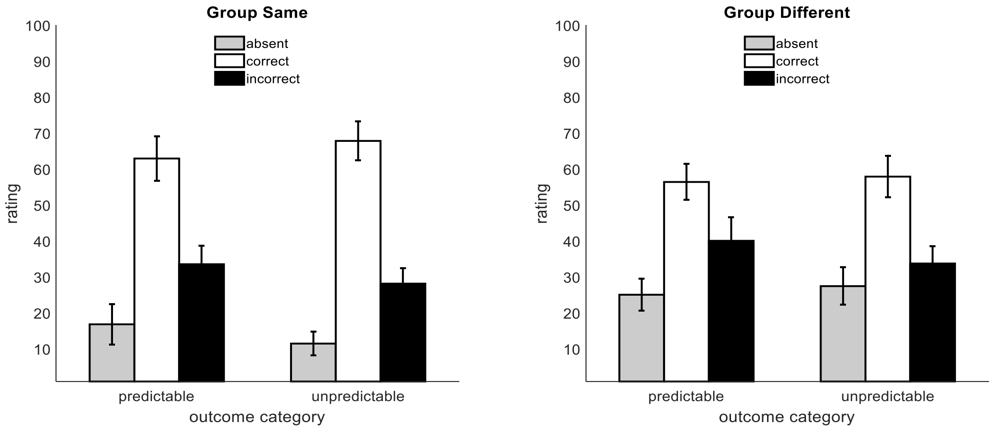

Figure 7. Mean likelihood ratings of all outcomes in Experiment 2, averaged across the predictive cues E to H. The left panel shows the results of Group Same, the right panel the results of Group Different. The grey bars labeled “absent” show the mean rating of the “no reaction” outcomes. The rating of the correct outcome for each cue is shown as white bars in the middle, and the ratings of the incorrect outcomes are shown as black bars on the right. Error bars indicate SEM of normalized data.

An ANOVA with two repeated measures factors Predictability (Predictable vs. Unpredictable) and Correctness (Absent, Correct vs. Incorrect) and a between-subject factor Groups (Same vs. Different) revealed a significant main effect of Correctness ($F(2, 76) = 37.37$, $p < .001$, $\eta_p^2 = .50$), with the correct outcomes’ ratings being higher than both the incorrect ($F(1, 38) = 34.72$, $p < .001$) and absent outcomes ($F(1,38) = 76.69$, $p < .001$). The main effects of Predictability and Group were non-significant (Fs < 1.07, ps > .30). The overall interaction between Correctness and Group did not reach significance ($F(2,76) = 2.32$, $p > .11$, $\eta_p^2 = .06$). Crucially for the Outcome Predictability effect, there was also no significant two- or three-way interaction containing both Predictability and Correctness (Fs <

1). Similarly, the Bayesian ANOVA only found extreme evidence for an effect of Correctness (*BF* > 100). Support for the inclusion of the interaction between Correctness*Group was inconclusive (*BF* = 1.69). All other effects received moderate support for their exclusion (*BFs* < .25).

Response Times during training. Figure 8 shows the median log-transformed response times for the first prediction in each block, averaged across participants, for each outcome category. In Phase 1, response times decreased for all outcomes across training. Further, response times across training decreased most for the predictable, high reward outcome in Group Same (solid line with black squares). Similarly, Group Different also responded first to their predictable but low reward outcomes (solid lines with white circles). An ANOVA with two repeated measures factors Predictability (Predictable vs. Unpredictable) and Blocks (1 – 16) as well as one between-subject factor Group (Same vs. Different) confirmed a main effect of Block ($F(15, 570) = 37.50$, $p < .001$, $\eta_p^2 = .50$) and a significant Predictability*Block interaction ($F(15,570) = 4.20$, $p < .001$, $\eta_p^2 = .10$). All other effects were non-significant, with the main effect of Predictability having the highest *F* value ($F(1,40) = 3.53$, $p > .07$, $\eta_p^2 = .07$). The analysis of effects in the Bayesian ANOVA revealed extreme support for effects of both Predictability and Block on response time (*BFs* > 100). Evidence for the effects of Group (*BF* = .44) as well as the Predictability*Group interaction (*BF* = .89) was inconclusive. The *BFs* for effects of Predictability*Block, Block*Group and the triple interaction extremely supported models excluding them (*BFs* < .01).

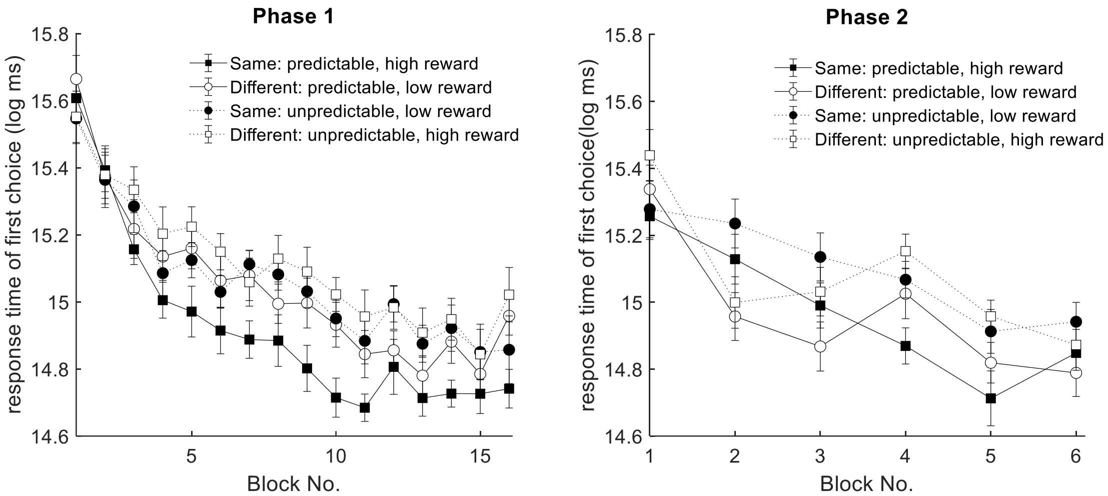

Figure 8. Mean median response times (log-transformed) in both training Phase 1 and Phase 2 for Group Same (black) and Group Different (white) in Experiment 2. Solid lines represent the predictable outcome category and dashed lines represent the unpredictable outcome category. Squares represent the high rewarded outcome category and circles represent the low rewarded outcome category. Error bars indicate the SEM of the normalized data.

In Phase 2, all participants became faster across trials. In addition and in line with the expected effect of prior predictability, response times were overall smaller for previously predictable outcomes (solid lines) in both groups. An ANOVA with two repeated measures factors Predictability (Predictable vs. Unpredictable) and Blocks (1 – 6) and the between-subjects factor Group (Same vs. Different) revealed, in addition to a significant main effect of Block ($F(5,190) = 17.38$, $p < .001$, $\eta_p^2 = .31$), a significant main effect of Predictability ($F(1,38) = 5.31$, $p < .03$, $\eta_p^2 = .12$) as well as a Block*Group interaction ($F(5,190) = 2.65$, $p < .04$, $\eta_p^2 = .07$). The latter was based on differences in the cubic trend between the groups ($F(1,38) = 10.64$, $p < .003$, $\eta_p^2 = .22$). All other effects or interactions were non-significant (*F*s < 1.71, *p*s > .16). Evidence of the analysis of effects in the Bayesian ANOVA was in line with these results. Extreme evidence supported effects of Block and Predictability on response times (*BFs* > 100). Inclusion of the Block*Group interaction was also strongly supported (*BF*

= 6.79). In contrast, there was moderate to extreme evidence for missing effects of the remaining factors (*BFs* < .29).

Discussion

Experiment 2 investigated the effects and interactions of predictability and reward on current and subsequent learning, in particular whether manipulating the reward associated with an outcome's prior correct prediction can abolish any effects of prior predictability on new learning. In Phase 1, participants learned the contingencies and hence the predictability of the two outcome categories. Furthermore, participants correctly identified the predictability and the associated reward of each outcome category in the final manipulation check. In contrast to previous studies however (Griffiths et al. 2015, Thorwart et al. 2017), participants demonstrated no improved learning as measured by accuracy for previously predictable outcomes over previously unpredictable outcomes in Phase 2 or the test stage. This was true for both Groups and therefore irrespective of the reward associated with the outcomes. In turn, any effects of prior reward on prediction accuracy, which were observed in Experiment 1, also disappeared. We observed, however, an effect of predictability on response times and therefore a systemic effect of response preference. In addition, an interaction of the two manipulations was observable in the perceived predictability.

Turning first to the perceived predicatility, while we did not explicitly expect any interaction on this measure, the pattern of results was in line with the predictions for the other measures: participants for which both manipulations were combined showed a greater difference between predictable and unpredictable outcomes than participants for which the manipulations opposed each other. This confirms our assumption that an outcome's predictability and the reward for its correct prediction are in some way linked. The rewards were assumed to moderate the effect of predictability on the motivation to learn and thereby on learning itself. The results of the manipulation check indicate instead that they impacted the experience of predictability itself. In Group Different, participants received a smaller reward for correct predictions of the predictable outcomes on each trial and accumulated fewer points at the end of Phase 1 for this category compared to participants of Group

Same. Furthermore, predictable outcomes resulted in fewer points than the unpredictable outcomes within Group Different. This might lead participants in Group Different to perceive the predictability of the predictable outcome as being reduced compared to the perceptions of participants in Group Same, where the predictable outcomes resulted in more points than the unpredictable outcomes.

At this point, we can only speculate why these differently perceived predictabilities did not result in any differences in prediction accuracy in Phase 2 or the test stage, not least as the interpretation of non-significant results always comes with a caveat. It could be that effects of reward and predictability in the allergy task are already on their own small and malleable, even though independent effects had been observed in Experiment 1 as well as in previous studies of Griffiths et al. (2015) and Thorwart et al. (2017). For example, Liu et al. (2020) observed in a different learning paradigm that learning in a subsequent phase was not reliably affected by the outcomes' prior predictability.

If the current disappearance of any effects of prior reward and predictability can be replicated together with the occurrence of the effects when they are manipulated on their own, the results would speak to a more complex interaction of reward and predictability than previously postulated. For example, in each trial of Phase 1 the low reward manipulation for unpredictable outcomes might have decreased the relative aversiveness of an incorrect prediction as participants missed out on fewer points than they would do if the reward were as high as for the predictable outcomes. The lower reward for the unpredictable outcomes in Group Same might then have been perceived as rather beneficial and not additionally detrimental by the participants as they missed out on fewer points whenever they made an incorrect prediction. (Participants might reason that if they have to be bad at something, they might as well be bad at the task from which there is less to gain.) This mechanism, focusing on the effects of the two manipulations in each trial of Phase 1 and not so much at their interactions across the entire phase, would explain the missing differences between predictable and unpredictable outcomes in Group Same. However, it would instead predict a difference between the two outcome categories in Group Different, as the high reward for unpredictable outcomes would further increase the aversive consequences of frequent incorrect predictions. This is not what we observed either and even more complex interaction between these different approaches would be necessary to account for the data.

In contrast to prediction accuracy, predictability clearly biased the response times and therefore response preference in Phase 1 and Phase 2 as participants of both groups consistently chose to respond first to the (previously) predictable outcome category. This measure has not been inspected so far in Outcome Predictability studies using the allergy tasks. An Outcome Predictability effect has been observed as faster response times for trials with previously predictable outcomes, albeit in paradigms specially designed for such research questions and where response times are employed as measures of learning (cued search tasks, Griffiths et al., 2018; serial letter-prediction task, Quigley et al., 2018). On the one hand, this was not the case for the current paradigm. For example, no time pressure was induced in the task. On the other hand, response preferences should be more sensitive to differences in motivational characteristics of the outcomes than the traditional learning measures in the allergy task. We will come back to this in the following.

General Discussion

The current paper focuses on attributes associated with the correct prediction of outcomes in human predictive learning, in particular whether and how they bias participants' motivation to learn and the learning itself. Previous studies have shown that a history of unpredictability can attenuate the outcome-specific motivation to learn in subsequent tasks (Hartanto et al., 2021) as well as learning about that outcome (Griffiths et al, 2019). Based on the ideas of expectancy-value theories of motivation, the current experiments explored another manipulation: the reward associated with the correct prediction of an outcome. We argued that both, low reward and low predictability, would be detrimental to participants' motivation to learn about an outcome and would thereby attenuate learning about the respective outcomes, even when the manipulations were removed in subsequent tasks.

Overall, the results support the notion that people in simple predictive learning tasks are motivated by being correct as both the past amount of reward for, and the prior predictability of, correct predictions influence how people performed in learning tasks. The effects were observed when new learning about the same outcomes was required in Phase 2. As the outcomes were the only features that linked the two learning phases, such effects of reward and predictability are mediated by the outcomes and their influence on learning and performance. Additionally, these effects were caused by the learning histories of specific outcomes and they were limited to the specific outcomes, rather than modulating the participant's motivation to engage in *any* learning in the task or other general performance changes. This outcome-specificity indicates that the features and characteristics of the outcomes and their prior learning history play a crucial role in controlling learning and performance. It also distinguishes the Outcome Predictability effects from effects observed in the *Learned Helplessness* paradigm. Learned Helplessness effects refer to the observation that human and non-human animals tend to be demotivated after learning about their inability to control the occurrence of an aversive situation and therefore the unpredictability of the motivationally significant outcome (Burger & Arkin, 1980; Maier & Seligman, 1976, 2016). The Learned Helplessness effect is, however, characterized by its generalizability across different instrumental tasks and situations, as discussed by Griffiths et al. (2019).

In the current study, the effects of reward and predictability were not only specific for outcomes and the learning phase but also for the behavioral measures during learning, prediction accuracy and response preference. Increasing the prior reward for correct predictions improved the initial accuracy of new predictions for the corresponding outcome in Experiment 1 (effect of reward on prediction accuracy in Phase 2) but did not bias participants' decision on how to indicate these predictions behaviorally (no difference in response preference). When confronted with new learning about several cue-outcome relationships, prior reward seems to be one of the factors that governs the distribution of learning resources across the different outcomes. Notably, this is the case even when i) instructions clarify that no rewards for correct predictions of the outcomes are given anymore and ii) the prior reward is only "imaginary". Participants in the current study did not receive any actual reinforcer, like money, for the points they gained in the experiments.

We assumed that any effect of reward in predictive learning tasks would be based on its influence on the perceived value of an outcome's correct predictions. Rather surprisingly then, prior reward was not one of the factors that governed the decision to engage with an outcome behaviorally. We expected to see any effect observed in prediction accuracy to be present in response preferences too, as the latter should be influenced by current confidence in the prediction, and therefore by previous prediction accuracy, as well as by the current motivation to engage with this outcome more generally. The divergence between prediction accuracy and response preference in Experiment 1 hints that reward instead operates more specifically, for example on cognitive processes that lead to the predictions before behaviorally indicating them or cognitive processes after responding, when learning based on feedback takes place. While this manipulation of reward was strong enough to demonstrate an effect when introduced on its own, it failed to result in observable differences when combining it with a predictability manipulation.

The opposite divergence was observed with respect to predictability in Experiment 2: No effect of prior predictability on learning was apparent. This is surprising as both Griffiths et al. (2015) and Thorwart et al. (2017) observed the effect in highly similar experiments. Participants' decisions about which predictive response to indicate first was, however, affected by the current or prior predictability of the outcome: participants responded first to the predictable outcomes. Therefore, the manipulation of predictability was effective in the current study, albeit not in the dependent variables that were the focus of prior studies. We will therefore focus the following discussion on this divergence. Faster response times for the predictable outcome have been observed in other studies, which used response times as the main measure of learning, in particular a cued visual search task of Griffiths et al. (2018) and a serial-letter-task of Quigley et al. (2018). A slower response in these paradigms might stem from a lack of underlying knowledge that forces participants to trade off speed in order to achieve the same accuracy for both previously predictable and unpredictable outcomes. These studies therefore concluded that participants responded faster to previous predictable than previous unpredictable outcomes because they had already learned better about the outcomes' new relationships. However, participants in the current experiment did not know the answers to either outcome category in the first blocks of training in Phase 2 and the accuracy showed that knowledge developed equally for both categories. Participants nevertheless showed consistently faster response times for the predictable outcomes. One interpretation of the results is then that predictability might affect participants' behavior towards the outcome in predictive learning tasks more generally and without necessarily affecting learning.

One possible mechanism that could explain the divergence in learning and response preference involves habitual responding. As all participants responded consistently to the predictable outcomes first throughout Phase 1, this response pattern might become to some degree habitual and govern the behavior in Phase 2, without affecting the cognitive processes underlying learning. Participants responded first to the previously predictable outcomes in Phase 2 because this was what they did in a similar task in the same environment in Phase 1.

A second account of the results also distinguishes between several processes governing the behavioral expression of the prediction. Response times in simple decision-making tasks as used in the current and previous studies depend on several parameters. As described by Sewell et al. (2019), diffusion models for example decompose response times into two components: One that reflects the time course of decision-making and another that summarizes the time required for other processes not involved in decision-making (e.g., stimulus encoding and response execution). Decisions are in turn made by repeatedly sampling stimulus information and accumulating that information through time. Once a sufficient quantity of evidence has been accumulated and the process reaches a decision threshold, the corresponding behavioral response is initiated. Predictive learning and practice are known to affect parameters like the rate of information processing, which is conceptually related to learned knowledge about the cue-outcome relationships, or the decision threshold, which determines how much evidence is required before a prediction is made and reflects response caution (Sewell et al., 2019). Dutilh et al. (2011) further showed that some of these changes can be stimulus-specific. The current results might suggest that people have outcome-specific parameters, and these are transferred to new learning tasks with the same outcomes. For example, the decision threshold might decrease throughout Phase 1 but this decrease might be smaller for unpredictable outcomes than for predictable outcomes because participants remain more cautious due to the frequent incorrect responses. Such a difference in the decision threshold would affect response times already at the beginning of any new learning task, without the necessity of affecting learning. It also does not rely on differences in what has been already learned about the new cue-outcome relationships. Overall, the current divergence suggest then that faster responding in other paradigms might not be solely indicative of superior learning.

The discussion so far has treated the effects of prior reward in Experiment 1 and of prior predictability in Experiment 2 as rather independent. This is not what the hypotheses based on the expectancy-value-theories predicted and what Experiment 2 set out to investigate. The discussion relies on the double divergence between both the two dependent measures - response preference and prediction accuracy - and the two manipulations - reward and predictability - in the empirical results across the two experiments. In sum, we would argue only that the current results support the general hypothesis that people in simple predictive learning tasks are motivated by being correct: both the past amount of reward for and the prior predictability of correct predictions influence how people perform in subsequent learning tasks. They continue to have an influence on behavior even when the task changes so that there is no objective basis to be motivated to respond faster or learn more. The results also warrant further experiments into the interaction between the continuing influence of outcome predictability and value. Such experiments are necessary for reliable and valid conclusions concerning the processes supporting each factor and their interactions. For example, a key aim will be to determine whether the observed changes in learning and performance are the results of a single process that determines motivation based on the perceived expectancy and value of correct predictions.

Open Practices Statement

None of the experiments was preregistered The data for all experiments are available at https://osf.io/djqyr/.

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The influence of outcome unpredictability and uncontrollability on subsequent learning in an instrumental task

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Abstract

Outcome predictability is described as learning bias in a new environment, where participants learn better about an outcome with a history of predictability than an outcome with a history of unpredictability. Several studies have shown evidence of this effect. However, the characteristics and mechanism of the outcome predictability effect are not well understood yet. The outcome predictability effect has been proven to have the similarities with learned helplessness effect in terms of the lack of motivation to learn about an outcome. Despite their similarities from a motivational perspective, these two effects have been investigated using different paradigms and study designs. Also, the generalizability of these two effects differs broadly. In this study, we investigated the relationship between the two effects. We designed a new computer-based instrumental conditioning experiment inspired by Tiggemann and Winefield (1987) where participants had to stop different tones of different controllability and predictability properties. We expected to find both the learned helplessness and outcome predictability effect, in which participants would learn better about the controllable and predictable outcomes compared to the uncontrollable and unpredictable ones. Two experiments were conducted for this matter, manipulating both the controllability and predictability of the tone. We observed a global learned helplessness-like effect, that is, participants learned better about the previously controllable and predictable outcome. Our results suggest that a learned helplessness-like effect could be observed in this computer-based task. However, we did not observe the outcome predictability effect using this task.

Keywords: outcome predictability, outcome controllability, learned helplessness, instrumental conditioning, learning bias

1. Introduction

Studies have shown that learning of *cue-outcome* relations (predictive learning) could be biased by the properties of stimuli. Studies dealing with learned predictiveness, for example, showed that participants in a new situation learned about cue-outcome relations with previously predictive cues faster than with previously unpredictive ones even though new outcomes were presented (Le Pelley & McLaren, 2003; Lochmann & Wills, 2003). More recent studies investigated the effect of the *predictability* of an outcome on learning. Griffiths et al. (2015) found that learning could be affected by the unpredictability of the outcome. They showed that participants learned faster about the previously predictable outcomes than the previously unpredictable ones when they were presented with new cues in a new situation. This so-called *outcome predictability effect* has been investigated in different paradigms (Griffiths et al., 2018, 2015; Quigley et al., 2017; Thorwart et al., 2017).

Even though the outcome predictability effect has been found across paradigms (Griffiths et al., 2019), the basic characteristics and the mechanism of the effect are not well understood yet. One hypothesis is that the outcome predictability effect is related to the change of motivation to learn about one specific outcome. Hartanto et al. (2021) investigated the relationship between the outcome-specific motivation and outcome predictability effect by measuring participants' motivational changes after being exposed to both predictable as well as unpredictable outcomes. The authors used a typical predictive learning paradigm: an allergy task with two phases. The participants were asked about which outcome category they would like to learn in the second phase. Participants were less motivated to learn about the previously unpredictable outcome than the previously predictable one. Despite the absence of the typical outcome predictability effect (see e.g., Griffiths et al., 2015), they successfully demonstrated that outcome unpredictability could cause motivational change towards that specific outcome.

A similar type of demotivation towards an outcome was hypothesized decades ago to be responsible in a different learning paradigm for the so-called learned helplessness effect (Maier & Seligman, 2016; Seligman & Maier, 1967). Learned helplessness paradigms in the past involved the exposures towards an uncontrollable outcome, which biased participants' learning in a new situation. For instance, in the tone-stopping task by Hiroto and Seligman (1975), the group that had experienced uncontrollable tones responded slower in stopping these tones than the group that had experienced controllable tones. This learning bias in a new situation was based on changes in motivation due to the exposure to uncontrollable outcomes (Burger & Cooper, 1979; Miller & Seligman, 1976). This demotivation in the learned helplessness effect did not only involve the uncontrollability of the outcomes but also their unpredictability. Burger and Arkin (1980) investigated this aspect by separating controllability and predictability of the outcome using a "noise pollution" experiment and manipulating the perceived control and noise exposure duration. They showed that the presence of both uncontrollability and unpredictability was interpreted as essential for the motivational change in these tasks, hence inducing the learned helplessness effect. Taken together, the change of motivation could be the main cause of subsequent learning bias in both the outcome predictability and the learned helplessness effects.

However, there are at least two major procedural differences in experiments studying these two effects. Firstly, outcome predictability tasks were based on classical conditioning (cue-outcome relationships). Almost all learned helplessness paradigms, from electric shock tasks (Houston, 1972), tone-stopping tasks (Burger & Arkin, 1980; Hiroto, 1974; Tiggemann & Winefield, 1978, 1987), anagram tasks (Gatchel et al., 1977; Miller & Seligman, 1975), and even across tasks (Hiroto & Seligman, 1975) used instrumental conditioning (reaction-outcome relationships). Secondly, the outcome predictability effect has been investigated so far only with within-subject designs. Surprisingly, little is known about the learned helplessness effect in within-subject designs, most likely due to the methodological difficulties in realizing a design with within-subjects yoking of the exposure of the controllable and uncontrollable outcomes (see, e.g., Winefield, 1982). Due to the difference in experimental designs, all outcome predictability experiments have shown biased learning specific only to certain outcomes as they learn about those outcomes that had been experienced as unpredictable, as compared to learning about those outcomes that had been experienced as predictable. The learned helplessness effect, on the other hand, is known to generalize. Hiroto and Seligman (1975), for example, investigated the induction of the learned helplessness effect using both, a tone-stopping task, and an anagram task in two learning phases of the same experiment. They showed that the learned helplessness effect could even transfer from one learning situation to another. Griffiths et al. (2019) discussed these differences between the two effects, concluding that outcome predictability could be a “qualitative distinct sub-process of the more widely studied and prototypical form of learned helplessness effect.” (p. 6)

Experiment 1 of this study was conducted to attempt to converge the procedures. If the hypothesis of Griffiths et al. (2019) is true, an outcome-specific effect of uncontrollability might also be observable in a within-subject design using an instrumental task, in which the general learned helplessness effect has been found using between-subject designs.

2. Experiment 1

Experiment 1 consisted of two phases and was designed as a computer-based instrumental task similar to the tone-stopping task of Tiggemann and Winefield (1987). Throughout an initial Training Phase, each participant learned about the contingencies between different tones and different buttons. Each trial consisted of the presentation of one out of four different tones together with four buttons of different colors on a computer screen. These tones could either be completely stoppable, or partially stoppable, or completely unstoppable, and participants had to learn which button to press to immediately stop the tone. A subsequent Test Phase examined the effects of the initial training on learning new contingencies. While the task and the tones remained the same, the number and the colors of buttons now differed (eight instead of four) from the ones used in the Training Phase.

Each participant was assigned to one of three groups (see Table 1). In the Training Phase, participants in the controllable group (C Group) experienced three tones completely stoppable (controllable-predictable, CP, tones) by pressing one of the four buttons within a certain time. Participants in the uncontrollable group (U Group) experienced three unstoppable tones. The tone durations and the trial orders for each participant in the U Group were yoked to the tone duration of a participant in the C Group so that pairs of participants in the C Group and U Group had identical tone exposure durations. Participants in the within-subject group (WS Group) experienced one stoppable tone (CP), one partially stoppable tone (controllable-unpredictable, CUP, tone), and one completely unstoppable tone (uncontrollable-unpredictable, UCUP). The CUP tone was stoppable by pressing a certain button. However, the correct button was randomly determined for each trial. Participants therefore could control the tone, but they could not predict by which action they could do so in a certain trial. The durations of CUP and UCUP tones were yoked between blocks to the CP tone duration in the previous block so that the overall tone exposure was similar at the end of the Training Phase. In the Test Phase, all participants of all groups were presented with a new set of eight buttons and each tone was stoppable by pressing one of the different buttons. Additionally, a stoppable new tone was presented as a control tone to evaluate whether any learning bias would affect learning about this tone as well.

We expected to find a general learned helplessness effect between C Group and U Group, where U Group would take longer to learn to stop the previously experienced tones. For participants in the WS Group, we expected them to take longer to learn to stop the uncontrollable UCUP than the previously stoppable CP tone if learned helplessness effects could become outcome-specific like the outcome predictability effect. We further expected the performance for the CUP to be worse than the performance for the CP tone, but better than for the UCUP tone. On the contrary, if the learned helplessness effect could not become outcome-specific, we expected that WS Group and U Group would perform similarly, as the effects of the experienced uncontrollability of the CUP tone would generalize to the learning of the other tones as well.

Table 1.

Experimental Design for Experiment 1

Training			**Test**
C Group	**U Group**	**WS Group**	**All Groups**
Tone 1 → Button A	Tone 1 → Ø	Tone 1 → Button A	Tone 1 → Button X
Tone 2 → Button B	Tone 2 → Ø	Tone 2 → Button B	Tone 2 → Button Y
Tone 3 → Button C	Tone 3 → Ø	Tone 2 → Button C	Tone 3 → Button Z

Tone 2 → Button D	Tone 4 → Button O
Tone 3 → Ø	

Note. Four different tones were used in the experiments. Buttons labeled with letters represent the virtual buttons that had to be pressed once to terminate the tone.

2.1 Methods

2.1.1. Participants

Seventy-five undergraduate students of the Philipps-Universität Marburg completed the experiment (informed consent was obtained). They were randomly assigned to the groups so that there were 25 participants per group. They received money (9€ per hour) or course credits. Participants' ages ranged from 18 to 41 (*M* = 24.00, *SD* = 5.08). The sample consisted of 52 students identifying as female, and 23 students identifying as male.

2.1.2 Apparatus and Stimuli

This experiment was developed using JavaScript and HTML language and the JsPsych plugin (https://www.jspsych.org/; see: de Leeuw, 2015). Participants were individually seated in front of a 21" screen, which was used to present all the written instructions and visual stimuli, and a loudspeaker, which was used to present the auditory stimuli. Four different tones were used in this experiment: ticking tone, "wah-wah" tone, white noise, and square wave tone. During the Training Phase, only three out of the four tones were presented. In the Test Phase, all four tones were presented. In the Training phase, four buttons with four different colors were presented on the screen. For the Test Phase, eight buttons with eight different colors (different from the colors used in the Training Phase, see Fig. 1) were presented in circular order. The assignments of the tones and the buttons were randomized for each participant.

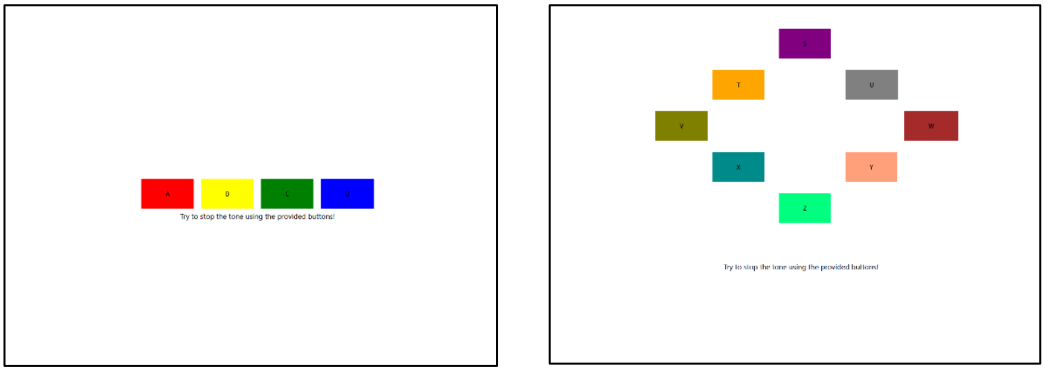

Figure 1. Button layouts for Training Phase (left) and Test Phase (right). Four buttons were presented during the Training Phase, and eight buttons, arranged circularly, were presented in the Test Phase.

2.1.3. Procedure

The experiment started with a page where the participants could fill in their gender and age. Afterward, participants of all groups received the following instruction:

"In this experiment, different tones will be played from time to time. Four buttons will be presented on the screen, and it is your task to find a way to stop each tone by clicking these buttons using the mouse. On each trial, the computer will stop each tone after a while if you have not done so. You must work out for yourself, however, whether you or the computer stopped the tone. Disconnecting the speaker is not the way to stop the tone."

Then, participants were directed to a page where they were instructed to adjust the volume of the tones so that they are as loud as tolerable but not unpleasant. Next, they were given a chance to ask any questions to the experimenter before the Training Phase started.

2.1.3.1. Training Phase

The Training Phase consisted of 7 blocks of 9 trials each, where each of the 3 tones was presented 3 times per block. The intertrial intervals, defined as the time from tone offset to the onset of the next trial, ranged from 5 to 10 seconds. The trial order was randomized within each block. In each trial, they were instructed: *"Try to stop the tone by using the provided buttons."* There were four buttons presented in the Training Phase. Participants in the C Group could terminate the tones by pressing one of the buttons once for each tone so that the duration and offset were both controllable and predictable by them. If they pressed the wrong button, they had the chance to try again until the correct button had been pressed or the maximum duration had been reached, in which case the trial would end, too. The maximal duration for the C Group was always 5 seconds. Participants in the U Group were yoked individually to experience the same trial sequence, tone types, and tone duration as their counterpart participants in the C Group. The tone duration in the WS Group was yoked between blocks. The actual duration of all three CP tones from all three trials was averaged and then used to calculate the maximum tone duration for the CUP and UCUP tones in the following block. More specifically, the maximal tone duration for CUP and UCUP tones in each trial was determined as a random number in the 1000-millisecond range around the average tone duration of the CP tone in the previous block.

2.1.3.2. Test Phase

The instruction for the Test Phase was similar to the one in the Training Phase. The Test Phase consisted of 6 blocks of each trial type shown in Table 1. Here, participants would only have one trial for each tone in a block. In addition to the three tones in the Training Phase, a new tone was introduced in the Test Phase as a control to evaluate the amount of generalization of both outcome predictability and learned helplessness effect. Eight buttons were presented in the Test Phase, arranged circularly in the middle of the screen. Participants could successfully stop the tones if they pressed the correct button once. In the Test Phase, all tones were therefore controllable as well as predictable. The maximal duration of all tones for all participants was 5 seconds.

2.1.3.3. Manipulation Checks

At the end of the experiment, the participants were asked for each of the 4 tones: *"How confident were you to stop the tone during the* ***first*** *phase?"* They had to give a rating between 0 and 100 for each tone to evaluate whether the participants in the Training Phase had perceived the controllability of the tones as intended.

2.1.4. Data Analysis

Data normalization based on Cousineau (2005) was performed for the standard error of means (SEMs) in the result figures to better reflect the error terms used in the within-subject analyses. Significance level after Greenhouse-Geisser correction of the degree of freedom was reported.

The main dependent variables used throughout Exp. 1 were: (a) the cumulative number of first hit across trials (first button press in a trial), indexing learning (a correct first hit was counted as 1 and an incorrect hit was counted as 0), and (b) the tone duration per trial, indexing either how quick participants in the C Group terminated all tones (and the WS Group terminated the CP and CUP tones) by pressing the correct button, but also that the computer stopped the tone based on the maximal duration of a certain trial.

2.2. Results

2.2.1. Training Phase

We will start with the analyses of cumulative number of first hits, followed by analyses of tone duration.

The results for the cumulative number of first hits will be illustrated by mere description (see Fig. 2). The C Group (left panel of Fig. 2) showed a steady increase in the cumulative number of first hits (at Block 7: *M* = 17.45, with the maximum of potential first hits = 21, *SD* = 1.64). Since all tones in the U Group were unstoppable, the cumulative number of first hits there stayed at zero for all blocks (see Fig. 2, middle panel).

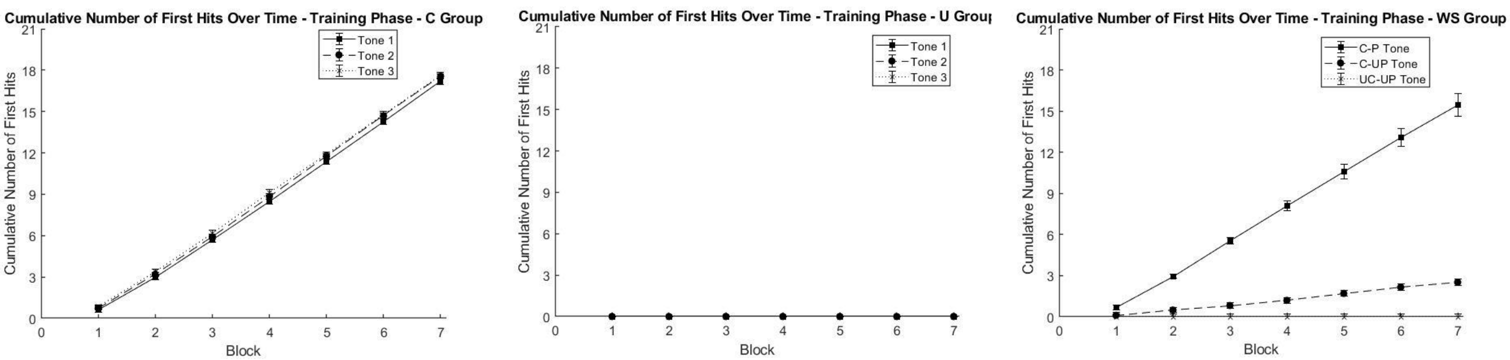

Figure 2. The cumulative number of first hits per block during the Training Phase for the C Group (left panel), U Group, and WS Group (right panel). The cumulative number of first hits for the U Group stayed at zero, as there was no possible hit for the U Group. In the C Group, since all tones were equally controllable and predictable, the different line types simply represent the hits for the three different tones. In the WS Group, the solid line represents the hit for the CP Tone, the dashed line represents the hits for the CUP Tone, and the dotted line represents the hits for the UCUP Tone. Error bars indicate the *SEM* of the normalized data.

Participants in the WS Group (see Fig. 2, right panel) also successfully learned the correct response for stopping the CP tone (*M* = 15.44, out of 21; *SD* = 5.13). As expected, the cumulative number of first hits was lower (*M* = 2.52, out of 21; *SD* = 1.59) since randomly one out of four buttons had been effective for the CUP tone. For the UC-UP Tone, the cumulative number of first hits stayed at zero as was the case with the tones in the U Group.

Overall, the tone duration decreased over time as depicted in Figure 3. All participants in the C Group learned the appropriate responses for stopping the tones. Since the tone durations were yoked to the participants in the U Group, the curves for the Training Phase for both groups are identical. Therefore, we only analyzed the tone durations of the C Group (see left panel of Fig. 3) with a repeated-measures ANOVA with two within-subject factors Tone (1 – 3) and Blocks (1 – 7). It confirmed a significant main effect of Blocks ($F(6, 144) = 22.67$, $p < .001$, $\eta_p^2 = .486$). No significant main effect of Tone, nor Tone*Block interaction was found ($F < 1.574$, $p > .195$).

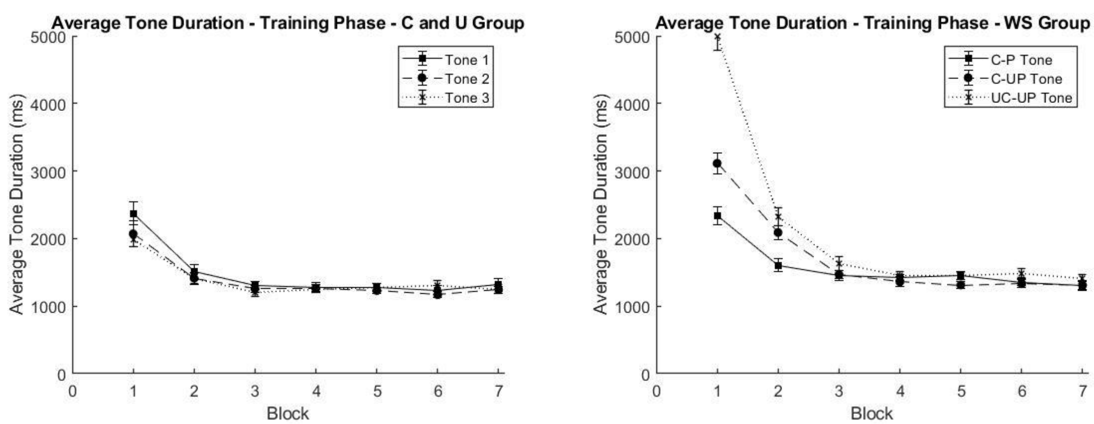

Figure 3. Average tone duration per block during the Training Phase for both the C and U Group (left panel) and the WS Group (right panel). In the C Group, since all tones were equally controllable and predictable, the different line types simply represent the duration for the three different tones. In the WS Group, the solid line represents the durations for the CP Tone, the dashed line represents the durations for the CUP Tone, and the dotted line represents the durations for the UCUP Tone. Error bars indicate the *SEM* of the normalized data.

For the WS Group, the duration also decreased for the CUP and UCUP tones, as expected due to the yoking to the CP tone duration (see right panel of Fig. 3). A repeated-measures ANOVA with two within-subject factors Tone (CP, CUP, and UCUP) and Blocks (1 – 7) was performed for the tone duration. The main effects of Tone ($F(2, 48) = 136.45$, $p < .001$, $\eta_p^2 = .850$) and Blocks ($F(6, 144) = 111.96$, $p < .001$, $\eta_p^2 = .823$) as well as the Tone*Block interaction ($F(12, 288) = 39.04$, $p < .001$, $\eta_p^2 = .619$) were significant. Simple main effect analyses showed that the tone duration of the CP tone was significantly lower than both the CUP and UCUP tones in Blocks 1 and 2 ($p < .003$).

2.2.2. Test Phase

We will start with the analyses of cumulative number of first hits, followed by analyses of tone duration.

Figure 4 depicts the cumulative number of first hits. Since participants only needed one button press to stop the tone, this data represents how well the participants learned about the response to stop the tone in the Test Phase. Overall, it showed that participants learned to stop the tones equally across all groups, perhaps faster for the control tone in the U Group. We analyzed the tone duration of the C and U groups (see Fig. 4, left and middle panel) with a repeated-measures ANOVA with two within-subject factors Tone (1 – 4) and Blocks (1 – 6), and the between-subject factor Group (C and U). It revealed a significant main effect of Blocks ($F(5, 240) = 402.48$, $p < .001$, $\eta_p^2 = .893$). Neither main effect of Group, Tone nor significant interaction between the factors was found ($F < 2.36$, $p > .076$). We further tested the difference between the tones in Block 6, to see if the participants learned about the tones differently. A repeated-measures ANOVA with a within-subject factor Tone (1 – 4) and a between-subject factor Group (C and U) showed no significant main effect of Tone, Group, nor a significant Tone*Group interaction ($F < 2.13$, $p > .100$). This showed that the participants in the two groups did not learn differently about the previously experienced tone and the control tone.

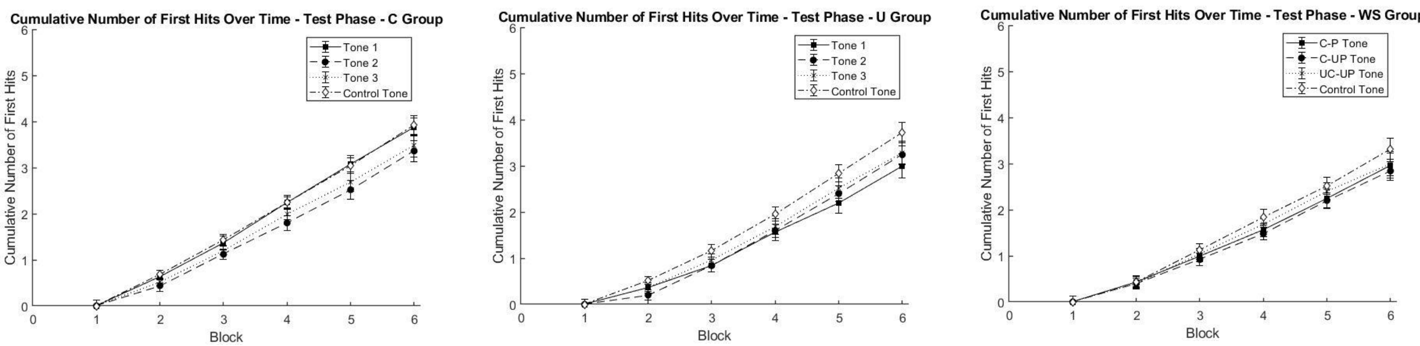

Figure 4. The cumulative number of first hits per block during the Test Phase for the C Group (left panel), U Group (middle panel), and WS Group (right panel). Since all tones in the C Group and U Group had equal properties within each group in the Training Phase, the solid, dashed, and dotted lines simply represent the hits for the three different tones. In the WS Group, the solid line represents the hits for the CP Tone, the dashed line represents the hits for the CUP Tone, and the dotted line represents the hits for the UCUP Tone. In all groups, the dot-dashed line represents the hits for the control tone. Error bars indicate the *SEM* of the normalized data.

For the WS Group (see Fig. 4, right panel), a repeated-measures ANOVA with two within-subject factors Tone (CP, CUP, UCUP, and Control) and Blocks (1 – 6) showed a significant main effect of Blocks ($F(5, 120) = 114.11$, $p < .001$, $\eta_p^2 = .826$). Neither main effect of Tone nor a significant interaction between the factors was found ($F < 1$, $p > .535$). We further tested the difference between the tones in Block 6, to see if the participants learned about the tones differently. A repeated-measures ANOVA with a within-subject factor Tone (1 – 4) showed no significant main effect of Tone ($F < 1$, $p = .448$). This showed that the participants did not learn differently about the previously experienced tone and the control tone.

Figure 5 shows the average tone duration, which represents the amount of time the participants took to stop the tone (or fail to stop the tones, in which case the tone duration would be 5 seconds). Similarly, but contrary to our hypothesis, participants took an equally long time to stop the tones across all groups. For C and U Group (see Fig 5, left and middle panel), a repeated-measures ANOVA with two within-subject factors Tone (1 – 3, and Control) and Blocks (1 – 6), and the between-subject factor Group (C and U) revealed a significant main effect of Blocks ($F(5, 120) = 25.24$, $p < .001$, $\eta_p^2 = .513$). Neither the main effect of Tone nor the Tone*Block interaction was found significant ($F < 1$, $p > .588$).

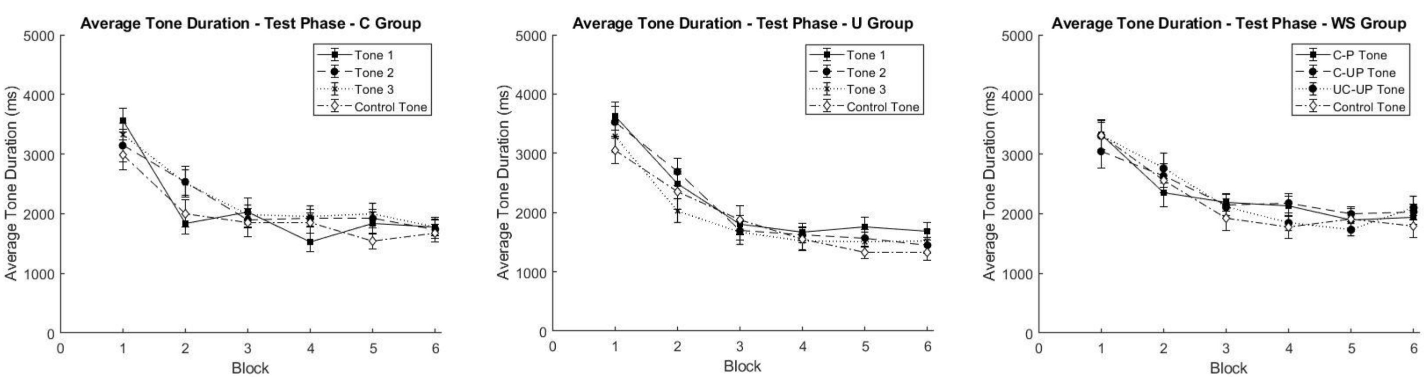

Figure 5. Average tone duration per block during the Test Phase for the C Group (left panel), U Group (middle panel), and WS Group (right panel). Since all tones in the C Group and U Group had equal properties within each group in the Training Phase, the solid, dashed, and dotted lines simply represent the durations for the three different tones. In the WS Group, the solid line represents the durations for the CP Tone, the dashed line represents the durations for the CUP Tone, and the dotted line represents the durations for the UCUP Tone. In all groups, the dot-

dashed line represents the durations for the control tone. Error bars indicate the *SEM* of the normalized data.

For the WS Group (see Fig. 5, right panel), a repeated-measures ANOVA with two within-subject factors Tone (CP, CUP, UCUP, and Control) and Blocks (1 – 6) confirmed a significant main effect of Blocks ($F(5, 240) = 77.66$, $p < .001$, $\eta_p^2 = .618$). Neither main effect of Tone nor significant interaction between the factors was found ($F < 1.78$, $p > .150$).

2.2.3. Manipulation Check

Participants perceived the controllability of the tone as intended. The ratings are presented in Figure 6.

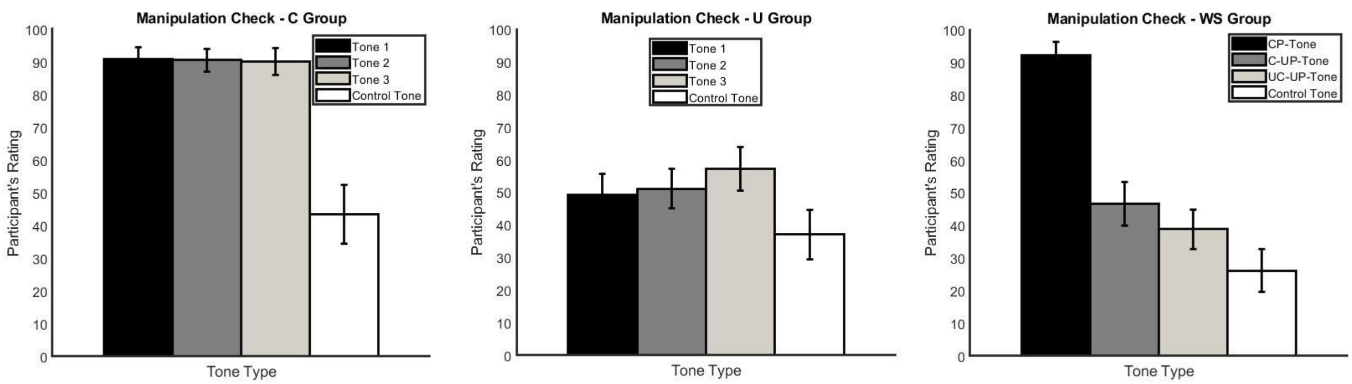

Figure 6. Manipulation check for the C Group (left panel), U Group (middle panel), and WS Group (right panel). Since all tones in the C Group and U Group had equal properties within each group in the Training Phase, the different colors simply represent the ratings for the three different tones. In the WS Group, the black bar represents the rating for the CP Tone, the dark grey bar represents the rating for the CUP Tone, the light grey bar represents the rating for the

UCUP Tone, and the white bar represents the rating for the Control Tone. Error bars indicate the *SEM* of the normalized data.

For C and U Group (see Fig. 6, left and middle panel), we performed an analysis using a repeated measures ANOVA with one within-subject factor Tone (1 – 4), one between-subject factor Group (C and U). It revealed that there was a significant main effect of Tone ($F(3, 144) = 19.49$, $p = .001$, $\eta_p^2 = .289$), Group ($F(1, 48) = 23.81$, $p < .001$, $\eta_p^2 = .289$) and a significant Tone*Group interaction ($F(3, 144) = 5.213$, $p < .001$, $\eta_p^2 = .332$). Simple main effect analyses showed that in C Group the rating for the control tone was significantly lower than for the other tones ($F(3, 45) = 10.32$, $p < .001$, $\eta_p^2 = .402$). In U Group, the overall rating for all the tones did not differ ($F(3, 46) = 1.86$, $p = .150$, $\eta_p^2 = .108$).

For WS Group (see Fig. 6, right panel), analysis using a repeated-measures ANOVA with one within-subject factor Tone (1 – 4) revealed that there was a significant main effect of Tone ($F(3, 72) = 26.61$, $p < .001$, $\eta_p^2 = .526$). Simple main effect analyses showed that the rating for the CP tone was significantly higher than for the other 3 tones ($F(3, 22) = 37.11$, $p < .001$, $\eta_p^2 = .835$), while the rating for the CUP tone was not higher than for the UCUP tone and the Control tone ($p > .245$). The ratings of the UCUP tone and the Control tone in the WS Group did not differ significantly ($p > .911$).

2.3. Discussion

In Experiment 1 we investigated whether the outcome-specific effect of previous uncontrollability could be found in an instrumental conditioning paradigm. Like classic learned helplessness paradigms, we also implemented a between-subject design (C Group vs U Group) to see if the learned helplessness effect could be replicated in this computer-based task. As the control tone was not presented in the Training Phase, participants' rating in the manipulation check for this tone could be seen as a baseline for guessing. The higher rating for the controllable tones in the C Group confirms that they perceived the controllability. While the ratings for the uncontrollable tones in the U Group and WS group were not lower than for the control tone, they were lower than the rating of the controllable tones in the C Group or the WS Group, respectively. Participants therefore clearly differed in their perception of the tones in the Training Phase. Nevertheless, we did not find any significant effect.

In WS Group, if the outcome-specific effect could be found using the instrumental conditioning paradigm, we expected that we would find different performances for different tones. However, we did not see differences in the number of cumulative first hits or tone duration between the tones in the Test Phase, indicating that there was no difference in learning about the tones. Furthermore, no learned helplessness effect between the C Group and U Group was evident as none of the dependent measures in the Test Phase showed a difference between the two groups. This makes interpretations of any results in WS Group futile, in particular, the missing outcome-specific effects might be due to missing effects overall.

How could there be no learned helplessness effect even though the participants perceived the controllability properly and the effect has been widely studied and observed? One reason could have been that, even though the participants perceived the tones as uncontrollable, all tones were perceived as predictable. As shown in Figure 3, the tone durations in all groups almost consistently stayed around 1500 milliseconds. This was due to rather consistent behavior in the C Group. As the duration of the uncontrollable tones in the U Group was yoked to the duration of these controllable tones in the C Group, all participants could easily predict when all the tones would stop. As described above, Burger and Arkin (1980) argued that both uncontrollability and unpredictability of the outcome must be present for a learned helplessness effect to occur. This account is supported by the result from Tiggemann and Winefield (1987) that an additional predictable, yet uncontrollable group did not differ significantly from the controllable and predictable group. Furthermore, since the participants in the C Group responded relatively fast to stop the tone during the Training Phase, participants in the U Group could not have enough time to react to the uncontrollable yoked tones. In other words, there was a limited experience of uncontrollability because the tones almost immediately stop.

We intended to test this explanation for any missing effect between the C and U groups by increasing both the randomness and range of the tone durations for the uncontrollable tones in the Training Phase and thereby focusing only on the between-subject learning bias. This should increase the perceived unpredictability of these tones and induce a learning bias. An increased variance of tone durations should also enable participants to press several buttons in some trials, and thereby also increase the experience of uncontrollability.

3. Experiment 2

This experiment focused on the global effect of predictability in an instrumental task. It investigated if the global predictability effect, which Experiment 1 failed to observe, could be induced by increasing the unpredictability of the outcomes in the uncontrollable group. The design is presented in Table 2. There were three groups: a controllable group (C Group), an uncontrollable group with a yoked mean (U-YM Group), and an uncontrollable group with high variance (U-HV Group). Like Experiment 1, participants in the C Group experienced three completely stoppable tones in the Training Phase. Participants from both the U-YM Group and

U-HV Group experienced three completely unstoppable tones in the Training Phase. The assignments of tone durations were as follows. The tone durations in Training Phase for the U-YM Group were taken from a uniform distribution around the overall mean of all participants in the C Group with a 2000 millisecond range. For the U-HV Group, the tone durations were not yoked. Instead, they were randomly generated from a uniform distribution between 500 and 5000 milliseconds throughout the Training Phase. Note that this however meant that the overall exposure to the tones in this group was larger than in the other two groups.

Like Experiment 1, a new tone as control was introduced in the Test Phase and all tones in the Test Phase were completely stoppable. We expected the participants in both uncontrollable groups, both the yoked and not yoked groups, to learn and respond slower than the controllable group.

Table 2.

Experimental Design for Experiment 2

Training			**Test**
C Group	**U-YM Group**	**U-HV Group**	**All Groups**
Tone 1 → Button A	Tone 1 → Ø	Tone 1 → Ø	Tone 1 → Button X
Tone 2 → Button B	Tone 2 → Ø	Tone 2 → Ø	Tone 2 → Button Y
Tone 3 → Button C	Tone 3 → Ø	Tone 3 → Ø	Tone 3 → Button Z
			Tone 4 → Button O

Note. Four different tones were used in the experiments. Buttons labeled with letters represent the virtual buttons that had to be pressed once to terminate the tone.

3.1. Methods

Only the differences to Experiment 1 are reported.

3.1.1. Participants

Seventy-nine students of the Philipps-Universität Marburg completed the behavioral experiment (informed consent was obtained). Seven participants were excluded from the analysis. Five of them were due to technical errors during the experiment and two did not make any response in either or both phases. The rest of the participants (72 participants) were assigned to the groups so that there were 24 participants per group. Due to the yoking between groups, U-YM Group was collected last after collection of C group had finished. The age of the participants ranged from 18 to 31 (M = 21.85, SD = 3.343). The sample consisted of 55 students identifying as female and 17 students identifying as male. They were paid with course credit.

Twenty-two participants participated in the lab, while the rest of the participants participated online at their convenience. This was done due to the new regulations during the pandemic. A chi-square test of independence was performed to examine the relationship between locations of data collection and the group assignment. The relation between these variables was not significant ($\chi^2(2, N = 72) = 1.8$, $p = .407$).

3.1.2. Design and Procedure

The design of the experiment is summarized in Table 2. The task in this experiment was identical to Experiment 1. Just like Experiment 1, participants in the C Group experienced all 100% stoppable tones. Participants in U-YM and U-HV Group experienced all 100% unstoppable tones. The tone durations were yoked between the C Group and the U-YM Group. But instead of trial-by-trial yoking, the overall mean duration in the C Group was calculated

(1561 milliseconds) and the tone duration in each trial of U-YM Group was a random number within a 2000-millisecond range around this mean. So overall, participants in the U-YM Group experienced tone durations between 561 and 2561 milliseconds throughout the Training Phase. Participants in the U-HV Group were not yoked to the C Group. Instead, the tone durations were randomly taken from a uniform distribution between 500 and 5000 milliseconds throughout all trials in Training Phase.

3.1.2.1. Manipulation Checks

We implemented two manipulation checks: one to measure the controllability as perceived by participants (like Experiment 1), and a second to measure the predictability as perceived by participants. The participants were asked again for each of the 4 tones: *"How sure could you predict when this tone was going to stop during the* ***first*** *phase?"* They had to give a rating for each tone between 0 and 100. This was performed to see their perception of predictability for each tone, while the other check asked their perception of controllability.

3.2. Results

3.2.1. Training Phase

We will start with the analyses of cumulative number of first hits, followed by analyses of tone duration.

The cumulative number of first hits was depicted in Figure 7. All participants in the C Group learned the appropriate responses to stop the tones. The results for the cumulative number of first hits will be illustrated by mere description (see Fig. 7). The C Group (left panel of Fig. 7) showed a steady increase in the cumulative number of first hits (at Block 7: M = 16.83, with the maximum of potential first hits = 21, SD = 2.60). Like Experiment 1, since all tones in the U-YM and U-HV Group were unstoppable, the cumulative number of first hits stayed at zero for all blocks (see Fig 7, middle and right panel).

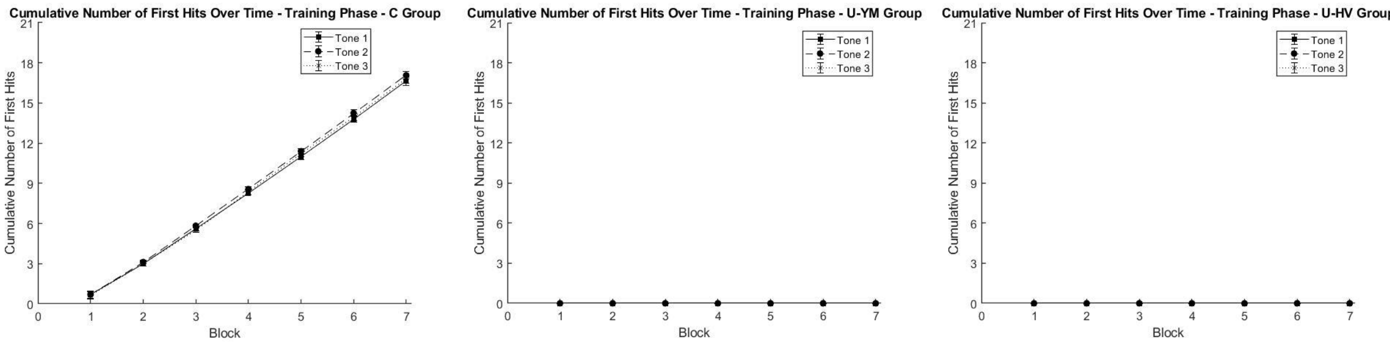

Figure 7. The cumulative number of first hits per block during the Training Phase for the C Group (left panel), U-YM Group (middle panel), and U-HV Group (right panel). The plots for the cumulative number of first hits of the U-YM and U-HV groups stayed at zero, as there was no possible hit for both groups. Since all tones were equally controllable and predictable, the different line types represent the hits for the three different tones. Error bars indicate the *SEM* of the normalized data.

The average tone duration per block is shown in Figure 8. Participants in the U-YM and U-HV Group were exposed to tone durations with more variance than in the C Group. This was confirmed by an F-test of variance which revealed that the exposure variance differed significantly between groups in all blocks ($F(2, 69) > 14.94$, $p < .001$).

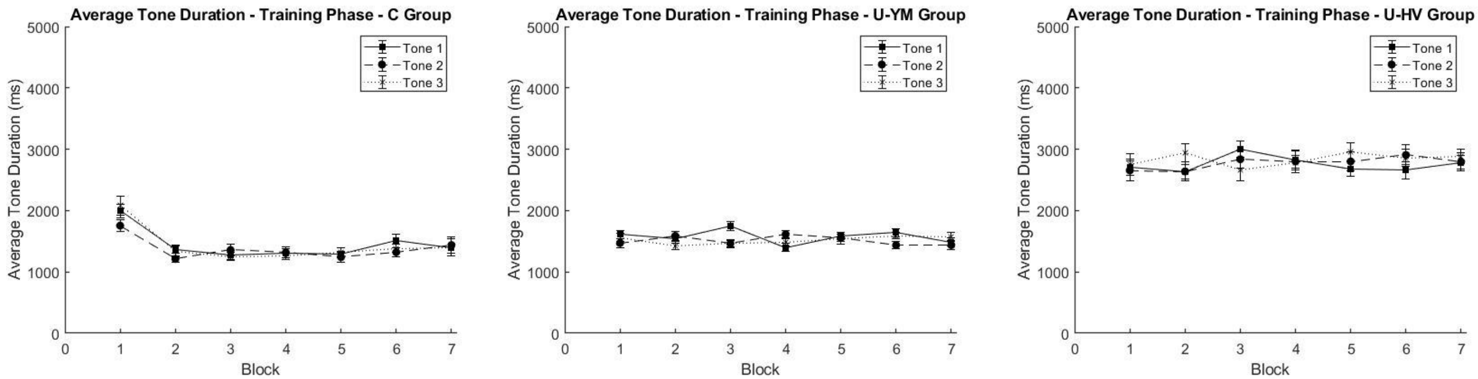

Figure 8. Average tone duration per block during Training Phase for the C Group (left panel), U-YM Group (middle panel), and U-HV Group (right panel). Since all tones in all groups had equal properties within each group, the three different lines simply represent the hits for the three different tones. Error bars indicate the *SEM* of the normalized data.

A repeated-measures ANOVA with two within-subject factors Tone (1 – 3) and Blocks (1 – 7), and one between-subjects factor Group (C, U-YM, and U-HV) was performed for the tone duration analysis (see Fig. 8). It showed significant main effects of Blocks ($F(6, 414) = 2.91$, $p = .015$, $\eta_p^2 = .040$) and Group ($F(2, 69) = 256.41$, $p < .001$, $\eta_p^2 = .881$). A significant Block*Group interaction was also found ($F(12, 414) = 4.38$, $p < .001$, $\eta_p^2 = .112$). Further post-hoc ANOVAs for pairwise comparisons between the groups showed that there was no significant difference between C Group and U-YM Group across all blocks ($F = 3.52$, $p = .067$), indicating that the exposure durations between C and U-YM Group were similar, as it was expected due to yoking procedure. Both comparisons between C Group and U-HV Group, and U-YM Group and U-HV Group showed significant differences (C vs U-YM: $F(1, 46) = 293.88$, $p < .001$, $\eta_p^2 = .865$; U-YM vs U-HV: $F(1, 46) = 988.05$, $p < .001$, $\eta_p^2 = .956$). No significant main effect of

Tone nor other significant interaction was observed ($F < 1.24$, $p > .269$). These analyses showed that the experimental manipulation worked as intended.

3.2.2. Test Phase

All participants learned the appropriate responses to stop the tones. We will start with the analyses of cumulative number of first hits, followed by analyses of tone duration.

Figure 9 shows the cumulative number of first hits. Participants in the C Group overall learned faster to stop the tone compared to those in the U-YM and U-HV Group (see Fig. 9). A repeated measures ANOVA with two within-subject factors Tone (1 – 4) and Blocks (1 – 6), and one between-subject factor Group (C, U-YM, and U-HV) showed significant main effects of Blocks ($F(5, 345) = 294.07$, $p < .001$, $\eta_p^2 = .810$) and Group ($F(2, 69) = 9.02$, $p < .001$, $\eta_p^2 = .207$). We also observed significant Block*Group ($F(10, 345) = 7.08$, $p = .001$, $\eta_p^2 = .170$) and Tone*Block interaction ($F(15, 1035) = 2.65$, $p = .036$, $\eta_p^2 = .037$). Further post-hoc ANOVAs for pairwise comparison revealed significant differences between C Group and U-YM Group ($F(1, 46) = 14.54$, $p < .001$, $\eta_p^2 = .240$), and between C Group and U-HV Group ($F(1, 46) = 14.80$, $p < .001$, $\eta_p^2 = .243$), but not between U-YM Group and U-HV Group ($F < 1$, $p = .696$). Neither main effect of Tone nor any other significant interactions between the factors was observed ($F < 2.11$, $p > .107$). We further tested the difference between the tones in Block 6, to see if the participants had learned about the tones differently. A repeated measures ANOVA with a within-subject factor Tone (1 – 4) and a between-subject factor Group (C, U-YM, and U-HV) revealed significant main effects of Tone ($F(3, 207) = 3.17$, $p = .029$, $\eta_p^2 = .044$) and Group ($F(1, 69) = 7.79$, $p = .001$, $\eta_p^2 = .184$) but the Tone*Group interaction was not significant ($F(6, 207) = 1.10$, $p = .366$). Using difference contrast, a significant difference between the control tone and the other three tones was found ($F(1, 69) = 9.70$, $p = .003$, $\eta_p^2 = .123$).

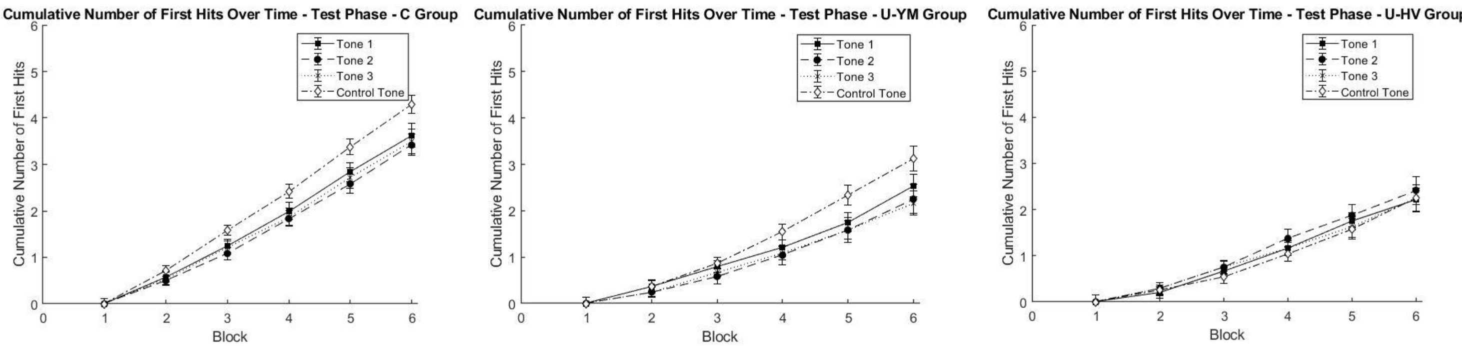

Figure 9. The cumulative number of first hits per block during the Test Phase for the C Group (left panel), U-YM Group (middle panel), and U-HV Group (right panel). Since all tones in all groups had equal properties within each group, the solid, dashed, and dotted lines simply represent the hits for the three different tones. In all groups, the dot-dashed line represents the hits for the control tone. Error bars indicate the *SEM* of the normalized data.

Figure 10 shows the average tone duration per block. Overall, it showed that participants in U-YM and U-HV Group took longer to stop the tones. A repeated measures ANOVA with two within-subject factors Tone (1 – 4) and Blocks (1 – 6), and one between-subject factor Group (C, U-YM, and U-HV) revealed a significant main effects of Blocks ($F(5, 345) = 69.78$, $p < .001$, $\eta_p^2 = .503$) and Group ($F(2, 69) = 6.86$, $p = .002$, $\eta_p^2 = .166$). A significant Block*Group interaction was also found ($F(10, 345) = 3.72$, $p = .002$, $\eta_p^2 = .097$). Further post-hoc ANOVAs for pairwise comparisons between the groups revealed significant differences between C Group and U-YM Group ($F(1, 46) = 5.50$, $p < .023$, $\eta_p^2 = .107$), and between C Group and U-HV Group ($F(1, 46) = 12.34$, $p = .001$, $\eta_p^2 = .212$). The difference between U-YM Group and U-HV Group across all blocks was not significant ($F = 2.61$, $p = .113$, $\eta_p^2 = .054$). No significant main effect of Tone nor any other significant interaction was observed ($F < 1.56$, $p > .107$).

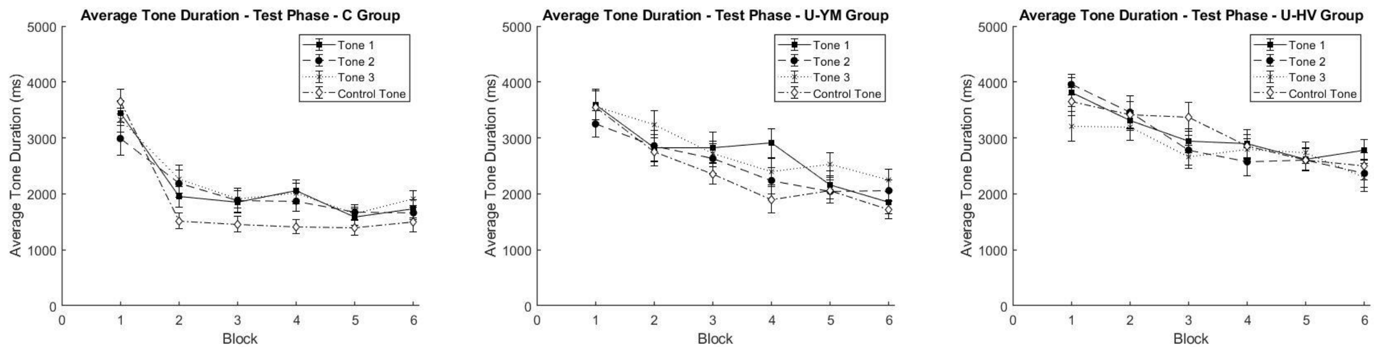

Figure 10. Average tone duration per block during Test Phase for C Group (left panel), U-YM Group (middle panel), and U-HV Group (right panel). Since all tones in all groups had equal properties within each group in the Training Phase, the solid, dashed, and dotted lines simply represent the hits for the three different tones. In all groups, the dot-dashed line represents the durations for the control tone. Error bars indicate the *SEM* of the normalized data.

3.2.3. Manipulation Check

Participants perceived both the controllability and predictability of the tones as intended. The ratings for the controllability and predictability checks are presented in Figure 11 and Figure 12, respectively. We will start with the analysis of the controllability manipulation check, followed by the analysis of the predictability manipulation check.

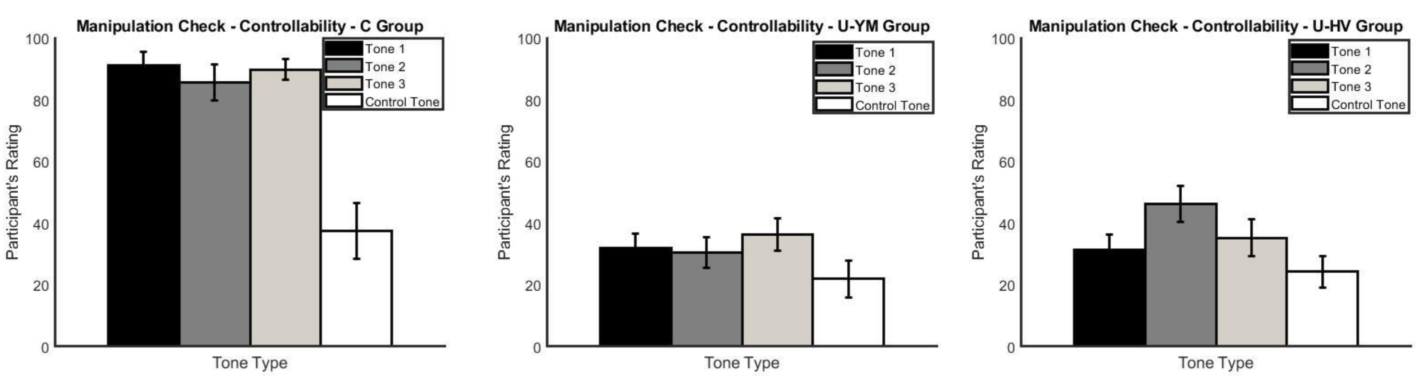

Figure 11. Controllability manipulation check for C Group (left panel), U-YM Group (middle panel), and U-HV Group (right panel). Since all tones in all groups had equal properties within each group in the Training Phase, the black, dark grey and light grey bars simply represent the ratings for the three different tones. In all groups, the white bar represents the rating for the Control Tone. Error bars indicate the *SEM* of the normalized data.

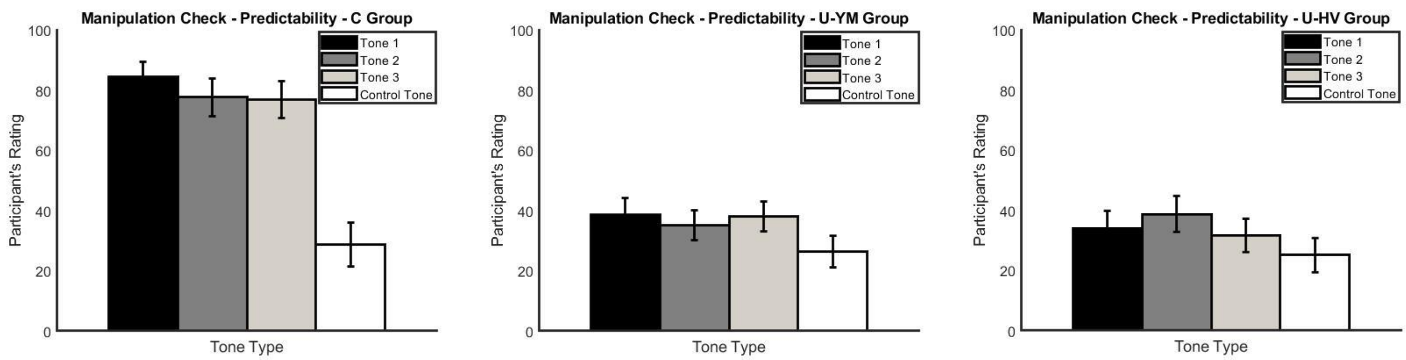

Figure 12. Predictability manipulation check for C Group (left panel), U-YM Group (middle panel), and U-HV Group (right panel). Since all tones in all groups had equal properties within each group in the Training Phase, the black, dark grey and light grey bars simply represent the ratings for the three different tones. In all groups, the white bar represents the rating for the Control Tone. Error bars indicate the *SEM* of the normalized data.

We analyzed participant's perception of controllability (see Fig. 11) using a repeated measures ANOVA with one within subject factor: Tone (1 – 4), and one between subject factor: Group (C, U-YM, and U-HV). It revealed significant main effects of Tone ($F(3, 207) = 21.54$, $p < .001$, $\eta_p^2 = .238$), Group ($F(2, 69) = 43.77$, $p < .001$, $\eta_p^2 = .559$), and a significant Tone*Group interaction ($F(6, 207) = 6.81$, $p < .001$, $\eta_p^2 = .165$). Further simple main effect analyses showed that in C Group, the rating for the control tone was significantly lower compared to the other tones (F(3, 67) = 16.61, $p < .001$, $\eta_p^2 = .427$). Further post-hoc ANOVAs for pairwise comparison revealed overall significant differences between C Group and U-YM Group (F(1, 46) = 77.57, $p < .001$, $\eta_p^2 = .628$), and C Group and U-HV Group (F(1, 46) = 59.67, $p < .001$, $\eta_p^2 = .565$), but not U-YM Group and U-HV Group ($F < 1$, $\eta_p^2 = .012$).

Participant's perception of predictability (see Fig. 12) was also analyzed using a repeated measures ANOVA with one within subject factor: Tone (1 – 4), and one between subject factor: Group (C, U-YM, and U-HV). It revealed significant main effects of Tone (F(3, 207) = 23.78, $p < .001$, $\eta_p^2 = .256$), Group (F(2, 69) = 19.49, $p < .001$, $\eta_p^2 = .361$), and a significant Tone*Group interaction (F(6, 207) = 8.02, $p < .001$, $\eta_p^2 = .189$). Further simple main effect analyses showed that in C Group, the rating for the control tone was significantly lower compared to the other tones (F(3, 67) = 21.81, $p < .001$, $\eta_p^2 = .494$). Further post-hoc ANOVAs for pairwise comparison revealed overall significant differences between C Group and U-YM Group (F(1, 46) = 28.20, $p < .001$, $\eta_p^2 = .380$), and C Group and U-HV Group (F(1, 46) = 32.11, $p < .001$, $\eta_p^2 = .411$), but not U-YM Group and U-HV Group ($F < 1$, $\eta_p^2 = .002$).

3.3. Discussion

Experiment 2 successfully manipulated both the controllability and predictability of the outcomes and showed that the exposure to uncontrollable and unpredictable outcomes biased subsequent learning. Overall, participants in the C Group learned to stop the tones faster in the Test Phase than the participants in the U-YM Group and U-HV Group.

The difference between participants' learning in C and U-YM Group during Test Phase indicated an effect similar to the learned helplessness effect, where the participants in the C Group learned better than the participants in the U-YM Group. As shown by learned helplessness studies (Burger & Arkin, 1980; Hiroto & Seligman, 1975; Tiggemann & Winefield, 1987), participants who had been exposed to uncontrollable and unpredictable tones developed helplessness in a new situation. Our results further confirmed this. However, even though U-YM Group was overall yoked to C Group (meaning participants in C and U-YM groups received equal tone exposures overall), we still could not say that this replicates the learned helplessness effect for two reasons. One, unlike the original studies, our yoking was not performed trial-by-trial, and two, our study design was not a triadic group design: we did not have a control group (see, e.g., Hiroto & Seligman, 1975). Regardless, the observed learning bias confirmed the effect of uncontrollability and unpredictability on subsequent learning. Our data on cumulative first hits, as well as tone duration, showed that the learning in the U-YM Group was impaired.

The effect we found from the comparison between the C Group and U-HV Group was also similar to the learned helplessness effect. However, these two groups were not yoked at all. The Training Phase of the U-HV Group clearly showed that the participants were exposed to the tones significantly longer than the other two groups. Participants in the U-HV Group might have perceived the tone as more aversive than participants in the C Group, as they were exposed to the tones for significantly longer durations (see Fig. 10). Not only were the tones aversive, but they were also uncontrollable and unpredictable. The learning bias we found in the Test Phase of the U-HV Group could be a compounded effect from aversiveness, uncontrollability, and unpredictability.

At this point, one may question the participant's behavior towards the control tone. From the cumulative first hits data we observed that in all groups, all participants learned faster about the new control tone compared to the previously exposed tone. The comparison of control tone at Block 6 showed however that the learning of the control tone was significantly faster in the C

Group than the U-YM and U-HV Group. This showed that the learning bias between the groups was a more global and general effect that affected learning even for the control tone.

4. General Discussion

In summary, we demonstrated that outcome uncontrollability and unpredictability can affect subsequent learning using an instrumental conditioning paradigm. Recent studies have shown the learning bias caused by an outcome's unpredictability using classical conditioning paradigms (Griffiths et al., 2018, 2015; Quigley et al., 2017; Thorwart et al., 2017). This study investigated the learning bias caused by the uncontrollability and unpredictability of an outcome using an instrumental conditioning paradigm. We successfully established a new instrumental learning task involving various tones to investigate this effect. This was remarkably similar to the learned helplessness effect, which also involved learning about uncontrollable and unpredictable outcomes in instrumental learning paradigms (Maier & Seligman, 1976, 2016).

The data from Experiment 2 showed that performance in subsequent learning could be affected by the exposure to uncontrollability and unpredictability. Although we did not measure the perception of predictability of the participants in Experiment 1, the results from Experiment 2 suggest that participants in Experiment 1 experienced the uncontrollable tones as rather predictable during the Training Phase and this might have been the reason for no learning bias was observed in Experiment 1. This was in line with the learned helplessness studies where both uncontrollability and unpredictability are crucial in inducing the learned helplessness effect (Burger & Arkin, 1980).

The introduction of the control tone in the Test Phase, however, showed in Experiment 2 a learning advantage of the newly introduced control tone over the already trained ones.

However, this advantage did not neutralize the effect of unpredictability and uncontrollability as the groups still differed. Although our results showed a global effect of unpredictability and uncontrollability in instrumental learning designs like the learned helplessness effect, further investigations on the generalizability versus specificity of the learned helplessness effect should be conducted. As the next step, the within-subject design of the WS Group in Experiment 1 should be combined with the manipulations of the U-YM Group and U-HV Group of Experiment 2. This would also help to answer the question of how this study relates to the outcome predictability effect.

4.2. Conclusions

In short, exposure to uncontrollability and unpredictability of an outcome impacted learning. We observed that participants in the uncontrollable groups learned slower in a new situation compared to the controllable groups. However, this was not true for all kinds of manipulation of controllability. Since our study did not specifically answer the effect from outcome predictability alone, further research investigating whether an outcome predictability effect without controllability could exist in an instrumental learning paradigm is required.

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