Model Expertise Does Not Influence Automatic Imitation

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Abstract

Social learning theories state that new skills can be learned by observing others. Automatic imitation is thought to play an important role in this process. However, whether imitation is beneficial to learning critically depends on the expertise of the imitated person. Therefore, the aim of this study was to investigate the influence of model expertise on automatic imitation, by comparing automatic imitation of an expert and non-expert model in two within-subject experiments. In a first experiment ($N = 61$), we manipulated the perception of expertise in one task and tested how this influenced automatic imitation in a separate task. However, in contrast to our hypothesis, and in spite of a successful manipulation check, we did not find evidence for an effect of model expertise on imitative behavior. To exclude the alternative explanation that this was due to a lack of transfer of expertise attribution, we then conducted a second, preregistered experiment ($N = 125$), in which we manipulated model expertise using the same task also used to measure automatic imitation. However, in line with the results of Experiment 1, we found no evidence for an effect of model expertise on imitative behavior. These results put important constraints on the role of automatic imitation in motor learning.

Keywords: Automatic imitation, selective social learning, motor learning, model expertise

In life, we often learn through imitation. When dancers have to learn a new choreography, for instance, they will typically start by imitating their dance instructor. This way of learning by observation is commonly known as social learning and is thought to play an important role in acquiring new motor skills (Bandura & Walters, 1977; Ramsey et al., 2021). Imitation and its role in social learning have been topics of interest in various domains, including developmental psychology (Brugger et al., 2007; Dickerson et al., 2013; Williamson & Meltzoff, 2011), cognitive psychology (Heyes & Foster, 2002), and cognitive neuroscience (Buccino et al., 2004; Losin et al., 2009; Sakreida et al., 2018).

To imitate other people's behavior, we have to be able to translate observed actions into a motor plan reproducing those actions (Brass & Heyes, 2005). According to ideomotor theory, such translation is possible because the visual image of an action is part of its motor representation (Greenwald, 1970; Prinz, 1997). More specifically, ideomotor theory assumes that action observation and action execution rely on shared representations and therefore that observing an action automatically primes the execution of that action (e.g., Chong et al., 2008; Dinstein et al., 2007; Kilner et al., 2009). This mechanism, known as motor simulation, is thought to enable imitation (Brass & Heyes, 2005; Fadiga et al., 1995) and is considered key for motor learning (Buccino et al., 2004; Ertelt et al., 2007; Iacoboni, 2005; Lagravinese et al., 2017).

In cognitive psychology, motor simulation is often studied via automatic imitation, defined as the tendency to copy observed actions, even when they are not relevant to the task at hand (Cracco, Bardi, et al., 2018; Heyes, 2011). Automatic imitation is typically measured with a stimulus-response compatibility (SRC) procedure. Brass and his colleagues (2000), for example, made participants respond to numbers by lifting one of their fingers while seeing brief videos of a hand executing an (in)congruent finger movement. Congruent finger movements were the same as the correct response, incongruent ones were not. The researchers

found a congruency effect: participants responded faster and made fewer errors on congruent than on incongruent trials (Brass et al., 2000). This congruency effect has been replicated in many studies (Brass et al., 2001; Cracco, Bardi, et al., 2018; Longo et al., 2008; Press et al., 2008) and is a reliable method (Genschow et al., 2017) to measure motor simulation (Cracco & Brass, 2019; Heyes, 2011).

Although multiple studies support the link between motor simulation and motor learning (Buccino et al., 2004; Ertelt et al., 2007; Lagravinese et al., 2017), imitation is not always beneficial to learning. Indeed, social learning is often selective (Heyes, 2018) and depends on a variety of contextual factors (for a review, see Rendell et al., 2011), such as model characteristics (e.g., Henrich & Broesch, 2011; McGuigan, 2013) and prior experience with a task (e.g., Williamson & Meltzoff, 2011; Wood et al., 2013). This selectivity is important because it is not efficient to copy every observed action. In line with this view, motor simulation is known to be a flexible mechanism (Cook et al., 2012; Gillmeister et al., 2008; Heyes et al., 2005; Wiggett et al., 2011) and to be sensitive to both model (Genschow, Cracco, et al., 2021; Press et al., 2005) and observer characteristics (Calvo-Merino et al., 2005, 2006; Haslinger et al., 2005).

A particularly important factor for learning is expertise. Indeed, both model and observer expertise are important in steering whom and what to imitate in order to facilitate learning. Current research has mainly focused on observer expertise. For example, Calvo-Merino and colleagues (2005, 2006) measured brain activity in the motor system as a measure of motor simulation and found stronger motor activation when dancers watched movements in their own dance style, compared to movements from another dance style. Similarly, Haslinger and colleagues (2005) found that professional pianists, compared to control participants, showed stronger activation in brain regions associated with imitation when observing piano-related but not piano-unrelated hand movements.

The effect of observer expertise on motor simulation is relevant for motor learning, because it may facilitate the execution of well-known movements, thereby helping experts to perfect their skill (Calvo-Merino et al., 2006). What is arguably more important, however, is model expertise. To optimize motor learning, observers should preferentially imitate people who are skilled at the to-be-learned task. If you want to learn how to dance, for instance, you better not imitate the worst dancer in your class. Instead, you want to imitate the movements of the dance instructor, the expert. Therefore, according to the idea of selective social learning (Heyes, 2018), we might expect observers to show stronger imitative tendencies for expert compared to non-expert models. The current study tested this hypothesis by investigating the influence of model expertise on automatic imitation. More specifically, because imitation of experts optimizes our chances for learning, and social learning is selective (Heyes, 2018), we hypothesized that automatic imitation would be stronger for expert than for non-expert models.

Experiment 1

Method

Participants

Seventy-two first-year psychology students at Ghent University participated in this experiment in return for course credit. The experiment was conducted as part of a student project and the sample size was determined by the number of participants assigned to the project. After the exclusion of eleven participants (see the Analysis section for details), the final sample consisted of sixty-one participants (57 female, $M_{\text{age}} = 20.51$, $SD_{\text{age}} = 5.91$). A post-hoc sensitivity analysis indicated that a sample size of $N = 61$ allowed us to detect effect sizes of $d_z = 0.36$ with 80% power. All participants were right-handed, with normal or corrected-to-normal vision. They were naïve to the purpose of the experiment and signed an

informed consent before the start of the procedure. Participants were debriefed via e-mail after data collection was finished.

Design

The effect of model expertise on automatic imitation was investigated with a 2X2 repeated measures design. The two factors were congruency (congruent vs. incongruent observed movement) and model expertise (expert vs. non-expert hand), creating four different conditions. Expertise was operationalized as the ability to execute a motor task without errors, meaning that one model (the expert) performed the task more accurately than the other (the non-expert).

Task and Procedure

The study took place in the faculty of Psychology and Educational Sciences of Ghent University. The experiment was combined with another experiment on a different topic. The order of the two experiments was counterbalanced across participants. Participants were tested individually and indicated their age, handedness, and gender prior to the start of the experiment. The experiment was programmed in Python with PsychoPy 3.0 (Peirce et al., 2019) and consisted of an inducer phase, in which model expertise was established, followed by a test phase, in which the effect of model expertise on automatic imitation was measured. The experiment ended with a manipulation check. Figure 1A provides an overview of the full experimental procedure for Experiment 1.

Figure 1*A Schematic Overview of Experiment 1 (A) and Experiment 2 (B)*

Inducer phase. The inducer task contained one block of 20 trials. In this task, participants watched a series of videos in which a hand tried to replicate a light sequence. Participants were asked to attentively watch the videos and had to indicate if the hand had correctly replicated the light sequence after every video. Participants were also notified that two different hands would appear across all videos and that one hand would perform the task correctly more often than the other hand. They were further told that they would have to indicate the overall accuracy of both hands later in the experiment, to ensure that they paid attention to the accuracy of both hands.

On every trial, participants watched one video of a hand trying to replicate a light sequence, similar to the Corsi block-tapping task (Sdoia et al., 2019). In the first part of every video, four grey circles on a black background lighted up sequentially in the upper half of the computer screen. The order of the light flashes was random and the same circle could light up twice, but never two times in a row. The duration of every light flash was approximately 1

second. The lower half of the screen showed a table with a hand presented in first person perspective waiting to respond. In the second part of the video, the hand tried to replicate the light sequence by lifting the correct fingers in order (see Figure 2 for an overview of the inducer phase procedure in Experiment 1).

Two different hands were used in the inducer phase, both created by adjusting the skin tone of the same digital hand model in Blender (Community, 2018). This ensured that both hands only differed in skin tone, which has previously been shown not to influence automatic imitation (Genschow, Westfal, et al., 2021). Each hand appeared in 10 trials, in randomized order. One hand – the expert hand – performed the task correctly in most of the trials (an error rate of 20%). In contrast, the second hand – the non-expert hand – had a high error rate (an error rate of 80%). The hand used as the expert or non-expert model was counterbalanced across participants.

To make the performance of the hands realistic, errors were relatively small on most trials: (a) lifting the wrong finger one or two times, (b) skipping a light flash in the sequence and lifting the corresponding or a random finger at the end, or (c) switching the position of two or three light flashes. After every video, participants were asked to indicate if the hand had replicated the sequence correctly by clicking on the “yes” or “no” mark of a two-point rating scale (Figure 2).

Figure 2*Procedure of the Inducer Phase for Both Model Hands in Experiment 1*

Test phase. The test phase consisted of an automatic imitation task (Brass et al., 2000) and started with 16 practice trials with accuracy feedback, followed by 160 experimental trials without such feedback, divided into two blocks, each with a duration of approximately 210 seconds. After the first block of 80 trials, participants repeated a shorter version of the inducer task, containing 10 new videos, to refresh the manipulation. After this, the second test block of 80 trials followed. The four conditions were randomized within each block and every condition contained 40 trials in total.

Each trial showed either the expert or non-expert hand lifting the index or middle finger. The hand was presented as a mirror image of the participant's right hand, on a light grey table with a black background. To produce an illusion of movement, participants first observed an image of the hand in resting position together with a fixation cross between its index and middle finger for 850 ms. This was followed by an image of the hand lifting either the index or middle finger (for a similar procedure, see Catmur & Heyes, 2011; Cracco et al., 2015), together with the number 1 or 2 replacing the fixation cross. Participants were asked to respond to the number by lifting their right index finger when the number 1 was shown and

their right middle finger when the number 2 was shown. The image remained on the screen until the participant responded, with a maximum of 2000 ms. The movement performed by the hand could be congruent or incongruent with the instructed response. Responses were registered using an optical response box with four sensors on a horizontal line, detecting a response whenever a finger was lifted from one of the sensors. Participants placed their right index finger on the middle-left sensor and their right middle finger on the middle-right sensor. After the second frame, the screen turned black for 1000 ms before the next trial started (Figure 3).

Manipulation Check. At the end of the experiment, participants were asked to indicate how often each hand replicated the light sequence correctly on a 10-point Likert scale. Zero was labeled as “Always wrong” and ten as “Always correct”. This was used as a manipulation check.

Figure 3

Procedure of an Incongruent Trial in the Test Phase of Both Experiment 1 and 2

Analysis

All analyses were performed in R (R Core Team 3.0.1., 2013). In total, eleven participants were excluded. One participant did not finish the experiment due to technical issues. Ten additional participants were excluded because they did not detect a difference in accuracy between both hands in the inducer phase. A participant was considered to not have detected a difference between the two hands when the indicated accuracy difference on the manipulation check was less than three scale-points in favor of the expert hand. As a result, sixty-one participants (57 female, $M_{\text{age}} = 20.51$, $SD_{\text{age}} = 5.91$) were included in the statistical analyses. All analyses were performed on the data of the test phase. Trial exclusions were based on our recent research on automatic imitation (e.g., Cracco, Genschow, et al., 2018; De Souter et al., 2021). Practice trials were excluded from both the reaction time (RT) and error rate (ER) analysis. In addition, trials with an incorrect response were excluded from the RT analysis (3.82%). A response was coded as incorrect when the participant lifted the wrong finger. Trials were further excluded from the RT analysis when the RT was faster than 100 ms (0.02%), exceeded the 2000 ms response deadline (0.00%), or deviated from the participant's mean RT by more than 3 SD (1.24%). In the ER analysis, trials with an RT faster than 100 ms (0.03%) or exceeding the 2000 ms response deadline (0.00%) were excluded.

The resulting RTs and ERs were analyzed using an expertise (expert vs. non-expert hand) x congruency (incongruent vs. congruent finger movements) repeated measures ANOVA, with a significance level of 0.05. The RTs were the main measure of interest, but the ERs are mentioned as a secondary measure. As a measure of effect size, we will also report Cohen's d_z .

Results

Inducer Phase and Manipulation Check

The mean accuracy in the inducer phase was 93.61% ($SD = 5.45\%$), indicating that participants were able to see when the hand made an error in the light sequence task.

Responses to the manipulation check further showed that participants rated the accuracy difference between the expert and non-expert hand to be 5.49 ($SD = 1.52$) points on a scale from minus ten to ten.

Test Phase

The RT analysis (Figure 4A) revealed a significant main effect of congruency, $F(1,60) = 383.93$, $p < .001$, $d_z = 2.51$, with faster responses on congruent trials ($M_{\text{Congruent}} = 398$ ms, $SD_{\text{Congruent}} = 46$ ms) compared to incongruent trials ($M_{\text{Incongruent}} = 457$ ms, $SD_{\text{Incongruent}} = 61$ ms). There was no main effect of expertise on RTs, $F(1,60) = 0.37$, $p = .547$, $d_z = 0.08$. Most importantly, we found no interaction between expertise and congruency, $F(1,60) = 0.05$, $p = .821$, $d_z = 0.03$. This suggests that the congruency effect did not differ over the two different levels of expertise and was confirmed by a Bayesian analysis with default JSZ priors showing that the data was 6.96 times more likely under the null hypothesis than under the alternative hypothesis.

The ER analysis (Figure 4B) likewise revealed a significant main effect of congruency, $F(1,60) = 68.84$, $p < .001$, $d_z = 1.06$, with lower error rates on congruent ($M_{\text{Congruent}} = 0.99\%$, $SD_{\text{Congruent}} = 1.54\%$) compared to incongruent trials ($M_{\text{Incongruent}} = 6.65\%$, $SD_{\text{Incongruent}} = 5.85\%$), but no main effect of expertise, $F(1,60) = 0.58$, $p = .450$, $d_z = 0.10$, or an expertise x congruency interaction, $F(1,60) = 0.26$, $p = .611$, $d_z = 0.07$. In line with the RTs, this suggests that the effect of congruency on the error rate did not differ over the two different levels of expertise, and this was again confirmed by a Bayesian analysis revealing

that the data was 6.30 times more likely under the null hypothesis than under the alternative hypothesis.

Figure 4

The Congruency Effect on the Reaction Times (A) and Error Rates (B) for Both Levels of Expertise in Experiment 1

Note. Reaction times are expressed in milliseconds and error rates in percentage. The line with the solid dot indicates the mean RT (A) and ER (B) across participants for each condition.

Discussion

Even though accuracy in the inducer phase was high ($M = 93.61\%$) and all participants included in the analyses detected an accuracy difference between the expert and non-expert hand, the first experiment did not show a significant effect of model expertise on

automatic imitation. However, the inducer task performed by the hands in the inducer phase was very different from the automatic imitation task performed by participants in the test phase. That is, while the hands in the inducer phase had to copy a sequence of four light flashes, participants responded to a single numerical cue in the test phase. Therefore, the first task was more difficult than the second, which could have caused participants to believe that the performance of the hands in the first task was irrelevant to their performance in the second. The absence of an effect of model expertise could thus be explained by a lack of transfer of expertise attribution from the inducer phase to the test phase. To exclude this alternative explanation, we conducted a second experiment, in which the inducer and test phase tasks were almost identical, thereby making a transfer of expertise attribution much more likely.

Experiment 2

Method

Participants

Experiment 2 was preregistered:

https://osf.io/k2ysa?view_only=de9d374246a54e9eaba82ee8342de31e. The sampling goal for this experiment was 120 participants, based on an a-priori power analysis indicating that a sample size of 119 participants would provide us with 90% power to detect a small effect size of $d_z = 0.3$ with a significance level of 0.05. To compensate for participant exclusion, we started with testing 130 participants and then iteratively added batches of 10 more participants until the sample size after exclusions was ≥ 120 participants.

Using this procedure, we collected data from 200 participants via Prolific Academic (<https://www.prolific.co/>). The total duration of the experiment was approximately 20 minutes. After the exclusion of 75 participants (see Analysis section for details), the final

sample consisted of 125 participants (74 female, 50 male, and 1 nonbinary, $M_{\text{age}} = 24.10$, $SD_{\text{age}} = 4.45$). All participants were right-handed, with normal or corrected-to-normal vision, were naïve to the purpose of the experiment, and signed an informed consent before the start of the procedure.

Task and Procedure

Experiment 2 was programmed in JavaScript, using the jsPsych library (de Leeuw, 2015), and conducted online. Participants indicated their age and gender before the start of the experiment and were debriefed after the experiment. Figure 1B provides an overview of the full experimental procedure for Experiment 2.

Practice test phase. The experiment started with a practice phase of the automatic imitation task, containing 16 trials with accuracy feedback. The task and materials (i.e., the numerical cues and the hands in the background) were identical to the task and materials used in the test phase of Experiment 1. However, responses were now recorded via the keyboard. Participants were asked to hold down the “G” key with their right index finger and the “H” key with their right middle finger during the task. When “1” appeared, they had to lift their index finger and hold it back down again. When “2” appeared, they had to lift their middle finger and hold it back down again. A response was registered whenever a finger was lifted from the “G” or “H” key. This method has been shown to produce similar effects compared to the laboratory version of the automatic imitation task (Westfal et al., 2020). The practice phase was repeated until participants responded correctly in at least 12 of the 16 trials.

Inducer phase. Like in Experiment 1, each block of the test phase was preceded by a block of the inducer phase. The first inducer block contained 20 trials and was repeated until participants responded correctly in at least 80% of the trials. At the beginning of the inducer phase, participants were told that they would now see two hands perform the same task they

had practiced, but that the hands would react to colored squares instead of numbers. They were also given the correct response for each cue. That is, if an orange square appeared, the hand had to lift its index finger. If a blue square appeared, the hand had to lift its middle finger. Participants were further told that the performance of both hands was based on the data of two participants in a previous experiment and that they would have to indicate whether the hand had correctly responded to the cue after each video. They were also notified that one of the hands would perform the task correctly more often than the other and that they would have to indicate the overall accuracy of both hands later during the experiment. On each trial, participants watched a video of a hand responding to a blue or orange square. Note that the cues to which the hands responded differed from the cues to which participants responded in the test phase (i.e., colored squares versus numbers, respectively). This was done to avoid interference of direct stimulus-response associations between the cues and the finger movements of the expert versus non-expert hand. That is, using identical cues could have caused stronger associations between the number “1” (“2”) and an index (middle) finger movement for the expert hand than for the non-expert hand, because the expert hand responded correctly more often. This could then be an alternative explanation for potential effects found on automatic imitation in the test phase. The two different hands used in the inducer phase were identical to the hands used in Experiment 1. Participants first observed one of both hands with a fixation cross between its index and middle finger for 1000 ms. Then, a colored square appeared at the location of the fixation cross, to which the hand responded after 600 ms by lifting its index or middle finger. After 1400 ms, the screen turned black and participants were presented with the question “Did the hand respond correctly to the cue?”. When they clicked the “yes” or “no” button and confirmed their answer, the next trial started after a 500 ms inter-trial interval.

Each hand appeared in 10 trials, in randomized order. One hand – the expert hand – performed the task correctly in most of the trials (an error rate of 20%), while the other hand – the non-expert hand – performed the task incorrectly in most of the trials (an error rate of 80%). The hand used as the expert or non-expert model was counterbalanced across participants (see Figure 5 for an overview of the inducer phase procedure for Experiment 2).

Test phase. The task and instructions in the test phase were similar to the practice phase, but participants now completed 160 experimental trials of the automatic imitation task without feedback. The test phase was divided into two blocks, each with a duration of approximately 210 seconds. Identical to the practice phase, one of the hands from the inducer phase appeared behind the numerical cue on each trial. After the first block of 80 trials, participants repeated a shorter version of the inducer phase, containing 10 trials, to refresh the manipulation. After this, the second test block of 80 trials followed. The four conditions were randomized within each block and every condition contained 40 trials in total.

Manipulation check. At the end of the experiment, participants were reminded that in alternating phases, they and two hands took turns in doing a task where either they or the hands responded to symbolic cues. They were then asked to indicate the performance of each hand on this task using a 10-point Likert scale, where zero was labeled as “Always wrong” and ten as “Always correct”. Participants could also select the option “I don’t know” on each Likert scale, to prevent them from guessing the performance of the hands if they did not know the answer.

Figure 5*Procedure of the Inducer Phase for Both Model Hands in Experiment 2*

Note. The relative size of accuracy question in the image is bigger compared to its true relative size during the experiment, to improve the readability of the image.

Analysis

All analyses were preregistered. Seventy-three participants were excluded based on the manipulation check, because they did not indicate the accuracy difference to be 3 or more points in favor of the expert hand or because they selected the option “I don’t know” for the performance of at least one hand. Three participants were additionally excluded because their error rate deviated more than 3 *SD* from the sample mean in the test phase. As a result, 125 participants (74 female, 50 male, and 1 nonbinary, $M_{\text{age}} = 24.10$, $SD_{\text{age}} = 4.45$) were included in the statistical analyses. All analyses were performed on the test phase data using R (R Core Team 3.0.1., 2013). Trial exclusions were identical to the first experiment. Practice trials were excluded from both the RT and ER analysis. In addition, trials with an incorrect response (3.63 %) and trials with an RT faster than 100 ms (0.02 %), exceeding the 2000 ms response deadline (0.00 %), or deviating from the participant’s mean RT by more than 3 *SD* (1.37 %)

were excluded from the RT analysis. In the ER analysis, trials where the RT was faster than 100 ms (0.03 %) or exceeded the 2000 ms response deadline (0.12 %) were excluded.

The resulting RTs and ERs were analyzed using an expertise (expert vs. non-expert hand) x congruency (incongruent vs. congruent finger movements) repeated measures ANOVA, with a significance level of 0.05. The RTs were the main measure of interest, but the ERs are mentioned as a secondary measure.

Results

Inducer Phase and Manipulation Check

The mean accuracy in the inducer phase was 93.41% ($SD = 12.37\%$) and participants rated the accuracy difference between the expert and non-expert hand to be 4.32 ($SD = 1.11$) points on a scale from minus ten to ten in the manipulation check.

Test Phase

In line with the results of Experiment 1, the RT analysis (Figure 6A) revealed a significant main effect of congruency, $F(1,124) = 415.98$, $p < .001$, $d_z = 1.82$, with faster responses on congruent trials ($M_{\text{Congruent}} = 451$ ms, $SD_{\text{Congruent}} = 65$ ms) compared to incongruent trials ($M_{\text{Incongruent}} = 516$ ms, $SD_{\text{Incongruent}} = 82$ ms). We found no main effect of expertise on RTs, $F(1,124) = 0.11$, $p = .742$, $d_z = 0.03$. Importantly, there was no interaction between expertise and congruency, $F(1,124) = 0.75$, $p = .387$, $d_z = 0.08$, which suggests that the congruency effect did not differ over the two levels of expertise. This was confirmed by a Bayesian analysis with default JSZ priors, showing that the data was 6.96 times more likely under the null hypothesis than under the alternative hypothesis.

The ER analysis (Figure 6B) likewise revealed a significant main effect of congruency, $F(1,124) = 179.24$, $p < .001$, $d_z = 1.20$, with lower error rates on congruent

($M_{\text{Congruent}} = 1.08\%$, $SD_{\text{Congruent}} = 1.45\%$) compared to incongruent trials ($M_{\text{Incongruent}} = 5.93\%$, $SD_{\text{Incongruent}} = 4.28\%$). There was no main effect of expertise, $F(1,124) = 0.27$, $p = .606$, $d_z = 0.05$, and no expertise x congruency interaction, $F(1,124) = 1.02$, $p = .315$, $d_z = 0.09$. In line with the RT analysis, this suggests that the effect of congruency on the error rates did not differ over the two levels of expertise. This was again confirmed by a Bayesian analysis revealing that the data was 6.13 times more likely under the null hypothesis than under the alternative hypothesis.

Figure 6

The Congruency Effect on the Reaction Times (A) and Error Rates (B) for Both Levels of Expertise in Experiment 2

Note. Reaction times are expressed in milliseconds and error rates in percentage. The line with the solid dot indicates the mean RT (A) and ER (B) across participants for each condition.

Discussion

Experiment 2 used a very similar task in the inducer and test phase to maximize transfer of expertise attribution. More precisely, in Experiment 2, the task performed by the hands in the inducer phase was identical to the task performed by the participants in the test phase, except for the cues to which they had to respond (i.e., colored squares versus numbers). Nevertheless, in line with the results of the first experiment, we found no effect of model expertise on automatic imitation. This suggests that the absence of an effect of model expertise is unlikely to be explained by a lack of transfer of expertise attribution from the inducer phase to the test phase.

General Discussion

Selection based on model characteristics plays an important role in selective social learning (Heyes, 2018). Because there are often different models in the environment, learners can optimize motor learning by imitating an expert instead of a non-expert model. The aim of the current study was to investigate the role of model expertise on automatic imitation, by comparing the congruency effect for an expert versus a non-expert model. In a first experiment, we manipulated the perceived expertise of two model hands using an inducer task in which both hands tried to replicate a light sequence. In a test phase, we then investigated whether model expertise moderated the congruency effect in an automatic imitation task. Contrary to our hypothesis, however, we did not find evidence for an effect of model expertise on automatic imitation. Because the inducer task performed by the hands was much more difficult than the automatic imitation task performed by the participants, a possible alternative explanation for the absence of an effect was that there was no transfer of expertise attribution from the inducer to the test phase. To exclude this alternative explanation, we conducted a second experiment in which we changed the inducer task to maximize expertise

transfer. However, in line with the results of our first experiment, we found no effect of model expertise on automatic imitation. This suggests that the absence of an effect cannot be explained by a lack of transfer of expertise attribution from the inducer to the test phase.

Instead, two other explanations seem more likely. First, it could be that model expertise only influences automatic imitation when there is a choice about whom to imitate. For instance, in our dancing class example, dancers are confronted with multiple models at the same time. To learn, they have to ignore the other dancers while following the movements of the dance instructor. It could thus be that a salient contrast of expert and non-expert models is needed for expertise to influence automatic imitation. This is consistent with theoretical models arguing that social evaluation is a comparative process (Mussweiler, 2003) and can be tested in future research by using an automatic imitation paradigm with multiple hands (e.g., Cracco et al., 2015; De Souter et al., 2021) that differ in expertise.

Second, it could be that model expertise only influences intentional imitation. In real-life observational learning, people often intentionally copy a model's actions to learn a new skill. Intentional imitation, like automatic imitation, relies on motor simulation (Brass & Heyes, 2005; Hamilton, 2015; Iacoboni et al., 1999), but additionally includes a gating mechanism that determines whether or not we act on triggered imitative responses (Bien et al., 2009). Hence, it could be that expert and non-expert models trigger similar imitative responses, but that these responses are then inhibited for non-experts, possibly via an explicit, metacognitive rule, such as "copy the expert, the best dancer in the dancing class" (Heyes, 2018). This way, initial automatic imitation for all models only results in overt, intentional imitation for the expert model, while it is inhibited for the non-expert model. In line with this hypothesis, Zmyj and colleagues (2010) found that model reliability influenced intentional imitation in infants, such that models showing high competence were copied more often when

infants learned how to use a novel object. A recent study also found greater over-imitation for a reliable model compared to an unreliable model in preschool children (Allen et al., 2021).

To conclude, we did not find evidence that model expertise influences automatic imitation. Although more research is needed to (dis)confirm these findings in other settings, the different findings in our study compared to studies on intentional imitation (Allen et al., 2021; Zmyj et al., 2010) suggest that model expertise does not modulate the mechanism underlying motor learning, motor simulation, but rather the explicit choice (not) to imitate someone.

Conflict of Interest Statement

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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