Individual Differences in Intelligence and Personality Guide Human Social Learning

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Abstract

Little is known about the extent to which individual differences guide social learning. Here we use individual differences in intelligence and personality, specifically openness to experience, to predict the social learning strategies people use. Participants ($N = 220$) completed a range of general intelligence tests, a personality questionnaire, and a battery of novel behavioral tasks. In each behavioral task participants were trained on the solution to a problem. They were then informed of an alternative solution to the same problem that varied in terms of its quality, simulating new social information. The extent to which participants switched to a superior solution measured content-biased social learning, and the extent to which they retained the trained solution, when presented with an alternative solution of equal or higher quality, measured egocentric bias. As predicted by cultural evolutionary theory, most participants exhibited content-biased social learning. However, a significant minority (20-40%) exhibited an egocentric bias, preferring to retain the familiar, but often suboptimal, trained solution. Higher general intelligence was associated with general solution switching but was more strongly related to switching to a superior solution. So, higher general intelligence predicted content-biased social learning. By contrast, higher openness to experience, and therefore lower egocentric bias, was uniquely associated with switching to an inferior solution. So, egocentric bias (or lower openness to experience) was adaptive as it inhibited participants from switching to a maladaptive solution. Our findings highlight the importance of individual differences in intelligence and personality to human social learning.

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Cumulative cultural evolution (CCE) is the historical process through which adaptive modifications to artifacts (material or social) accumulate over time through social learning (Mesoudi & Thornton, 2018). There is considerable evidence of CCE in humans, such as the evolution of stone tools (Stout, Toth, Schick, & Chaminade, 2008), clothing (Gilligan, 2010) and kayaks (Boyd & Richerson, 2009). Although social learning is widespread in the animal kingdom (Whiten et al., 1999), there is little evidence of CCE in non-humans (Marshall-Pescini & Whiten, 2008; although see Lehner, Burkart, & van Schaik, 2011 and Sasaki & Biro, 2017). This suggests a qualitative difference in social learning between human and non-human primates (Whiten, McGuigan, Marshall-Pescini, & Hopper, 2009; Dean, Kendal, Schapiro, Thierry, & Laland, 2012; Haun, Rekers, & Tomasello, 2012). Considerable research has been dedicated to studying species-level differences in social learning and CCE, but much less effort has been dedicated to the study of within-species differences in social learning (Mesoudi, 2016). Yet, humans differ widely in terms of intelligence and personality (Deary, 2013; Burton, Hafetz, & Henninger, 2007) – the cornerstones of individual difference research. Despite this, little research has studied the extent to which these traits may guide social learning.

The present study examined the extent to which individual-level differences in intelligence and personality guide the social learning strategies people use. We used a task in which participants were trained on a solution to a problem (e.g., a route to navigate through a computerized maze) and were later offered an alternative solution that varied in terms of its quality, being either objectively worse than, equal to, or better than the trained solution. Our key question was whether intelligence and/or personality affected participants' decisions to adopt the novel solution, or to retain the trained solution. In other words, we used these traits to predict the extent to which individual behavior was guided by content bias (Boyd & Richerson, 1985), a

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preference to adopt a solution based on its intrinsic value, and egocentric bias, a preference to stick with a familiar, tried and tested solution (Tamariz, Ellison, Barr, & Fay, 2014).

First, we review the literature on social learning strategies. Next, we consider the literature on individual differences and their influence on social learning. We then explain the present study, report its findings, and discuss their significance.

Social Learning and Cumulative Cultural Evolution

Humans accumulate culture through a combination of individual learning and social learning. Individuals, or groups of individuals, invent artifacts that are then acquired by others via social learning, and which may then undergo further adaptive modifications, leading to cumulative cultural evolution (CCE) (Tomasello, 1999; Tennie, Call, & Tomasello, 2009). There are a wide range of individual-level preferences, or biases, that guide human social learning, broadly categorized as *content-* or *context-dependent* social learning strategies (Henrich & McElreath, 2003; Laland, 2008; Kendal et al., 2018). Content-dependent strategies rely on a direct assessment of the intrinsic value of the cultural variant. Examples include the preference for social information over asocial information (Mesoudi, Whiten, & Dunbar, 2010), negative information over positive information (Bebbington, MacLeod, Ellison, & Fay, 2017) and more effective solutions over less effective solutions (Fay et al., 2018). On the other hand, context-dependent social learning strategies rely on information that is not directly related to the quality of the variant. Examples include preferentially adopting a variant based on the characteristics of the model exhibiting it (e.g., prestige; Atkisson, O'Brien, & Mesoudi, 2012), the frequency of the variant (Haun et al., 2012), or the state of the observer (e.g., copy-if-uncertain; Wood et al., 2016).

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While social learning is common, people often do not copy the behavior of others (Eriksson & Strimling, 2009; Mesoudi, Chang, Murray, & Lu, 2014; Asch, 1951). Even when people know an observed solution is superior to their own solution, they can be reluctant to adopt the superior solution (Hodges, Meagher, Norton, McBain, & Sroubek, 2014). This conservatism, which we call an egocentric bias – a preference to retain familiar solutions – inhibits social learning and individual exploration. Behavioral conservatism may be more evident in non-human primates, who are found to be highly resistant to switching from a familiar solution to a novel solution (Hopper, Schapiro, Lambeth, & Brosnan, 2011; Hrubesch, Preuschoft, & van Schaik, 2009; but see Manrique, Völter, & Call, 2013).

Language evolution experiments suggest that the interplay between a content bias and an egocentric bias might act as a selection mechanism that drives the adaptive evolution of human communication systems. For example, in a dyadic communication game, participants copied their partner's object label when it was perceived to be more informative than their own label, indicating that a content bias was guiding behavior (Rogers & Fay, 2016). By contrast, when the object labels were perceived to be equally informative, participants tended to retain their own label, indicating that an egocentric bias was also guiding behavior. Furthermore, in a multiplayer communication game, in which participants communicated with others to form an 8-person micro-society (Fay, Garrod, Roberts, & Swoboda, 2010), label adoption and propagation were best modeled by a combination of content bias and egocentric bias (Tamariz et al., 2014). The interplay of these biases led to the survival and selection of an inventory of object labels that were well adapted for communication use and acquisition (Fay, Garrod, & Roberts, 2008; Fay, & Ellison, 2013).

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It is important to point out that, in these studies, variant quality was not objectively measured or manipulated; consequently, we cannot be confident of the extent to which behavior was guided by content bias or egocentric bias. In the present study, we developed a behavioral task in which solution quality was objectively measured and systematically varied. This allowed us to confidently isolate the influence of content and egocentric biases on social learning.

Individual Differences and Social Learning

Experimental psychology is concerned with the processes that affect performance under specific experimental conditions, or situations (Cronbach, 1957). By contrast, individual difference research (or differential psychology) is concerned with the stable differences among humans across diverse situations (Revelle, Wilt, & Condon, 2012). Cronbach (1957) contended that psychological science may be expected to advance best when both approaches, experimental and differential, are used. Intelligence and personality are the cornerstones of individual difference research. Yet, there is little research on social learning from an individual difference perspective (excluding age and gender; e.g., Molleman, van den Berg, & Weissing, 2014; Demps, Zorondo-Rodríguez, García, & Reyes-García, 2012). Next, we discuss what is known about the extent to which intelligence and personality guide social learning.

Intelligence

Intelligence has been defined as “an entity’s maximal capacity to achieve a novel goal successfully using perceptual-cognitive abilities” (Gignac, 2018, p. 440). Not surprisingly, intelligence is found to be one of the most influential individual difference variables (Revelle et al., 2012).

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For example, intelligence is a consistent predictor of academic success (Mellanby, Martin, & O'Doherty, 2000), job performance (Gottfredson, 1997) and life expectancy (Gottfredson & Deary, 2004). More intelligent people make better decisions, broadly considered. On the basis of a battery of intelligence tests, Bruine de Bruin, Parker and Fischhoff (2007) found that intelligence positively predicted performance on the Adult Decision-Making Competence (A-DMC) test battery. Intelligence is also found to correlate positively with individual differences in reflective ability ($r \approx .40$; Toplak, West & Stanovich, 2011), the disposition to reflect on a problem and resist stating the first solution that comes to mind. Reflective ability is important, because it predicts two important decision-making considerations: risk preference, or what the participant has to lose, and time preference, or how long they take to resolve the problem (Frederick, 2005).

Muthukrishna, Morgan, and Henrich (2016) examined the extent to which intelligence predicted conformist social learning (i.e., disproportionately copying the majority). Participants ($N = 101$) were presented with two to six lines and had to identify the longest line. This was first done individually, then socially, with participants receiving the decisions made by other participants before again deciding which line was the longest. Intelligence was measured using Raven's advanced progressive matrices (Raven & Court, 1998). They found a negative relationship between intelligence and social learning, such that more intelligent people were less influenced by the decisions of others. Importantly, this did not impede task performance. In fact, intelligence was positively correlated with task performance, indicating that more intelligent people were behaving adaptively, by strategically using social information to make better decisions (see also Vostroknutov, Polonio & Coricelli, 2018).

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So, in standard individual decision-making tasks, and tasks in which people also have the opportunity to acquire information socially, more intelligent people make better decisions. When people have the option to learn from others, intelligence can enhance decision making by guiding the choice between when to learn socially and when not to learn socially, and rely instead on individual learning. In light of the research reviewed, it is hypothesized that there will be a positive association between intelligence and switching to a superior solution (i.e., a solution favored by content bias) given that such behavior would be consistent with successful adaptation – a key definitional component of intelligence (Jensen, 1998). Specifically, we predict that individuals with higher intelligence will be more likely to switch to an objectively better solution compared to individuals with lower intelligence.

Personality

Like intelligence, personality also predicts decision-making behavior (Judge, Higgins, Thoresen, & Barrick, 2005; Mroczek & Spiro, 2007). Although there is no consensus on the number of primary dimensions of personality, most models include dimensions such as extraversion, emotional stability, openness to experience, agreeableness, and conscientiousness (Goldberg, 1990; Ashton & Lee, 2016; Costa & McCrae, 2008). In the context of decision making, openness to experience is particularly relevant, because it represents an individual's tendency to be curious intellectually, to consider alternative approaches, to be imaginative and original, and to enjoy artistic pursuits (Barrick & Mount, 1991; Ross et al., 2009).

A moderate, positive correlation has been reported between openness to experience and general intelligence ($r \approx .30$; DeYoung, Peterson, & Higgins, 2005; Revelle et al., 2012). Although the causal relationship remains to be determined, given this positive correlation, if

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intelligence predicts a phenomenon positively then openness likely will too. So, if intelligence predicts switching to a superior solution (via content bias), then so too will openness to experience. This is supported by a study showing that, in a task where adaptability was important to making the best decision, individuals scoring higher in openness to experience performed better, indicating that higher openness improved decision making (Le Pine, Colquitt, & Erez, 2000).

Although intelligence and openness to experience are associated positively, the correlation between them is not so large as to suggest redundancy. In fact, the majority of the true score variance is distinct, suggesting that openness to experience may have unique effects on decision-making behavior. Importantly, openness to experience also correlates positively with divergent thinking, a dimension that is unrelated to intelligence (McCrae, 1987). Operationally, divergent thinking involves the ability to generate a large number of solutions to a problem or uses for an object, including both *good* and *bad* solutions (Silvia et al., 2008). For example, Ziegler, Schroeter, Lüdtke and Roemer (2018) found that ‘investigative interests’ (a facet of openness to experience) correlated *negatively* with grades. One possible explanation for this finding is that a strong ‘investigative interest’ may distract from the task at hand, in this instance a rote-learning task. In another study, Lauriola and Levin (2001) examined the association between personality (measured using the Big 5) and risk-taking (measured using an experimental task). They found that individuals who scored higher in openness made more high-risk and suboptimal decisions.

Taken together, openness to experience is associated with adaptive decision making (via its association with intelligence) and maladaptive decision making (via its association with divergent thinking). To reconcile this contradictory pattern, openness to experience may be best

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thought of as being predictive of solution switching in general, irrespective of solution quality, consistent with its definition as intellectual curiosity and exploration. Thought of in this way, openness to experience will be predictive of egocentric behavior. People high on openness will have a low egocentric bias, as evidenced by more frequent behavior switching, whereas people scoring low on openness will have a higher egocentric bias, as evidenced by less frequent behavior switching. It is therefore hypothesized that openness to experience will increase the probability that a person will adopt a novel solution, regardless of the degree to which it may be superior or inferior to a previously learned solution.

The Current Study

We present a large-scale study that examined the extent to which individual differences in intelligence and personality guide human social learning ($N = 220$). Participants completed a battery of behavioral tasks. In each task, they were trained on the solution to a problem. They were then offered an alternative solution to the same problem that varied in terms of its quality, simulating new social information. The quality of the alternative solution was systematically varied, such that it could be worse than, equal to or better than the trained solution. The extent to which participants switched to a superior solution measured content bias. The extent to which participants remained with the trained solution, when presented with an alternative solution of equal or higher quality, measured egocentric bias. Consistent with content-biased social learning, it is predicted that participants will be more likely to switch to a superior alternative solution (Hypothesis 1).

Our primary interest is the extent to which individual differences in intelligence and personality guide human social learning. A comprehensive battery of intelligence tests was

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administered to derive a measure of general intelligence (*g*). Personality, including openness to experience, was measured using the 60-item HEXACO personality inventory. Consistent with the literature on intelligence, we predicted that people with higher general intelligence will be more likely to switch to the alternative solution if it is superior to their current solution; that is, higher general intelligence will predict content-biased social learning (Hypothesis 2). Consistent with the literature on personality, we predict that people with higher openness to experience will be more likely to switch to the alternative solution irrespective of its quality; that is, higher openness to experience, and therefore lower egocentric bias, will predict general social learning (Hypothesis 3).

Method

This study received approval from the University of Western Australia Ethics Committee. Participants viewed an information sheet before giving written consent to take part in the study. The information sheet and consent form were both approved by the Ethics Committee. All methods were performed in accordance with the guidelines from the NHMRC/ARC/University Australia National Statement on Ethical Conduct in Human Research.

Sample

The initial sample consisted of 220 participants. The data from nine participants were removed due to technical difficulties preventing them from completing the task. Data from a further nine individuals was removed as they reported English as a second language. Of the 202 remaining participants (63% female), the age range was 17 to 48 years ($M = 20.50$, $SD = 4.62$). The

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participants were first year undergraduate students from the University of Western Australia, who received partial course credit for participating.

Measures

Behavioral tasks. Three behavioral tasks were developed to measure decision making: the Padlock task, the Travel task and the Maze task. The solution quality for each task was systematically varied over seven levels: from 7 (complex) to 1 (simple). Participants were always trained on a solution of level 5 (moderate) quality. Training was completed when the participant successfully solved the problem three times in a row; if they failed to solve the problem, the training restarted. After training, the participant was shown a novel solution to the problem and given the opportunity to stick with the trained solution or to switch to the novel solution. This process was completed seven times, once for each quality level, in descending order from the most complex solution (level 7) to the simplest solution (level 1). This process was then repeated, giving 14 trials per task, with 2 for each quality level. Every solution was unique (i.e., no solution repeated across the 14 trials), but solutions of the same difficulty level had specific features in common. Next, we describe each behavioral task.

Padlock Task. The aim of the Padlock task was to open a chest to gain a reward. To open each chest the participant had to open four padlocks (see Figure 1, Panel A). To open each padlock the participant needed to enter a combination – a string of seven numbers. To open the first three (training) padlocks the participant learned a combination of (moderate) level 5 complexity. For this task, quality was determined by the number of times the participant would need to change buttons when inputting the combination; a level 7 solution required six changes (e.g., 7843723), and with each increase in quality the number of changes decreased by one, so that a level 1

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solution required no changes (e.g., 2222222). The training solutions, at level 5, required four changes (e.g., 9577754). After training, the participant was shown a novel combination and given the opportunity to stick with the trained combination, or switch to the novel combination (see Figure 1, Panel B). This process was completed seven times, once for each level of solution complexity (in descending order from most complex to least complex), and then the process was repeated, giving 14 trials.

Travel Task. The Travel task involved choosing an airline to use to travel across four legs of a journey. Participants were shown the average customer ratings for the airline (out of a score of 10). For the first three legs of the journey, the participant was presented with one airline and its corresponding customer rating (see Figure 1, Panel C). So, for the first three legs of the journey there was only one option the participant could choose. For the fourth leg of the journey the participant was presented with an alternative airline and its corresponding user rating. The participant had to decide whether to stick with the airline they have travelled with for the first three legs of the flight, or switch to the new airline (see Figure 1, Panel D). This process was completed seven times, once for each level of rating quality, in descending order from level 7 airline rating quality (i.e., lowest possible rating out of 10 stars) to level 1 airline rating quality (i.e., highest possible rating out of 10 stars). This process was then repeated, giving 14 trials.

Maze Task. The Maze task involved navigating a taxi through a computerized maze to a pre-determined location. Participants had to navigate each maze four times. For the first three (training) routes the participant had to learn a route of level 5 quality. For this task, quality was determined by the length and number of turns for each route; a level 7 route required the

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participant to move 32 times, turning 14 times, and with each increase in quality the route length and number of turns were reduced, so that a level 1 route required 14 moves, turning twice. The training routes, at level 5, required 24 moves, turning 10 times. After being presented with the training route, the participant clicked “OK”, the route marking was removed from the screen, and the participant had to follow the route from memory, using the arrow keys on the computer. They were then asked to take the same route twice more to complete the training. On the fourth route, after the trained route had been successfully navigated three consecutive times, the participant was shown an alternative route on the same map (see Figure 1, Panel F), and then was free to navigate using either route. This process was completed seven times, once for each level of route quality (in descending order from most complex to least complex), and then the process was repeated, giving 14 trials.

A)

B)

C)

D)

E)

The first passenger wants you to take them home via **this route**. They will be very angry if you deviate from it!

OK

F)

Just one more passenger to go! You return to the taxi rank. The next passenger says **you can take the old route, or this new one** - whichever you prefer!

OK

Figure 1. In the training phase of the Padlock task the same lock combination had to be memorized and accurately reproduced three consecutive times to open the first three padlocks (Panel A). The fourth padlock could be opened using the same combination or using an alternative combination that varied in its quality (Panel B). In the Travel task, only one airline was available for the first three parts of the journey (Panel C). The fourth leg of the journey could be completed using the same airline or using an alternative airline that varied in its quality (Panel D). In the training phase of the Maze task the same route had to be memorized and accurately reproduced three consecutive times (Panel E). The fourth route could be completed using the same route or using an alternative route that varied in its quality (Panel F).

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Intelligence. Four subtests were used to measure general intelligence (*g*): the Advanced Vocabulary Test, Raven's Advanced Progressive Matrices, Letter-Number Sequencing and the Connections Test.

Advanced Vocabulary Test (AVT; Gignac, Shankaralingam, Walker, & Kilpatrick, 2016). The AVT is a 20-item multiple-choice vocabulary test that provides a measure of crystallized intelligence (*Gc*). For each item, participants were provided with a word, and asked to select one of five alternatives that best represented the meaning of that word. For example, the word 'plausible' was accompanied by the following five alternatives: a) next to the last, b) good intention, c) within grasp, d) seeming reasonable and e) irreducible. If they selected the correct response, they received a score of 1. If they selected an incorrect response, or failed to answer the item, they received a score of 0. Participants were given 5 minutes to complete as many items as possible. Acceptable levels of internal consistency reliability ($\alpha = .73$) have been reported for the AVT (Gignac et al., 2016). In this investigation, the internal consistency was $\alpha = .68$.

Raven's Advanced Progressive Matrices (APM; Raven & Court, 1998). The original APM consists of 48 items and provides a measure of fluid intelligence (*Gf*). A 12-item short form was used in this investigation (Bors & Stokes, 1998, $\alpha = .73$). Each item pattern was presented on a piece of paper. The item pattern was a 3×3 square panel with the final ninth square missing. Participants were required to select one of eight alternatives to fill the blank in the ninth square and the pattern as a whole. There was no time limit. In this investigation, the internal consistency was $\alpha = .73$.

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Letter-Number Sequencing task (LNS; Wechsler, 2008). The LNS task provides a measure of working memory. This task consisted of seven items, each containing three trials (21 trials in total). On each trial, the participant listened to a recorded voice giving a string of letters and numbers. Once the recording was finished, the participant was asked to recite the letters and numbers back to the experimenter, reordering the string to give the numbers first, from biggest to smallest, and then the letters in alphabetical order. For example, if the participant heard ‘Y, 3, T, 4’ then the correct response would be ‘3, 4, T, Y’. The length of the sequence increased by one item each trial, so items became progressively more difficult. The task was discontinued if the participant made errors on two consecutive trials. The participant scored one point for each correct trial. In this investigation, the internal consistency was $\alpha = .86$.

Connections Test (Salthouse et al., 2000). The Connections Test provides a measure of processing speed. The present study used two subtests from the original four subtests, including the ‘Numbers’ test and the ‘Numbers – Letters’ test. In the ‘Numbers’ test, the participants were presented with a page of numbers and given 20 seconds to draw lines connecting the numbers in numerical order, as quickly as possible. For example, 1—2—3—4—5. In the ‘Numbers – Letters’ test, the participants were presented with a page of numbers and letters and had 20 seconds to connect the numbers and letters in numerical and alphabetical order, alternating between numbers and letters, as quickly as possible. For example, 1—A—2—B. The participants scored one point for each correct connection, with no penalties for errors. In this investigation, the internal consistency was $\alpha = .64$.

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Personality. Personality was measured using the HEXACO-60 personality inventory.

HEXACO-60 (Ashton & Lee, 2009). The HEXACO-60 is a short-form personality inventory (60 items) that assesses six major dimensions of personality: Honesty-Humility (H), Emotionality (E), Extraversion (X), Agreeableness (A), Conscientiousness (C) and Openness to Experience (O). For each item, the participant indicated their response on a scale of 1 (strongly disagree) to 5 (strongly agree). This questionnaire has been shown to have high levels of internal consistency reliability and sufficient convergent validity (Ashton & Lee, 2009). In this investigation, the internal consistency associated with each dimension was as follows: H ($\alpha = .58$), E ($\alpha = .64$), X ($\alpha = .71$), A ($\alpha = .61$), C ($\alpha = .63$), O ($\alpha = .61$), and overall $\alpha = .75$. Although the entire HEXACO-60 was administered, we were interested only in the Openness to Experience scores.

Procedure

Participants were seated at a table facing a computer monitor. First, demographic information was collected, including age, sex, and whether English was their first language. Next, the participants completed the battery of tests in the following order: AVT, Padlock Task, APM, Travel Task, LNS, Maze Task, Connections, HEXACO-60. The intelligence tests were administered face-to-face, while the remaining tasks and questionnaire were completed online. Total testing time was approximately 90 minutes.

Data Analysis

To test Hypothesis 1, that participant switching behavior was driven by content bias (i.e., solution quality), we ran one-way repeated measures ANOVAs for each task. We then

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performed a psychometric analysis on each behavioral task to evaluate its reliability and factorial validity. To test Hypotheses 2 and 3, that intelligence (IQ) and Openness to Experience (O) predict switching behavior, we performed a series of Pearson correlations to estimate the association between the behavioral tasks, the intelligence tests and the personality questionnaire. We then created three latent variables and ran a Structural Equation Model (SEM) based on data from 202 participants with the AMOS 22 statistical package (Arbuckle, 2014) using maximum likelihood parameter estimations. The data is available on the Open Science Framework: <https://osf.io/w6g3c/>

Results

Data Preparation

In the Travel Task nine outliers were identified based on the outlier interquartile range rule with a 3.0 multiplier (Hoaglin & Iglewicz, 1987). Winsorizing was employed to deal with the outlying observations (Wilcox, 2010). After Winsorizing, the data were considered sufficiently normally distributed ($\text{skew} < 2.0$) for the purposes of parametric analyses (Bishara & Hittner, 2012).

Content-Biased Social Learning

To test Hypothesis 1, that participants' task switching would be guided by content bias, a one-way repeated measures ANOVA was performed for each task. The independent variable was solution quality (7-1) and the dependent variable was the mean number of times they switched solution (at each quality level).

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Prior to running the ANOVA, the assumption of sphericity was tested. For each task, the assumption was violated: Padlock ($X^2 = 225.413$, $df = 20$, $p < .001$, $\varepsilon = .734$), Travel ($X^2 = 1004.276$, $df = 20$, $p < .001$, $\varepsilon = .537$) and Maze ($X^2 = 406.960$, $df = 20$, $p < .001$, $\varepsilon = .535$). Consequently, the Huynh-Feldt adjusted results were consulted. Participants were more likely to switch to the novel solution when it was simpler (i.e., favored by content bias): Padlock ($F(113.109, 202) = 113.109$, $p < .001$, $\eta^2_{\text{partial}} = .360$), Travel ($F(113.109, 202) = 3130.044$, $p < .001$, $\eta^2_{\text{partial}} = .940$), and Maze ($F(113.109, 202) = 326.431$, $p < .001$, $\eta^2_{\text{partial}} = .619$). Hypothesis 1 was supported; participants were more likely to switch solutions if the novel solution was superior to their current solution (see Figure 2).

Figure 2. Average proportion of trials on which participants switched solutions, at each level of solution quality, for each task.

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Psychometric Analyses

The mean inter-item correlations within the Padlock task, the Travel task and the Maze task were .36, .17, and .38, respectively. The corresponding internal consistency reliabilities were .89, .75, and .89, respectively. Finally, the corrected item-total correlation ranges were .35/.70, -.01/.91 and .07/.76, respectively. Overall, the three behavioral tasks had reasonable psychometric properties, i.e., reliability greater than the minimal acceptable .70 for research purposes (Nunnally, 1978).

Table 1 presents the correlations and descriptive statistics for each task. Note that the Pearson correlations between the Travel task and the other two tasks (Padlock and Maze) were only .12 ($p = .341$) and .05 ($p = .864$), respectively. Given that the Travel task correlated so weakly with the other two tasks, it was excluded from further analyses, on the basis that it was not a valid indicator of the switching construct.

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Table 1

Correlations Across all Tasks and Descriptive Statistics

	1.	2.	3.	4.	5.	6.	7.	8.	<i>M</i>	<i>SD</i>	<i>Skew</i>
1. Pad.	.82								5.53	4.20	.28
2. Trav.	.12	.59							7.98	3.99	-.58
3. Maze	.46	.05	.86						6.69	1.53	.01
4. AVT	.12	.09	.12	.68					9.89	3.52	-.04
5. APM	.23	-.14	.21	.18	.73				7.50	2.64	-.50
6. LNS	.18	-.01	.13	.17	.15	.86			11.94	3.30	.61
7. Con.	.14	.00	.13	.20	.31	.39	.64		43.72	11.82	.32
8. Hex_O	.18	.15	.17	.30	.12	.05	-.00	.58	37.88	4.24	.46

Note. $N = 202$; correlations that were statistically significant ($p < .05$) are in bold; internal consistency reliability values are on the main diagonal (*Pad.* = Padlock task; *Trav.* = Travel task; *Maze* = Maze task; *AVT* = Advanced Vocabulary Test; *APM* = Advanced Progressive Matrices; *LNS* = Letter Number Sequencing Test; *Con.* = Connections Test; *Hex_O* = HEXACO Openness to Experience Sub-dimension).

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Latent Variable Measurement Models

There were three key dimensions to represent as latent variables in the model: IQ, Openness, and Switching Behavior. Prior to testing the full model with all of the dimensions, we examined each dimension individually. General intelligence was represented by a single latent variable defined by scores from the AVT, APM, LNS and Connections tests. The general intelligence single-factor model was associated with acceptable model fit, $\chi^2(2, N = 202) = 2.36, p = .031$, CFI = .994, TLI = .982, RMSEA = .030, SRMR = .027. Furthermore, all four intelligence subtests loaded onto the general intelligence factor positively and significantly (range: .36 – .61). Next, openness to experience was represented by a single latent variable defined by three parcels, each containing items making up its four facets: Aesthetic Appreciation, Inquisitiveness, Creativity and Unconventionality. All three parcels loaded onto the general Openness factor positively and significantly (range: .51 – .70) and the model was associated with perfect fit (i.e., no degrees of freedom). Finally, Switching Behavior was represented by a single latent variable defined by seven indicators (each level of solution quality) from the combined scores on the Padlock task and the Maze task. However, the single-factor model was not associated with acceptable model fit, $\chi^2(14, N = 202) = 213.56, p = .000$, CFI = .769, TLI = .653, RMSEA = .266, SRMR = .1167.

Consequently, an exploratory factor analysis (within SPSS; maximum likelihood estimation with promax rotation) was conducted on the seven Switching indicators. The scree plot and corresponding parallel analysis suggested the extraction of two factors. The first factor was associated with an unrotated eigenvalue to 4.15 and accounted for 59.3% of the total variance (rotated eigenvalue = 3.40). As can be seen in Table 2, the component loadings that defined the first factor consisted of the combined total scores of the Padlock and Maze tasks for solution quality levels 1-4. This factor represented switching from the initial solution to a less complex, or more adaptive, solution. Thus, we labeled the first switching

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dimension Adaptive Switching. The second factor was associated with an unrotated eigenvalue to 1.32 and accounted for 18.8% of the total variance (rotated eigenvalue = 3.11). The factor loadings for the second factor consisted of the combined total scores of the Padlock and Maze task for solution quality levels 4-7. This factor represented switching from the initial solution to a similarly complex, or more complex, and therefore maladaptive solution. Thus, we labelled the second switching dimension Maladaptive Switching. We note that there was a cross-loading from the 4th indicator (level 4 solution quality). When the Switching indicators were specified as a correlated two-factor latent variable model with one cross-loading indicator (within Amos), we obtained acceptable model fit, $\chi^2(11, N = 202) = 20.278$, $p = .042$, CFI = .989, TLI = .979, RMSEA = .065, SRMR = .046. Furthermore, the correlation between the two switching latent variables was $r = .60$ ($p < .001$), suggesting some general switching processing variance.

Table 2

Switching Task Item-Level Factor Analysis: Pattern Matrix Loadings

Item	<i>h</i>		λ	
		Adaptive Switching	Maladaptive Switching	
1	.54	.90	-.22	
2	.70	.91	.01	
3	.67	.66	.27	
4	.69	.28	.67	
5	.61	-.01	.85	
6	.57	.00	.80	
7	.48	-.20	.84	

Note. $N = 202$; Loadings greater than $|.20|$ are in bold; h = communality; λ = loading; maximum likelihood with promax rotation; the seven indicators represent the quality level associated with the two switching tasks (Padlock and Maze); the scores represent sum scores

for the same quality level across the two tasks (thus, four scores each).

Structural Equation Modeling (SEM)

On the basis of a series of latent variable inter-correlation analyses (see Table 3), intelligence (IQ) correlated positively with Adaptive Switching ($r = .37, p = .001$) and Maladaptive Switching ($r = .30, p = .002$), suggesting that more intelligent people were more likely to switch to a novel solution. Similarly, Openness to experience correlated positively with Adaptive Switching ($r = .22, p = .021$) and Maladaptive Switching ($r = .29, p = .002$), suggesting that more open people were more likely to switch to a novel solution, irrespective of solution adaptiveness. In addition, intelligence correlated positively with openness ($r = .26, p = .019$).

Table 3

Latent Variable Correlations

	1.	2.	3.	4.
1. Adaptive Switching	1.0			
2. Maladaptive Switching	.60	1.0		
3. IQ	.37	.30	1.0	
4. Openness	.22	.29	.26	1.0

Note. $N = 202$; all of the correlations were significant statistically ($p < .05$).

Next, we tested a multivariate multiple regression latent variable model. The theoretically derived latent variable model was associated with acceptable levels of model close-fit, $\chi^2(70, N = 202) = 111.30, p = .001$, CFI = .960, TLI = .948, RMSEA = .054, and

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SRMR = .58. As can be seen in Figure 3, general intelligence was associated uniquely with Adaptive Switching ($\beta = .39, p = .001$) and Maladaptive Switching ($\beta = .27, p = .001$), indicating that more intelligent people were more likely to switch to adaptive and maladaptive solutions. To determine whether general intelligence was associated uniquely with Adaptive Switching and Maladaptive Switching equally strongly, the paths leading from general intelligence to the two Switching latent variables were constrained to equality. Based on a chi-square difference test (Pearson, 1900), IQ was uniquely associated with Adaptive Switching more substantially than Maladaptive Switching, in a statistically significant way, $\Delta\chi^2 (2, N = 202) = 165.15, p = .001$. Thus, the positive, unique effect of general intelligence was more substantial on adaptive switching compared to maladaptive switching, supporting Hypothesis 2.

Openness to experience was associated positively, uniquely and significantly with Maladaptive Switching ($\beta = .16, p = .001$), but not uniquely with Adaptive Switching ($\beta = .01, p = .995$). Thus, there was only a significant unique effect of Openness on Maladaptive Switching. This partially supported Hypothesis 3, which stated that people with higher openness to experience, and therefore lower egocentric bias, will be more likely to switch to the alternative solution, regardless of solution quality.

The total model (intelligence and openness combined) accounted for 15.5% and 12% of the true score variance in Adaptive Switching and Maladaptive Switching, respectively.

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Figure 3. The latent variable model with completely standardized estimates. IQ = general intelligence factor; avt_total = Advanced Vocabulary Test total score; apm_total = Advanced Progressive Matrices total score; Ins_total = Letter Number Sequencing total score; con_total = Connections total score; open = general Openness factor; open_p1 = Openness to Experience questionnaire items 1-3; open_p2 = Openness to Experience questionnaire items 4-6; open_p3 = Openness to Experience items 7-10; Adaptive Switching = total score from quality level 1-4 for both Padlock and Maze; Maladaptive Switching = total score from quality level 4-7 for both Padlock and Maze.

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Discussion

The present study investigated the extent to which individual-level differences in intelligence and personality guide human social learning. To do so, we developed a battery of novel behavioral tasks to examine social learning under controlled laboratory conditions. In each task, participants were trained on a solution to a problem, and were later presented with an alternative solution to the same problem, simulating new social information. The quality of the alternative solution was systematically varied such that it was objectively worse than, equal to, or better than the trained solution. We were interested in the extent to which intelligence and personality (measured using standard tests) guided content-biased social learning, a preference to adopt a solution based on its intrinsic quality, and egocentric bias, a preference to retain the familiar, but sometimes suboptimal, trained solution.

We found that participant behavior was guided by content bias; participants tended to adopt a novel solution if its quality was higher than the trained solution, especially when the novel solution represented a substantial improvement over the trained solution, supporting Hypothesis 1. However, and consistent with an egocentric bias, a substantial proportion of participants (see supplementary materials for descriptive statistics) preferred to retain the trained solution, even when the novel solution was clearly superior. Our primary interest was the extent to which individual differences guided social learning. Higher general intelligence was uniquely associated with more frequent solution switching (irrespective of solution quality), but was more substantially related to switching to a superior solution. So, higher general intelligence was associated with content-biased social learning, supporting Hypothesis 2. The personality dimension openness to experience was uniquely associated with switching to a suboptimal solution. So, higher openness to experience, and therefore lower egocentric bias, was associated with maladaptive social learning, partially supporting Hypothesis 3.

Psychometric Measurement of the Behavioral Tasks

To our knowledge, this is the first set of behavioral tasks designed to objectively measure content bias and egocentric bias. Consequently, we conducted some basic psychometric analyses to evaluate the properties of the scores. First, the analyses revealed that two of the three task composite scores yielded internal consistency reliabilities in excess of .80 (Padlock = .82; Travel = .59; Maze = .86), which is appreciably greater than the .70 commonly suggested to be minimally required for research purposes (i.e., > .70; Ponterotto & Ruckdeschel, 2007). Internal consistency reliabilities in the .80s are commonly observed for well-regarded task-based measures, including cognitive abilities (e.g., WAIS-IV; Wechsler, 1955) and the Iowa Gambling Task (e.g., split-half reliability = .80; Monterosso, Ehrman, Napier, O'Brien, & Childress, 2001). In contrast to the Padlock and the Maze tasks, the Travel task was associated with an internal consistency reliability of only .59. This suggests that the items within the Travel task were not inter-related strongly enough to suggest that there was a common construct of interest. This may partly explain why the Travel task correlated weakly with the Padlock and Maze tasks ($r = .12$ and $r = .05$, respectively).

The Pearson correlation between the Padlock and Maze tasks ($r = .46$) suggested the presence of construct validity, i.e., the tasks were measuring, at least to some degree, a construct in common (solution switching behavior). The construct validity of these tasks is comparable to a battery of task-based executive function measures, such as the Continuous Performance Task (Rosvold, Mirsky, Sarason, Bransome, & Beck, 1956), the Stroop test (Stroop, 1935), the Wisconsin Card Sorting Test (Heaton, 1981) and the Trails Making Task (Reitan, 1958). However, due to the weak correlation between the Padlock/Maze tasks and the Travel task ($r = .12$ and $r = .05$, respectively), the Travel task was excluded from further analyses. The weak correlation may have been due to the fact that the Travel task was

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distinct from the Padlock and Maze tasks in that it did not require the participant to engage as wholly with the task, i.e., there was minimal learning involved, and therefore no cost to switching between solutions. Consequently, at this stage, we consider only the Padlock and Maze tasks to be valid indicators of individual differences in the sensitivity to content bias and egocentric bias.

Individual Differences

Our primary aim was to assess the extent to which individual differences in intelligence and personality guided human social learning. We hypothesized that people with higher general intelligence would be more likely to switch to the alternative solution if it was superior to their current solution. That is, higher general intelligence would relate positively to content-biased social learning (Hypothesis 2). On the basis of zero-order correlations, general intelligence was found to correlate positively with adaptive and maladaptive switching. This suggests that people with higher intelligence were more likely to switch from their current solution to a new solution, irrespective of solution quality. Furthermore, on the basis of the multiple-regression latent variable analysis, general intelligence was found to be associated uniquely and positively with both adaptive and maladaptive switching. It remains to be determined why more intelligent people were more willing to switch to maladaptive options, in addition to adaptive options.

Importantly, general intelligence was more substantially associated with adaptive switching than maladaptive switching. This indicates that more intelligent people were more likely to switch to a better-adapted solution than a suboptimal solution, supporting Hypothesis 2. More intelligent people make better decisions (Bruine de Bruin et al., 2007) and perhaps this is why higher intelligence is associated with better outcomes in academia

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(Neisser et al., 1996; Mellanby et al., 2000), employment (Gottfredson, 1997), and life expectancy (Gottfredson & Deary, 2004).

We were also interested in the extent to which personality, in particular openness to experience, guided social learning. We hypothesized that people with higher openness to experience, and therefore lower egocentric bias, would be more likely to switch to an alternative solution, irrespective of the quality of the solution (Hypothesis 3). On the basis of the zero-order correlations, openness to experience correlated .22 and .29 with the adaptive and maladaptive switching latent variables, respectively. This suggests that people with higher openness to experience were more likely to switch from their current solution to a new solution, irrespective of solution quality, supporting Hypothesis 3. However, on the basis of unique effects, i.e., controlling for the effects of general intelligence, openness to experience was found to relate only to maladaptive switching (switching to a lower quality solution). This finding partially supports Hypothesis 3.

Openness is associated with a higher-order factor named ‘plasticity’, which is defined as a tendency towards variable, flexible behavior, driven partly by the unconventional and novel-seeking characteristics of openness to experience (DeYoung, 2006). This also includes a tendency towards suboptimal decision making, e.g., greater risk taking (Lauriola & Levin, 2001). This is consistent with the results of the present study, where lower egocentric bias (higher openness to experience) was also associated with suboptimal decision making. A higher egocentric bias was functionally adaptive, as it inhibited participants from switching to maladaptive solutions.

Content bias and Egocentric bias in Human and Non-human Primates

In the present study, most participants’ behavior was guided by content-biased social learning. However, there was considerable variation in the tendency to adopt a novel solution

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based on its intrinsic value. Specifically, 40% of people in the Padlock task and 20% in the Maze task did not switch to the alternative solution at any point during the task, even when it was clearly superior to the trained solution. This conservatism, suggestive of inertia, is consistent with a range of social psychological studies showing that people tend to be unwilling to change their behavior (e.g., O'Connor, Sperl-Hillen, Johnson, Rush, & Biltz, 2005; Ziemer et al., 2005). A preference for familiar things (the mere exposure effect, Zajonc, 1968), and a preference for objects people own over objects they do not own (the endowment effect, Kahneman, Knetsch, & Thaler, 1991; see also the status quo bias, Samuelson & Zeckhauser, 1988) may help explain why people tend to be reluctant to change their behavior.

It has been argued that non-human primates may be even more conservative in their actions than humans (e.g., Harrison & Whiten, 2018). Once they have found a solution to a task, non-human primates become fixed on it and are reluctant to switch, even when a potentially more rewarding alternative is available (Hrubesch et al., 2009; Marshall-Pescini & Whiten, 2008; Whiten et al., 2009; Hopper et al., 2011). This behavioral conservatism inhibits social learning and may constrain the species' capacity for cumulative culture (Marshall-Pescini & Whiten, 2008; see also Hopper et al., 2011; Hrubesch et al., 2009). However, there is accumulating evidence that this conservatism in apes may not be as pervasive as first thought (Lehner et al., 2011; Manrique et al., 2013). For example, when a preferred technique was made non-functional, captive orangutans were able to switch to a range of different functional techniques that were cumulative in nature (Lehner et al., 2011). A follow-up study confirmed that creating these novel exigencies through inhibiting preferred techniques was crucial for subjects to modify and improve on present solutions and thus produce ratcheted techniques (Lehner, Grueter et al unpubl.). Similarly, Manrique et al. (2013) have shown that chimpanzees, gorillas and bonobos abandoned a previously

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established technique to extract food from a puzzle box, when changes in the physical constraints of the task made the old technique ineffective. These findings indicate that apes are capable of overcoming their initial conservatism, but the threshold for this may be high (Dean, Vale, Laland, Flynn, & Kendal, 2013).

These findings, alongside the findings reported in the present study, suggest that conservatism – what we call an egocentric bias – may exist on a cross-species continuum, with humans exhibiting weaker behavioral conservatism than non-human primates. Although speculative, this suggests that cumulative cultural evolution may be more widely seen in human populations because of the greater human intelligence in combination with greater cognitive and behavioral flexibility, compared to non-human primates (i.e., a weaker egocentric bias in humans).

Conclusion

A battery of behavioral tasks were developed to examine the extent to which individual-level differences in intelligence and personality guide human social learning. As predicted by cultural evolutionary theory, participant behavior was guided by content bias: a majority of participants adopted a novel solution if it represented an improvement over the trained solution. However, a substantial minority of participants preferred to retain the trained solution, even when the novel solution was clearly superior. This behavioral conservatism is consistent with an egocentric bias that favors familiar, tried and tested solutions. Our primary interest was the extent to which individual differences influenced social learning. Higher general intelligence was associated with general solution switching, but was more substantially related to switching to a superior solution. So, higher general intelligence predicted content-biased social learning. By contrast, personality, specifically openness to experience, was uniquely associated with switching to an inferior solution. So, higher

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openness to experience (i.e., lower egocentric bias) led to maladaptive solution switching.

This highlights a benefit of an egocentric bias, which, in the context of the present study, inhibited switching to maladaptive solutions. In sum, our findings highlight the importance of individual differences in intelligence and personality to human social learning.

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Supplementary Materials*Descriptive Statistics for Each Task and Level of Solution Quality*

Task_Quality Level	<i>M</i>	<i>SD</i>
Padlock_Seven	.24	.34
Padlock_Six	.25	.36
Padlock_Five	.35	.39
Padlock_Four	.36	.42
Padlock_Three	.50	.42
Padlock_Two	.50	.43
Padlock_One	.57	.43
Travel_Seven	.02	.12
Travel_Six	.02	.13
Travel_Five	.23	.38
Travel_Four	.85	.33
Travel_Three	.93	.24
Travel_Two	.95	.20
Travel_One	.96	.18
Maze_Seven	.23	.36
Maze_Six	.25	.35
Maze_Five	.23	.37
Maze_Four	.46	.43
Maze_Three	.61	.42

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Maze_Two	.76	.39
Maze_One	.80	.36