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Evaluating Social Learning Strategies: The Impact of Skill Dependencies and Meta-Learning in an Agent-Based Model

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Abstract

Learning skills is tremendously important for humans. Social learning enables humans to transmit skills between individuals and across generations. Previous studies investigated different learning strategies but were limited in two ways: agents mostly applied one learning strategy and skills were perceived as independent from each other. We addressed these gaps with an agent-based model that investigates the efficacy of four social learning strategies (success-, similarity-, age-, conformity-based) and three types of meta-learning (fixed, flexible, integrative) in two skill trees (independent skills and linear dependence of skills). In a total of 16 simulations, we found that the level of dependency between skills influenced the performance of learning strategies and meta-learning types. While we found no differences between learning strategies and meta-learning types when skills were independent from each other, the similarity- and age-based strategy outperformed the other strategies when skills were linearly dependent. These findings propose a starting point for future research to further evaluate how constraints and dependencies between skills can influence the performance of learning strategies. Further, our exploratory research into meta-learning revealed promising theories about what learning of social learning strategies could look like.

Keywords: Social Learning, Meta-Learning, Skill Learning

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Over the course of their life, people need to learn many skills to survive and thrive (Tenenbaum et al., 2011; Yaman et al., 2022). However, not all learning is alike, with the most common distinction being made between individual and social learning (Bandura, 1977). During individual learning, a person learns from their own experiences (Laland, 2004). For example, a climber may require many attempts to ascend a new route. In contrast, during social learning an individual observes others and learns from their experiences (Bandura, 1977). Rather than using trial-and-error, a climber can watch other people and copy their movements to save time and energy.

Previous research suggests that social and individual learning work in tandem: Individual learning provides innovations which can be improved and transmitted through social learning (Legare & Nielsen, 2015). As a result, knowledge is not lost with an individual's death or forgetting but can be accumulated over a lifetime or even over generations (Hoppitt & Lala, 2013). Cultural evolution literature suggests that this is the basis for unique human technological advancements like smartphones or artificial intelligence (Legare & Nielsen, 2015). Social learning therefore has immense value to humanity and its development.

Previous literature agrees that social learning can be expressed in different ways (Laland, 2004; Rendell et al., 2010). For instance, people can use simplifying heuristics – so-called social learning strategies - to choose whom to copy (Heyes & Pearce, 2015; Olsson et al., 2020; Rendell et al., 2010). In our study, we focus on four such strategies, namely to copy the most successful individual (success-based strategy; Watson et al., 2021), to copy the most similar person (similarity-based strategy; Henrich and McElreath, 2003), to copy the person closest in age (age-based strategy; Wood et al., 2016), and to copy the most commonly observed behavior (conformity-based strategy; Laland, 2004).

For simplicity reasons, most models assume that individuals only apply one strategy at a time and over time (Mesoudi et al., 2016). The impact of inter-individual differences and experimental or environmental conditions on strategy use has been extensively researched (e.g., Wood et al. (2012, 2016)). Yet, how individuals change and adapt strategies within the same condition and shorter time frames has been largely overlooked (Lee & Gluck, 2021).

Recent formal models started to address this gap. They introduced the idea that individuals figure out over time which learning strategy works best, and as a result adjust their use of these strategies (Mesoudi, 2011; Yaman et al., 2022). This learning of learning strategies is referred to as meta-learning (Heyes, 2016; Yaman et al., 2022). Meta-learning allows individuals to learn about when and how well different learning strategies work, and to use them based on those experiences. We combine these recent models with findings from neuroscience (Hoffmann et al., 2023; O'Doherty et al., 2021) and computational biology (Yaman et al., 2022) to address meta-learning from an interdisciplinary perspective. In our model, individuals choose whom to learn from based on certain criteria. These criteria differ based on the type of meta-learning. We introduce three meta-learning types corresponding to those summarized in Hoppitt and Lala (2013).

Individuals using the first type of meta-learning – fixed learners - base every decision on a single learning strategy (e.g., age-based or success-based). This means that they use the same criterion (e.g. age) to choose a person to learn from each time they attempt to learn a skill socially.

The second type of meta-learning is the flexible learner. For each social learning attempt, these individuals consider all strategies, but only select to follow one of them. The decision which strategy to use is based on their past experiences. More specifically, the flexible learner saves and evaluates information on how well each learning strategy performed for them in the past, and chooses the one that performed best in previous learning attempts. This kind of meta-learning is built on principles of both reinforcement learning (Nussenbaum & Hartley, 2019; Yaman et al., 2022) and Bayesian knowledge updating (van Doorn et al., 2021).

The third type is an integrative learner. Similar to flexible learners, individuals assess how well each learning strategy performed in the past. Yet, instead of choosing the best performing strategy, they combine criteria (e.g., age and success) from all learning strategies to choose the demonstrator that is most promising according to all of them. This type of meta-learning is based on the mixture-of-experts idea from machine-learning (Jacobs et al., 1991), its recent application in neuroscience (O'Doherty et al., 2021), and principles of Bayesian Model Averaging (Hinne et al., 2020).

To get a first indication on how meta-learning performs in the social learning environment, we test our three types of meta-learning in a simulation model to answer the following questions:
1) Which learning strategy is most efficacious under what circumstances?
2) Which type of meta-learning is most efficacious? We want to evaluate these questions in the context of skill learning.

A notable gap in the literature is that most social learning studies treat skills as independent entities (Smolla et al., 2021). More specifically, they assume that individuals can learn any skill, thereby neglecting requirements or facilitation effects of other skills. This seems unrealistic because in reality there is at least some degree of interdependence between skills. To put it differently, learning a skill needs foundational elements and works incrementally (Smolla et al., 2021). To be able to climb up a wall, you need basic skills like pulling up your own weight and trusting your feet. After mastering these basic skills, you can work on how to best shift and balance your weight to get better at climbing.

Thus, the second goal of this study is to address this gap by incorporating findings from cultural evolution research (Buskell et al., 2019; Enquist et al., 2011). Specifically, we will model "skill trees" – tree-like structures of interconnected traits where lower-level skills are requirements for acquiring higher-level skills. We approach this with an agent-based model where agents progress through skill trees with varying constraints.

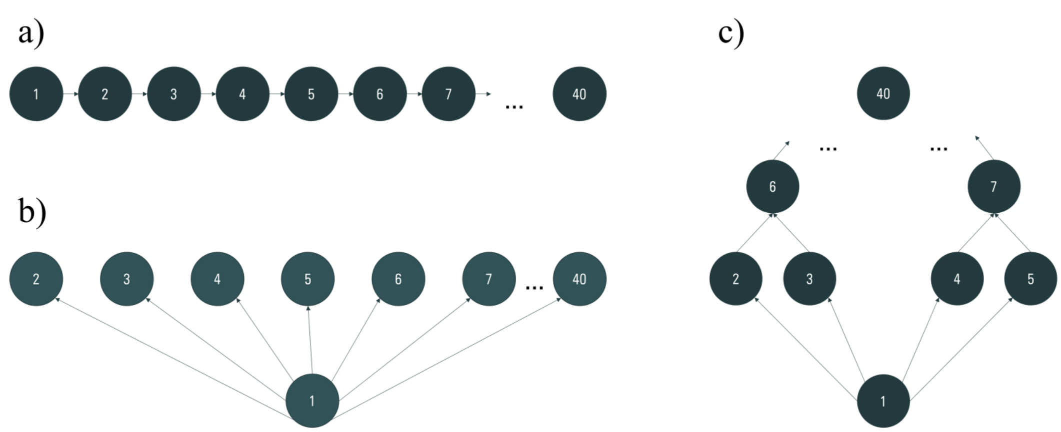
The first skill tree mimics stepwise acquisition where learners can only learn a skill if they master the preceding skill (Figure 1a). This forces learners to follow a strict sequence of learning. For example, an infant first needs to be able to stand before it can walk, and it needs to know how to walk before it can run.

For the second skill tree, the acquisition of skills does not depend on the acquisition of other skills (Figure 1b). For example, a student may sign up for a university class in cooking, dancing, yoga, or other activities that are mostly independent from one another. This structure is representative of most social learning studies which assume that traits are independent (Enquist et al., 2011).

The third skill tree combines the previous two structures (Figure 1c). Learners have some constraints of what they can learn, yet their choice is not as limited as in the stepwise acquisition. For example, being able to talk is a requirement for many other skills. But after a child learnt to talk, they can learn many independent skills like learning to sing, to converse, or even give a presentation about their favorite dinosaur.

Figure 1

Skill Structures



Note. Example dependencies between skills. Relationships between skills are illustrated as arrows. Structures entail (a) linearly dependent skills, (b) independent skills, or (c) a combination of varying dependencies.

We will tie these skill trees back to previous research on social learning and compare how the social learning strategies and meta-learning types perform in different tree structures. We do this to investigate:

1) How do tree structures affect the efficacy of different social learning strategies?

2) Which of the meta-learning types are most efficacious on an individual ("How do people best learn to learn?") and population level ("How do different meta-learning types impact the skill development of the population?").

Methods

General Parameters

We created an agent-based model with 100 individuals and 40 learnable skills. The skills were organized in one of two tree shapes (Figure 1 *a* and *b*). We originally planned to test all three tree shapes. Yet, due to the limited time of the project, we decided to focus on two tree shapes. Each skill had a skill level which determined how much payoff an individual receives when they successfully learn a skill. The skill level was defined by how high up a skill is placed in the skill tree (node depth), with higher-up skills receiving a higher skill level. In case of multiple skills on one layer, skill levels were assigned randomly. The payoff for each skill was determined at the beginning of a simulation. A randomly sampled number from a uniform distribution (lower limit = 0.1; upper limit = 1) was multiplied by the skill level, resulting in a payoff that, on average, increased with skill level. The payoff structure stayed the same throughout the simulation. In general, we conceptualized payoffs as indicator of importance. A skill with higher payoff can be understood as more important to the learner and their skill acquisition process, and vice versa.

At the start of a simulation, each individual received a number of skills, an age and a payoff. The number of skills for each individual could lie between one and 40 skills, and was determined randomly with higher probabilities for lower numbers and lower probabilities for higher numbers (see Table 2 in the Appendix for exact probabilities). Each individual mastered all skills with skill levels lower or equal to their number of skills. Further, each individual was assigned an age that is equal to their number of skills, and a payoff which reflects the summed payoff for all of their skills. Individuals with the meta-learning type flexible or integrative learner used weights to track over time how successful they believed each learning strategy to be (see Meta-Learning Types for a more detailed description). At the start of a simulation all weights were set to zero to indicate that flexible and integrative learners had no previous information about the learning strategies.

Each simulation ran for 5,000 timesteps. In each timestep one individual was randomly selected as a learner. The learner was either reset, attempted to learn a skill through individual learning, or attempted to learn through social learning. The individual was reset with $P_{Reset} = 0.05$. We chose this reset rate to aim for an average of 20 learning rounds per individual before a reset. If the individual was not reset ($1 - P_{Reset}$), they learnt individually with $P_{IL} = 0.01$ or socially with $P_{SL} = 0.99$.

Learners who learnt individually randomly selected one skill they did not master yet, and attempted to learn it. They only succeeded if they fulfilled the requirements determined by the respective skill structure (see Figure 1). If the individual did not fulfill the requirements of the skill structure, the learning attempt was counted as failed. In case the learner used the meta-learning type flexible or integrative learner, their weights were adapted accordingly (see Meta-Learning Types for a more detailed description).

If a learner attempted to learn socially, they randomly selected ten other individuals from the population. Out of these ten individuals, only those mastering a skill that was not in the learner's repertoire were selected as eligible demonstrators. If a learner found no eligible demonstrators, they selected ten new individuals from the population. If the individual did not find any eligible demonstrators after ten selection rounds, a new learner was selected from the population. Based on the learner's learning strategy and meta-learning type, they selected one of the eligible demonstrators to learn from. Then the learner randomly chose one skill that the demonstrator mastered but the learner did not. Again, the learner only succeeded if they fulfilled the requirements to learn this skill which was determined by the skill structure. If the individual succeeded in learning, for both individual and social learning, they received a payoff for the learnt skill. Additionally, the individual's age was increased by one, regardless of success or failure in their learning attempt.

When individuals were reset, they only kept the base skill (skill level one) and the respective payoff. The individual's age was set to zero. Additionally, if the individual was a flexible or integrative learner the weights for the learning strategies were set to zero. In this model, a reset is akin to the death of an individual and the birth of a new individual that takes its place in the population. This way the population size stays the same over time and we can observe the performance of learning strategies and meta-learning types over several 'generations'.

We ran eight simulations per skill structure (Figure 1), resulting in a total of 16 simulations. We ran four simulations with only one learning strategy and no meta-learning present. Three simulations contained all learning strategies and one meta-learning type. The last simulation included all learning strategies and meta-learning types. Our aim was to identify and potentially explain interplay between learning strategies and meta-learning types by comparing 'isolated' simulations with a single learning strategy or meta-learning type to the final simulation. Additionally, each simulation was replicated 100 times to ensure reliability of our results.

Table 1

Overview Simulations per Tree Structure

	Social Learning Strategy				Type of Meta-Learning		
Simulation No.	Success	Similarity	Age	Conformity	Fixed	Flexible	Integrative
1	✓						
2		✓					
3			✓				
4				✓			
5	✓	✓	✓	✓	✓		
6	✓	✓	✓	✓		✓	
7	✓	✓	✓	✓			✓
8	✓	✓	✓	✓	✓	✓	✓

Skill Structures

For each simulation, skills were organized in one of two structures (Figure 1 *a* and *b*). We chose these two structures because they represent the foundational elements of almost all other skill structures (Buskell et al., 2019).

The first structure is the most constrained form. It represents a linear succession of skills. This means that there is only one way in which the individual can progress through the skill tree. While the learners could attempt to learn any skill, this attempt was only successful if the individual mastered the preceding skill (e.g., the individual must master the second skill to unlock the third skill). No matter to which skill a learner has progressed, they were always only able to learn the next skill. The skill payoffs increased on average with skill level. This means that on average, the higher up a skill was placed in the skill tree, the higher was the payoff for this skill. For instance, learning skill four gave the learner on average a lower payoff than learning skill forty.

The second structure is the least constrained form. The skills are independent from each other. This means that mastering the first skill enabled individuals to learn all other skills. As a result, there were several ways in which individuals could progress through the skill tree. As the skill levels for this tree were randomly assigned so were the skill payoffs. To be more precise, an individual could learn the highest payoff skill or a low payoff skill with the same previous knowledge (mastering the base skill one).

Social Learning Strategies

Our model contains four social learning strategies (Henrich, 2004; Rendell et al., 2010). In simulations with all strategies present, individuals were randomly assigned to one of them at the beginning of the simulation.

1. Individuals copy the behavior of the most successful demonstrator (success-based) (McElreath et al., 2008; Mesoudi, 2011). In our model, we operationalized success with the total payoff of the demonstrator. This strategy is declared as most frequent social learning

strategy in computational models and experiments (McElreath et al., 2008; Mesoudi, 2011).

2. Individuals copy the demonstrator that is most similar to themselves (similarity-based). We calculated the similarity score by substracting the learner's number of skills from the demonstrator's number of skills. The lower this score, the more similar the learner perceives this demonstrator.

3. Individuals copy the demonstrator that is closest in age (age-based). We operationalized this strategy by calculating the age difference between the learner and each eligible demonstrator. The age- and similarity-based strategies are often used to explain the behavior of young children showing higher fidelity copying of peers than adults in play situations (Ryalls et al., 2000).

4. Individuals copy a demonstrator expressing the most common behavior (conformity-based). The learner checked which skill was most common in the group of eligible demonstrators and randomly chose one demonstrator with this skill. Still, the learner chose to attempt a random skill from this demonstrator which was not necessarily the most common skill. As every agent possessed the first skill, only skills two until skill forty were considered when choosing the most common skill. Again, studies with children show that they are more likely to copy with higher fidelity if several demonstrators perform the same behavior (Herrmann et al., 2013).

Meta-Learning Types

The here defined types of meta-learning are based on computational models and experimental findings of cultural evolution (Hoppitt & Lala, 2013; Mesoudi, 2011; Smolla et al., 2021), developmental psychology (Wood et al., 2016), computational biology (Yaman et al., 2022), decision psychology and neuroscience (Hoffmann et al., 2023; O'Doherty et al., 2021).

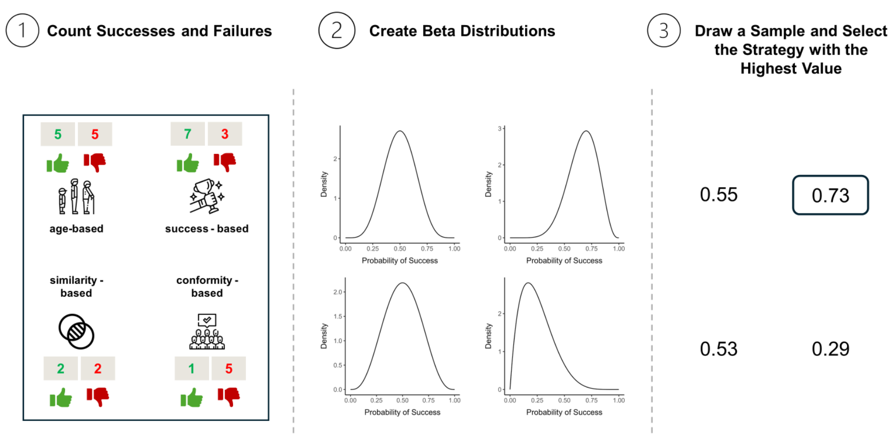
1. Fixed learners were assigned *one* of the social learning strategies at the start of a simulation. They chose whom to learn from solely based on this learning strategy (e.g.,

success-based) and stuck with it throughout the entire simulation.

2. Flexible learners considered their previous experiences with each learning strategy to determine which one to use (e.g., success-based *or* similarity-based). Each learner tracked their successes and failures for each strategy and each learning attempt. Once a learner was selected, they created a Beta distribution per learning strategy. These Beta distributions for each learning strategy were determined by the count of successes and failures with a learning strategy, weighed by the respective payoff of the attempted skill (in line with the Proportional Imitation Rule by Schlag (1998)). More specifically, shape parameter a takes the sum of the payoffs a learner received when the learning attempt with the respective learning strategy was successful. The shape parameter b takes the sum of payoffs a learner did **not** receive when the learning attempt was unsuccessful. As both parameters would be zero for an individual that was never chosen as a learner before, we added one to each parameter value. This is akin to using a flat prior where all values are equally likely (van Doorn et al., 2021).

Figure 2

Flexible Learners Creation of Beta Distributions



Note. Payoffs from successful attempts and non-payoffs from failed attempts are added to the prior Beta(1,1). Example: $Beta_{Success}(a = 7+1, b = 3+1)$

Then, the learner sampled one value from each distribution and selected the strategy with the highest value. If the learner successfully acquired the new skill, a was increased by the payoff of the attempted skill. In case of failure, b was increased by the payoff of the attempted skill. Thus, flexible learners continuously adjust their understanding of the learning strategies which in turn leads to a better estimation of which strategy is most effective. Furthermore, this learning is scaled by the skill payoff which means that learning strategies are rewarded or punished more if the skill was more important and vice versa.

3. Integrative learners did not chose whom to learn from based on a single learning strategy but integrated all strategies to choose the best demonstrator (e.g., success-based and similarity-based...). How much each learning strategy contributed varied based on how well it performed in previous learning attempts. Similarly to flexible learners, for each strategy integrative learners created and sampled a value from a Beta distribution with the summed payoffs of previous successes and failures.

$$Weight_{Age} = 1 \sim Beta_{Age}(a = 5+1, b = 5+1)$$

In contrast to flexible learners, all learning strategies contributed to the decision whom to copy. Each eligible demonstrator d received one score per learning strategy which assessed how well they performed relative to other demonstrators according to this strategy. To ensure that differences in performance between demonstrators were accurately represented, we z-standardized the scores for each learning strategy based on the scores for all demonstrators. This was done to ensure that larger differences in demonstrators' performance based on the learning strategy would lead to proportionally larger differences in their scores. As an example, assume that the learner has an age of 10. If demonstrator d_1 has an age of 12, demonstrator d_2 has an age of 13, and demonstrator d_3 has an age of 30, the scores for d_1 and d_2 are relatively similar while the score for d_3 is notably worse than the scores of d_1 and d_2.

$$\begin{cases} 0 & \text{if scores for all demonstrators are identical} \\ \text{zscore(scores)} & \text{otherwise} \end{cases}$$

$$Score_{d,Age} = zscore(d)_{Age}$$

We computed the total score for a demonstrator with the scores from each learning strategy multiplied by their weights. This way, learning strategies that are perceived as more successful by the learner contribute more to the decision whom to learn from and vice versa:

$$\begin{aligned} TotalScore_d = {} & Score_{d,Success} * Weight_{Success} - Score_{d,Similarity} * Weight_{Similarity} \\ & - Score_{d,Age} * Weight_{Age} + Score_{d,Conformity} * Weight_{Conformity} \end{aligned}$$

The learner then selects whom to copy based on the highest total score. The weights for each learning strategy are updated according to how much they contributed to the total score of the selected demonstrator times the payoff of the attempted skill. This means that integrative learners gain the most knowledge about the strategies that played the biggest role in deciding whom to learn from.

We achieved this by summing the absolute scores for each learning strategy. We added the constant of 10^{-12} so that in case that the sum of absolute scores is zero, the relative score for each learning strategy can still be calculated:

$$|TotalScore| = |Score_{Success}| + |Score_{Similarity}| + |Score_{Age}| + |Score_{Conformity}| + 10^{-12}$$

To calculate the contribution of each learning strategy to the total score, the absolute score for each learning strategy is divided by the absolute total score:

$$\frac{|Score_{Success}|}{|TotalScore|}$$

This value is then multiplied with the payoff of the attempted skill and added to the current weight for the learning strategy:

$$UpdatedWeight_{Success} = Weight_{Success} + \frac{|Score_{Success}|}{|TotalScore|} * Payoff_{AttemptedSkill}$$

Data Analysis

The simulations and analyses were performed using R Statistical Software (v4.3.1; R Core Team, 2021). Further, all of the reported analyses are exploratory.

We analyzed the simulations with regards to outcomes on both group and population level. Firstly, we compared number of acquired skills and total payoffs between simulations (population level). We did so by examining the distribution of the number of skills and payoffs of a population and compared it to populations from other simulations. This way, we answered the questions if there is interplay between learning strategies and/or meta-learning types, and which learning strategies and meta-learning types were most advantageous on a population level.

Secondly, we evaluated the performance of different learning strategies and types of meta-learning in the same population (i.e., simulation 8; Table 1). We operationalized the performance by the number of skills acquired and the total payoff for each group, i.e., learning strategy and/or type of meta-learning.

Thirdly, we tracked the weights for flexible learners and integrative learners to evaluate if a preference is developed for one or multiple learning strategies over time. Additionally, we compared this preference to the outcome from simulations with only fixed meta-learning present (simulations 1 to 4, see Table 1) to see if the estimates of the flexible and integrative learners match the actual success rate of the learning strategies.

Results

Due to limited time and computational demands of the simulations, we decided to focus on two of the three introduced tree shapes. We will report the results for the constrained (linearly dependent skills, Figure 1a) and the unconstrained (independent skills, Figure 1b) skill trees. Future research should look at the performance of the learning strategies and meta-learning types in a tree with varying dependencies between skills (Figure 1c).

Population Level Comparison

We examined the skill and payoff distributions between populations to:
a) evaluate how the number of skills and total payoffs of the populations develop over time, depending on which learning strategies and/or meta-learning types are present, and
b) to determine which population achieved the highest number of skills and total payoff at the end of a simulation.

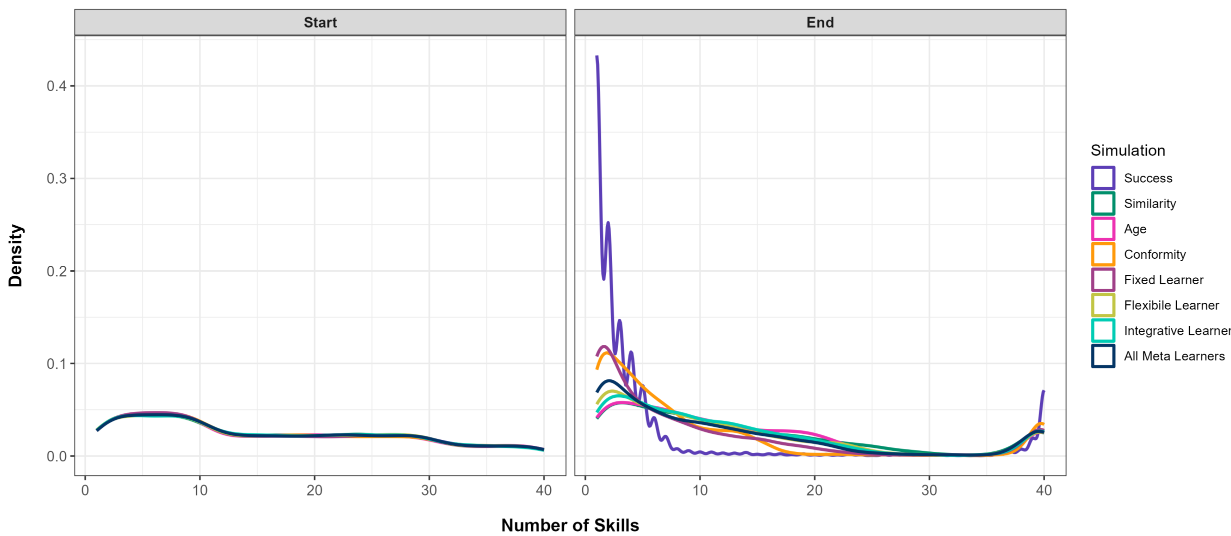
Differences in Number of Skills

Firstly, we find that all populations ended up having a bi-modal distribution of number of skills at the end of the simulation. More precisely, individuals either mastered few or many skills. This was the case regardless of skill tree, learning strategy and type of meta-learning. In spite of the superficial similarities in these findings, closer inspection revealed important differences between trees in the skill distributions.

In the simulations with the constrained tree (Figure 3), most individuals are on the lower end of the distribution. This means that at the end of the simulation, there are many individuals with few skills (up to five skills). Only few individuals end up at the upper end of the distribution, mastering between 35 and 40 skills. This suggests that most individuals have little to no success in their skill learning attempts. Further, the increase in density on the lower end of the distribution evokes the impression that it is difficult for new individuals (i.e., after a reset) to learn skills. This means that ’newborn’ individuals do not acquire as many skills as the individuals that ’died’. Yet, some individuals appear to be successful in their learning attempts as the density at the upper end of the distribution also increases.

Figure 3

Skill Distributions for Constrained Tree Simulations

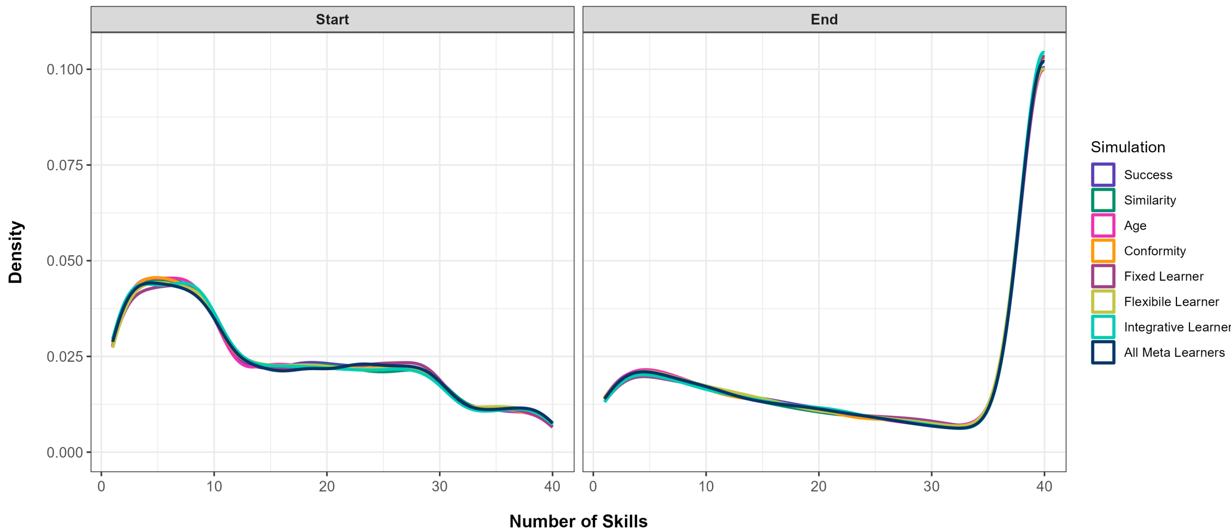


Note. This figure shows the density distributions for simulations in the constrained tree. Each line shows the density for each number of skills at the start (left) and end (right) of a simulation. The color of the line indicates which learning strategies and/or meta-learning types were present in the simulation.

In simulations with the unconstrained tree (Figure 4), most individuals end up at the upper end of the distribution, mastering between 35 and 40 skills. The density on the lower end of the distribution slightly decreases, even though compared to the constrained tree, the dip in density for individuals mastering 20-35 skills is less pronounced. Overall, it appears that the individuals moved relatively evenly through the number of skills. This suggests that the social learning attempts were successful and that learning the skills was relatively easy for new individuals in this population.

Figure 4

Skill Distributions for Unconstrained Tree Simulations



Note. This figure shows the density distributions for the simulations in the unconstrained tree. Each line shows the density for each number of skills at the start (left) and end (right) of a simulation. The color of the line indicates which learning strategies and/or meta-learning types are present in the simulation.

Next, we take a closer look at the population development within a skill tree. More specifically, we compare the skill distribution for each simulation (simulation 1-8; Table 1) within a skill tree.

For the constrained tree, we can see that most populations have similar skill distributions at the end of the simulation (Figure 3). The one population that has a considerably different skill distribution is the simulation with only success-based learners present. For these learners, the skill distribution is even more dense at the lower end of the distribution and the dip in density starts at an even lower number of skills. This suggest that the success-based learners are less successful in learning skills and that ’newborn’ success-based learners are less likely than those of other populations to reach the same skill level as the ’dead’ individuals. For the unconstrained tree, there are no considerable differences between simulations (Figure 4).

We find a similar picture when we compare the number of skills between simulations

(Figure 5). In line with the skill distributions, the large interquartile ranges support the notion that there is a lot of variance within populations. This means that the outcome for the same population differs between replications. More specifically, while most replications end with a median of 40 skills, this is not the case for all simulations. The shape of the skill density distribution remains similar for almost all replications, yet there are some differences between the exact densities of skills which in turn affect the median skill values (see Figures 15-22 in Appendix). As a consequence, differences between populations should be interpreted with caution as the medians are representative of most but not all replications.

For the constrained tree, we find that success-based learners show the lowest number of skills (median = 2; IQR[1, 4]; Figure 5, left). This is in line with their low social learning success rate. Success-based learners only succeed in about 8% of the social learning attempts. Due to the focus on demonstrators with the highest payoff (see Social Learning Strategies), these learners are more likely to choose demonstrators who master multiple skills that are learnable for the individual. As an example, learner L masters skills one to six. They can choose between demonstrator d_1 who masters skills one to 7, demonstrator d_2 who masters skills one to 10, and demonstrator d_3 who masters skills one to 20. If learner L uses the success-based strategy, they will choose d_3 as this is the demonstrator with the highest payoff (as the payoff for an individual is equal to the sum of the payoffs for each skill they master). Now, the learner selects one skill they attempt to learn. This attempted skill is randomly chosen from the range of skills that fulfills both criteria, the selected demonstrator masters the skill and the learner does not (yet) master this skill. Thus, the range of learnable skills learner L can choose ranges from skill seven to skill 20, encompassing 14 skills. The probability to choose exactly the skill with the next higher skill level (skill seven) is very low in this example ($\frac{1}{14}$). In general, the probability to choose the next higher skill decreases the more skills the chosen demonstrator masters. Thus, success-based learners tend to attempt skills that are notably above their current skill level (see Figure 23 in Appendix). This results in a poor performance of success-based learners in the constrained tree as the only way to successfully learn a skill in this skill tree is to attempt the skill with the next higher skill level. Interestingly, the interquartile range for the success-based learners in the constrained tree is remarkably smaller than for all other populations. This suggests that the median number of skills for the success-based learners did not change that much between replications.

On the contrary, similarity-based learners choose the demonstrator that is closest to them in number of skills (see Social Learning Strategies). This means that the range of learnable skills is very small and the probability of choosing the skill with the next higher skill level is very high. Following the example above, learner L would choose demonstrator d_1 and would select the next higher skill (skill seven) with a probability of 1. This is also reflected in the social learning success rate (0.5) and the median skills (10 skills; IQR[5, 18]) which are highest for the similarity-based learner.

Age-based learners have the same median value of skills as similarity-based learners (10 skills; IQR[5, 18]), and a similar social learning success rate (0.46). This is the case because the similarity-based and age-based strategies are very similar at the start of a simulation as an individual's age is equivalent to the number of skills they start with. Yet, it is surprising that they perform so similarly at the end of a simulation even though the correlation between age and number of skills should reduce over time. Checking the correlations between number of skills and age at the end of the simulations, we find that the correlation indeed reduces over time but that it is still quite high at the end of the simulation, for both the populations with age-based learners (mean = 0.85, sd = 0.03) and similarity-based learners (mean = 0.89, sd = 0.02).

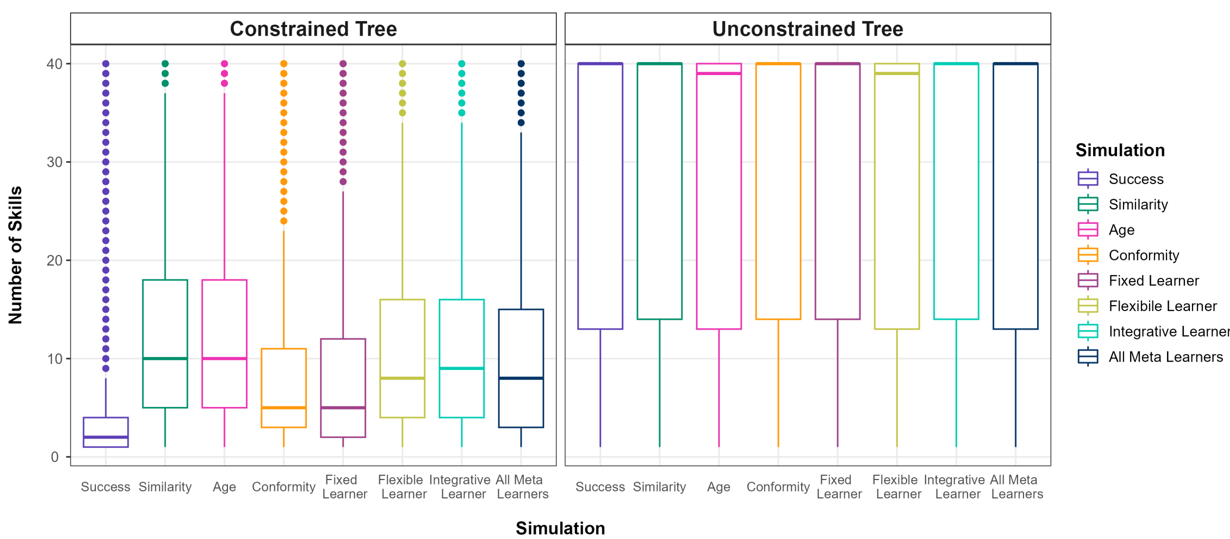
The conformity-based (median = 5, IQR[3, 11]) and the fixed learners (median = 5, IQR[2, 12]) tend to perform slightly better than the success-based learners (median = 2; IQR[1, 4]). The flexible (median = 8, IQR[4, 16]) and integrative learners (median = 9, IQR[4, 16]) as well as the population with all meta-learning types present (median = 8, IQR[3, 15]) tend to perform even better. This is especially interesting as the conformity-based learners are comparable to random learners in the constrained tree setting. Random learners choose whom to learn from randomly instead of using a learning strategy. As skills need to be learnt consecutively in the constrained tree, most individuals have the same base skills (e.g., skills two and three).

Referring back to the example above, according to the conformity-based strategy, there is no preference for any demonstrator d_1, d_2, or d_3 as they all share skill seven which implies that all of them express the most common skill (see Social Learning Strategies). Referring back to the fact that success-based learners perform worse than the conformity-based learners, as a consequence, it appears that success-based learners perform worse than random learning in the constrained tree setting. On the other hand, individuals using flexible or integrative meta-learning appear to perform better than random learning. Yet again, due to the large interquartile ranges, these differences should be interpreted with caution.

For the unconstrained tree, there are no differences visible regarding the number of skills. As expected from the skill distribution, there is a ceiling effect such that the median is at the higher end (39-40 skills) for all populations (Figure 5, right).

Figure 5

Skill Differences Between Simulations Based on Tree Shape



Note. This plot shows the number of skills for all simulations for the constrained (left) and unconstrained tree (right). As we found that the distributions of number of skills and payoffs were not normally distributed but skewed, we decided to report medians (thick lines) and interquartile ranges (boxes) instead of means and standard deviations.

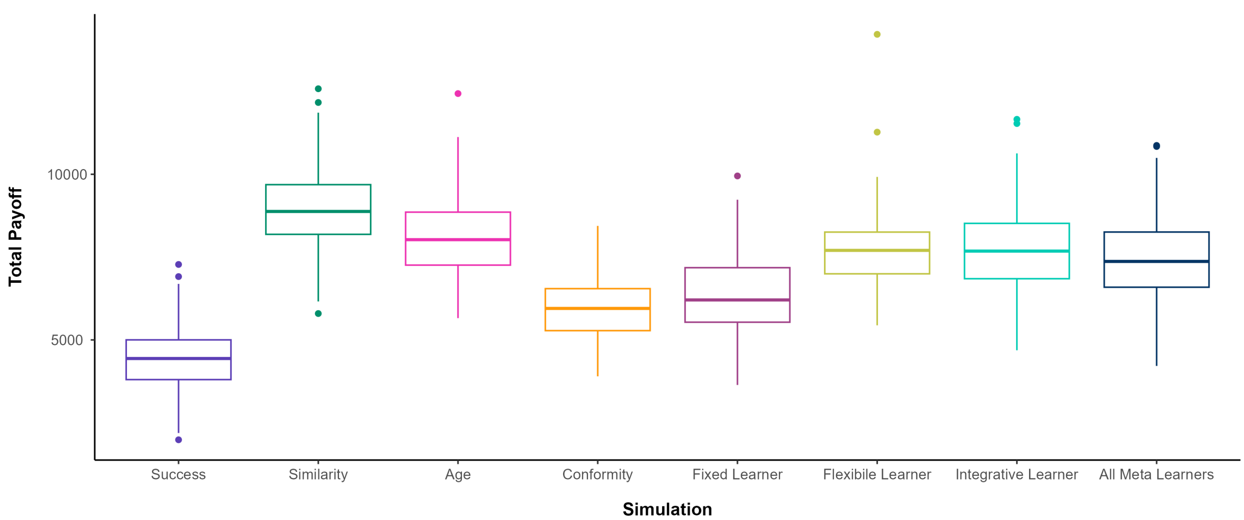
Differences in Total Payoff

Similar to the number of skills, the total payoff is higher in the unconstrained tree than in the constrained tree for all populations.

In the constrained tree, the differences in total payoff are more pronounced than the differences in skills. The success-based learners have the lowest total payoff (median = 4439; IQR[3802, 5001]) (see Figure 6). Similarity-based learners have the highest total payoff (median = 8877; IQR[8187, 9687]), closely followed by age-based learners (median = 8026; IQR[7258, 8857]). Flexible (median = 7703; IQR[6995, 8254]) and integrative learners (median = 7681; IQR[6847, 8518]), as well as the population with all meta learners (median = 7369; IQR[6590, 6547]), perform better than conformity-based (median = 5950; IQR[5280, 8256]) and fixed (median = 6206; IQR[5534, 7180]) learners but worse than the similarity- and age-based learners.

Figure 6

Total Payoffs for Constrained Tree Simulations



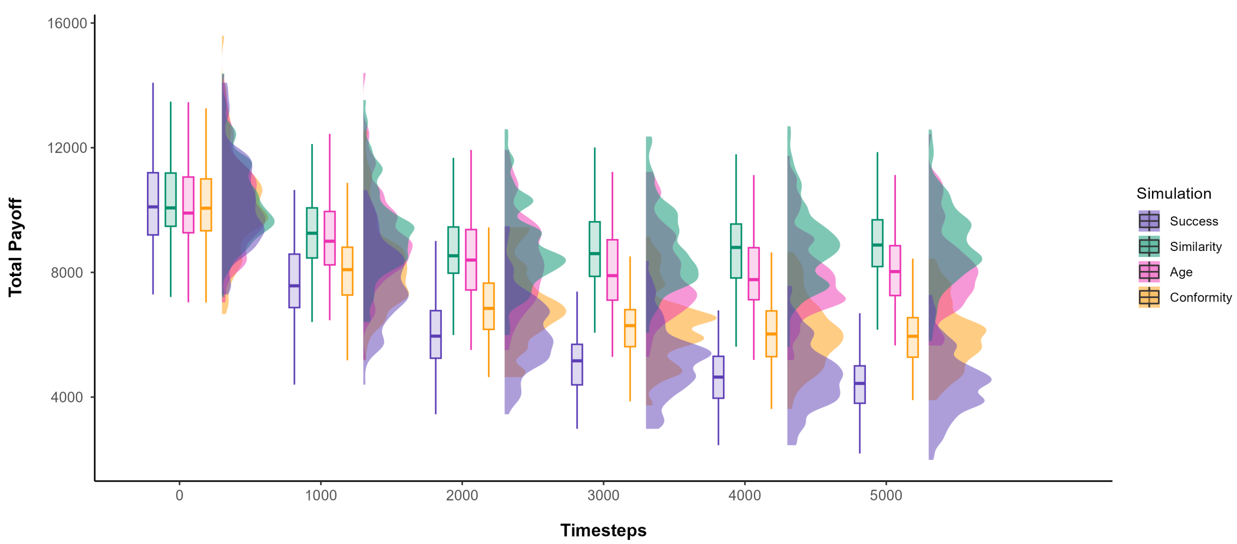
Note. This figure compares the total payoff for all simulations in the constrained tree setting. The thick lines represent the median value, the boxes indicate the interquartile range of replications.

For the constrained tree, we see that the total payoff goes down over time. Notably, this is the case for all learning strategies (see Figure 7) and all meta-learning types (see Figure 8). This indicates that 'newborn' learners in all populations have issues to reach the same skill level as the individual they replaced. To be more precise, new individuals tend to end up with less or lower payoff skills than the individuals they replaced.

We find that the success-based learners' payoff goes down most over time, corresponding to the findings from Figure 6. Further, their payoff goes down constantly and only seems to start stabilizing after timestep 4000. In comparison, the payoff of the age- and conformity-based learners starts stabilizing after about 3000 timesteps, while it appears to already stabilize after about 2000 timesteps for the similarity-based learners. Further, the half-density distributions for all populations are almost normally distributed at the end of the simulation. This suggests that the simulations reach similar outcomes when replicated.

Figure 7

Constrained Tree: Differences Between Learning Strategies in Total Payoff Over Time

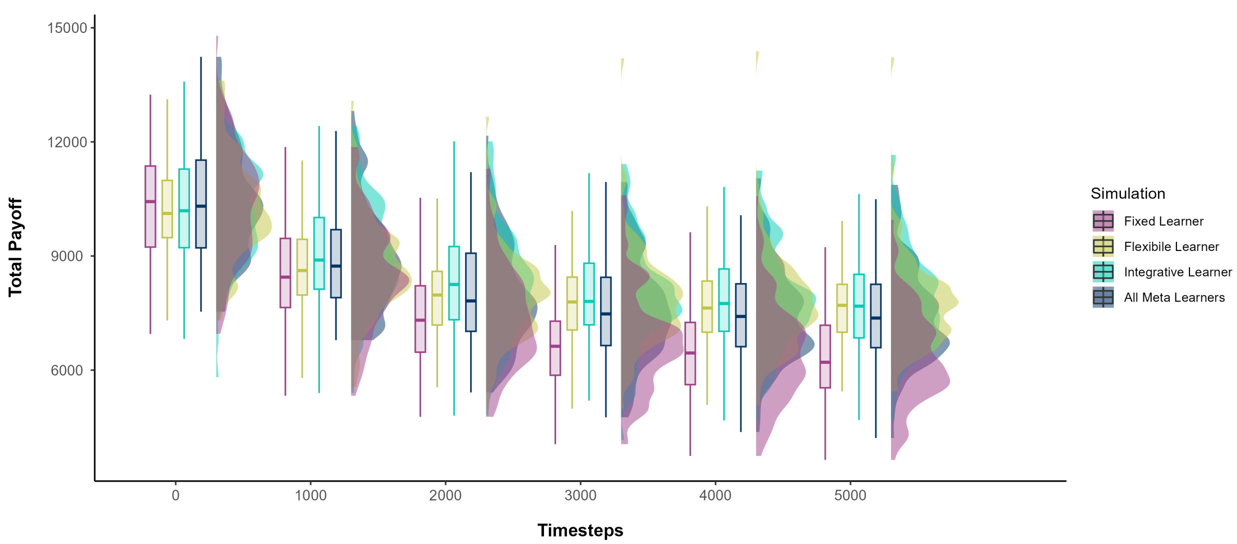


Note. This figure shows the differences in total payoff between populations with different learning strategies over time. Timestep 0 refers to the start of a simulation, timestep 5000 presents the end of a simulation. Per timestep, the total payoff for each group is represented by a traditional boxplot and a half-density distribution plot (raincloud plot). The boxplot visualizes the median and error range between replications for each group. The half-density distribution additionally shows where densities are clustered and gives (if present) an indication of multi-modality.

We see a similar picture for the meta-learning types (Figure 8). The total payoff goes down for all populations and stabilizes after 2000 to 3000 timesteps. The fixed learners, with all learning strategies present, lose most payoff while the integrative and flexible learners lose the least. Further, we find that the half-density distribution for all populations except the flexible learners are relatively wide and do not narrow over time. This suggests that while the flexible learners tend to arrive at similar outcomes over replications, there is a lot of variability in the performance of populations with fixed, integrative and all meta-learners between replications.

Figure 8

Constrained Tree: Differences Between Meta-Learning Types in Total Payoff Over Time

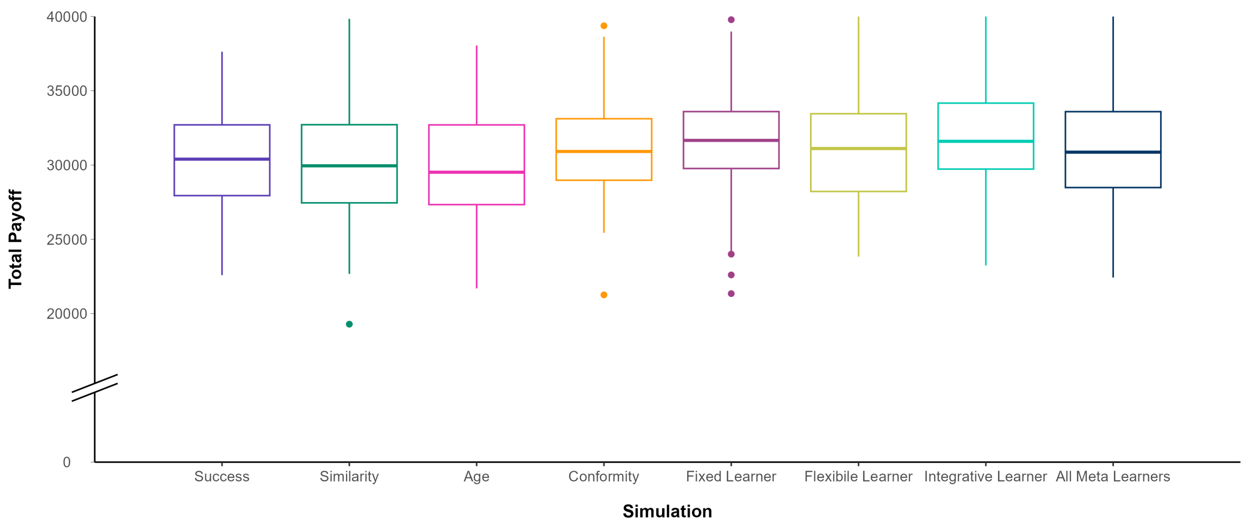


Note. This figure shows the differences in total payoff between populations with different meta-learning types over time. Please note that the fixed learner simulation includes all learning strategies (see Meta-Learning Types). All meta learners refers to the simulation with all meta-learning types and learning strategies present (simulation eight in Table 1). Timestep 0 refers to the start of a simulation, timestep 5000 presents the end of a simulation. Per timestep, the total payoff for each group is represented by a traditional boxplot and a half-density distribution plot (raincloud plot). The boxplot visualizes the median and error range between replications for each group. The half-density distribution additionally shows where densities are clustered and gives (if present) an indication of multi-modality.

For the unconstrained tree, we do not find considerable differences between populations with regards to total payoff (see Figure 9). In line with the number of skills (see Figure 5), the interquartile range is noticeably wide for all populations. This again suggests variability in outcomes between replications.

Figure 9

Total Payoffs for Unconstrained Tree Simulations



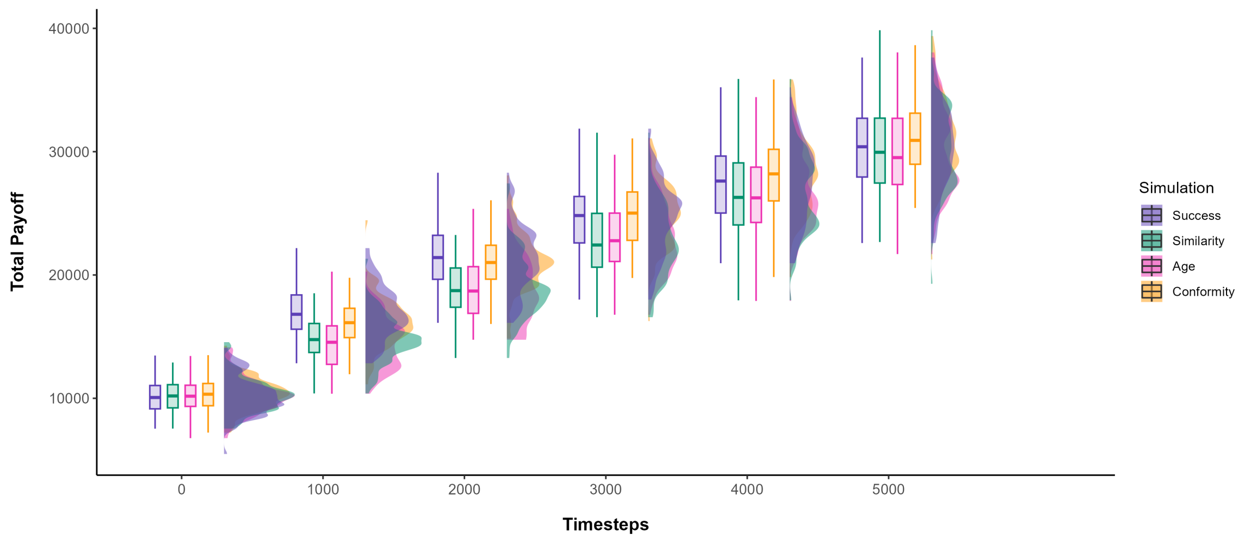
Note. This figure compares the total payoff for all simulations in the unconstrained tree setting. The thick lines represent the median value, the boxes indicate the interquartile range of replications.

Notably, the variability in the total payoff increases over time and this is the case for all populations (see Figures 10 and 25). In general, we can observe that all populations constantly increase their total payoff over time.

Further, we find that the success-based learners have a higher total payoff than the other populations after 1000 and 2000 timesteps (Figure 10). This is the case because the success-based learners are more likely to attempt higher payoff skills earlier than the other learners (see Figure 24 in Appendix). In contrast to the constrained tree, this behavior is successful in the unconstrained tree as learners can learn any skill without fulfilling any requirements. However, at timestep 3000 the conformity-based learners catch up, and at the end of the simulation all learning strategies have similar total payoffs.

Figure 10

Unconstrained Tree: Differences Between Learning Strategies in Total Payoff Over Time



Note. This figure shows the differences in total payoff between populations with different learning strategies over time. Timestep 0 refers to the start of a simulation, timestep 5000 presents the end of a simulation. Per timestep, the total payoff for each group is represented by a traditional boxplot and a half-density distribution plot (raincloud plot). The boxplot visualizes the median and error range between replications for each group. The half-density distribution additionally shows where densities are clustered and gives (if present) an indication of multi-modality.

Next, we evaluate if there are differences between simulations with one learning strategy / meta-learning type and simulations with all learning strategies / meta-learning types present. If the performance of strategies / types changes depending on the absence or presence of other strategies / types in the population, this would suggest an interplay between strategies / types.

More specifically, we compare the performance of a learning strategy (e.g., success-based strategy) in three different scenarios:

1. The whole population consists of learners using the learning strategy in question (simulation one, two, three, or four in Table 1)

2. The whole population consists of fixed learners and all learning strategies are present; but the results are filtered for the learning strategy in question (simulation five in Table 1)

3. All meta-learning types and all learning strategies are present; but the results are filtered for the learning strategy in question (simulation eight in Table 1)

Similarly, we compare the performance of a meta-learning type (e.g., flexible learner) in two scenarios:

1. The whole population consists of learners using the meta-learning type in question (simulation five, six, or seven in Table 1)
2. All meta-learning types and all learning strategies are present (simulation eight in Table 1); but the results are filtered for the meta-learning type in question

We find that neither the number of skills nor the payoff is notably increased or decreased for any learning strategy or meta-learning type when other strategies or types are present / absent. This holds true for both, the constrained and the unconstrained skill tree (see Figures 26-39 in the Appendix). We conclude that the interplay between learning strategies / meta-learning types has little to no effect on the performance of individual learning strategies / meta-learning types. Based on these findings, we deviate from the original analysis plan and refrain from additionally reporting the results for every group from simulation eight as the results are similar to those reported above (see Figures 40-43 in the Appendix).

Integrative and Flexible Learner Weights

Next, we take a closer look at the weights that flexible and integrative learners assign to each of the learning strategies. For the flexible learners, we examine how often they use each of the learning strategies. For the integrative learners, we examine the development of the weights, their estimations of each learning strategy's success probabilities, over time. Lastly, we compare the estimates of flexible and integrative learners at the end of the simulation to the actual success rates of the learning strategies. This way, we can evaluate how accurate the integrative and flexible learner estimates are.

Flexible learner. First, we look at how the use of the learning strategies develops over time. For each timestep, we calculate how often each learning strategy was used from learners in all 100 replications. Next, we divide this sum by the total number of learners in all replications at this timestep to normalize these numbers and get a proportion for every learning strategy per timestep. For Figure 11, we used the `geom_smooth` function from the ggplot2 package (Wickham, 2016) to make it easier to recognize trends in the data.

At the start of the simulation, the flexible learners have no information about how successful the learning strategies are. Thus, we find that they use all strategies about equally often at the start of the simulation in both trees (Figure 11).

For the constrained tree, flexible learners tend to use the similarity- and age-based strategies more while success- and conformity-based strategies are used less (Figure 11a). To put it differently, the flexible learners learn that the similarity- and age-based strategy are more successful than the conformity- and success-based strategy. This is in line with the finding that fixed learners using similarity- and age-based strategies perform best in the constrained tree (see Figure 6). After 1000 timesteps, the use of the age-based strategy stabilizes at about 35% while the use of the similarity-based strategy is still rising up to about 45%. This aligns with the earlier observation that similarity-based and age-based learners perform equally well at the start of the simulation, but similarity-based learners perform slightly better than age-based learners at the end (see Figure 7).

The use of the success- and conformity-based strategies steadily decreases until about timestep 2000. At this point, flexible learners seem to have figured out that the success-based strategy is least likely to lead to successful learning. This is again in agreement with previous findings that the success-based strategy performs worst in the constrained tree(see Figures 6 and 7). Notably, the success-based learning strategy is not fully discarded by the flexible learners but still used in about 5% of the learning attempts. The conformity-based strategy is used in about 10% of the learning attempts at the end of the simulation. That the use of all learning strategies stabilizes at 1000 to 2000 timesteps indicates that this is the time that it takes for the flexible learners to properly estimate how successful the strategies are.

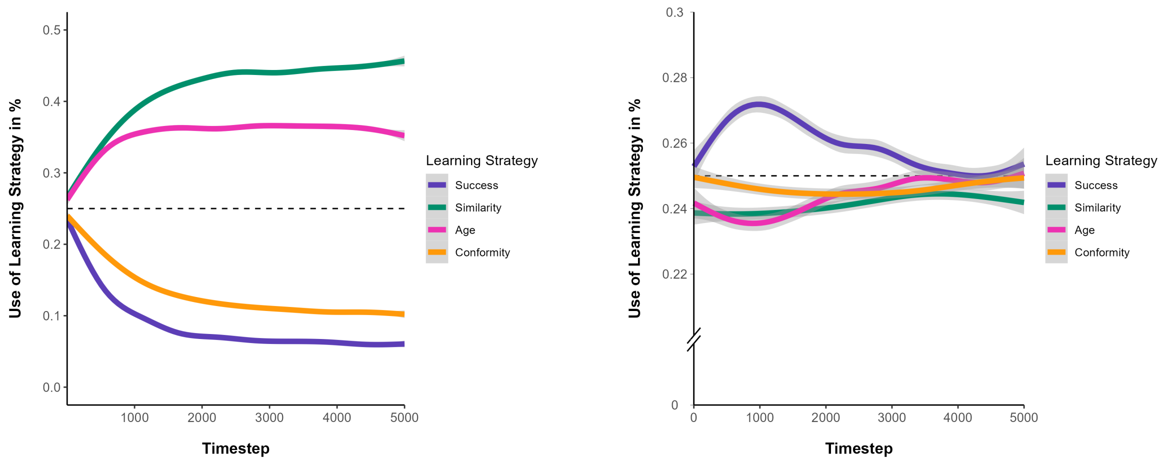
This warm-up period stays the same for the unconstrained tree (Figure 11b). After about

2000 timesteps, the use of all learning strategies stabilizes. At the end of the simulation, the flexible learners use all strategies about equally often. This is in line with the success rates for the unconstrained tree which are at one for all learning strategies. To put it differently, individuals always succeed in learning a skill, regardless of which learning strategy they use, because they can learn any skill without fulfilling any requirements. Thus, the flexible learners correctly identify that they learn successfully with all learning strategies. In agreement with the heightened performance of success-based learners in the beginning of the simulation in Figure10 we see a slight increase in the use of the success-based strategy in the first 1000 timesteps. Yet, this increase is again very small (3%), which indicates that although the success-based strategy leads to slightly higher payoffs at the start, the skill payoffs do not differentiate enough between skill levels to show a clear preference for the success-based strategy which is again in line with Figure 9).

Figure 11

Use of Learning Strategies for the Flexible Learner over Timesteps

(a) *Constrained Tree* (b) *Unconstrained Tree*



Note. These figures show how much each learning strategy was used per timestep. The use of learning strategy was calculated by summing the number of learners from each replication that use the respective learning strategy and dividing this sum by the total amount of learners in all replications. We used the `geom_smooth` function from the ggplot2 package (Wickham, 2016) to show smoothed conditional means. Please note that the figures differ in their y-axis scaling and upper limits. The dashed black line at y = 0.25 marks a state in which all strategies are used equally often.

Integrative learner. Contrary to the flexible learners, the integrative learners do not select the best performing strategy but use the input of all strategies, weighed by their past performance, to select a demonstrator. Thus, instead of reporting the use of learning strategies, we examine how the weights for the learning strategies develop over time. In the simulation, integrative learners track weights for both, successes and failures for each learning strategy. To make the results easier to interpret, we report one weight per learning strategy. The weights represent the expected probability of success for the learning strategies. Each weight can take any value between zero and one. A weight of zero means that the integrative learners rate this learning strategy as very unsuccessful while a weight of one means this learning strategy is rated as highly successful. A weight of 0.5 means that the probability of this learning strategy being successful is at chance level. In line with this, learning strategies that are rated as more successful contribute more to the decision whom to learn from (see Meta-Learning Types), while learning strategies with lower weights contribute less. To visualize the development of weights over time, we report the running averages in Figure 12.

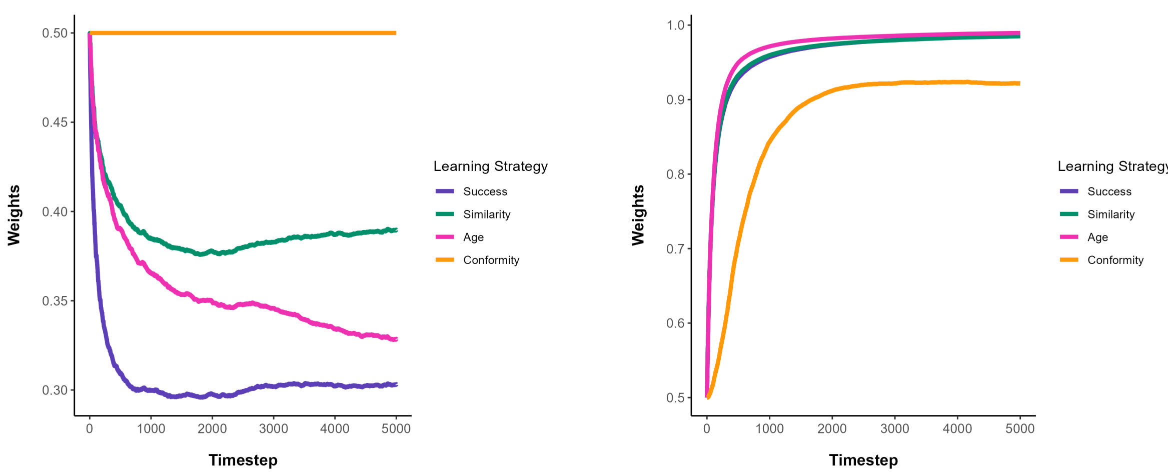
Integrative learners start each simulation with a uniform 'uninformed' prior. For each learning strategy the estimated probability of to be successful is at chance level (0.5).

In the constrained tree (Figure 12a), the weights for all learning strategies but the conformity-based strategy go down. To put it differently, integrative learners learn that they are more likely to fail than to succeed with these strategies.

Figure 12

Weights Learning Strategies for the Integrative Learner over Timesteps

(a) *Constrained Tree* (b) *Unconstrained Tree*



Note. These figures show the running average of the weights for each learning strategy over time. (a) shows the development over time of the weights in the constrained tree. (b) shows the development over time of the weights in the unconstrained tree. We calculated the weight for each learning strategy by dividing its weights for successful attempts by the sum of its successful and failed attempts. Please note that the figures differ in their y-axis scaling, and their upper and lower limits.

Similar to the flexible learners, integrative learners learn most about the learning strategies in the first 1000 timesteps. After 1000 timesteps, the weight for the success-based strategy appears to stabilize at around 0.3. After timestep 2000, the weight for the age-based strategy continues to decrease, while the weight for the similarity-based strategy slightly increases. Overall, integrative learners estimate that the similarity-based strategy is least likely to fail. At the end of the simulation, integrative learners estimate the success rate of the similarity-based strategy to be about 40%. On the contrary, the success-based strategy is rated to fail most with an estimated success rate of about 30% at the end of the simulation. Thus, the integrative learners learn that how similar the demonstrator is should contribute most while the success of a demonstrator should contribute least to the decision whom to learn from. This is again in line with the performance of the respective learning strategies in the constrained tree (Figure 7). The weight for the conformity-based strategy is a special case here. The estimated success rate does not change over time but stays at chance level (50%). This indicates that the conformity criteria does not help to distinguish between demonstrators. This is the case because most demonstrators perform equally well in terms of conformity. In the constrained tree all individuals have to learn the skills in the exact same order. This makes it very likely that at least one skill is mastered by all demonstrators (see also Differences in Number of Skills). Due to the z-standardization of scores (see Meta-Learning Types), this means that if all demonstrators master the most common skill, the conformity score for each demonstrator is equal to zero. As a consequence, the integrative learners do not consider the conformity score when choosing whom to learn from.

For the unconstrained tree, we see again that the integrative learners take about 1000 timesteps to learn about the learning strategies. After 1000 timesteps the estimates for all strategies appear to stabilize. For the unconstrained tree, we see that the integrative learners learn that all strategies are very successful. At the end of the simulation, the estimated success rates for the success-, similarity-, and age-based strategy are almost at one. The increase for the conformity-based strategy is less steep and it stabilizes at a lower value. This is the case because the individuals start off with a skill level that correlates perfectly with the number of skills the individual masters. Throughout the simulation, this correlation reduces in this tree. Yet, in some cases all eligible demonstrators own the same skill which then again makes the conformity score redundant for the demonstrator selection. As a consequence, the integrative learners are less sure about the successfulness of the conformity-based strategy compared to the other strategies.

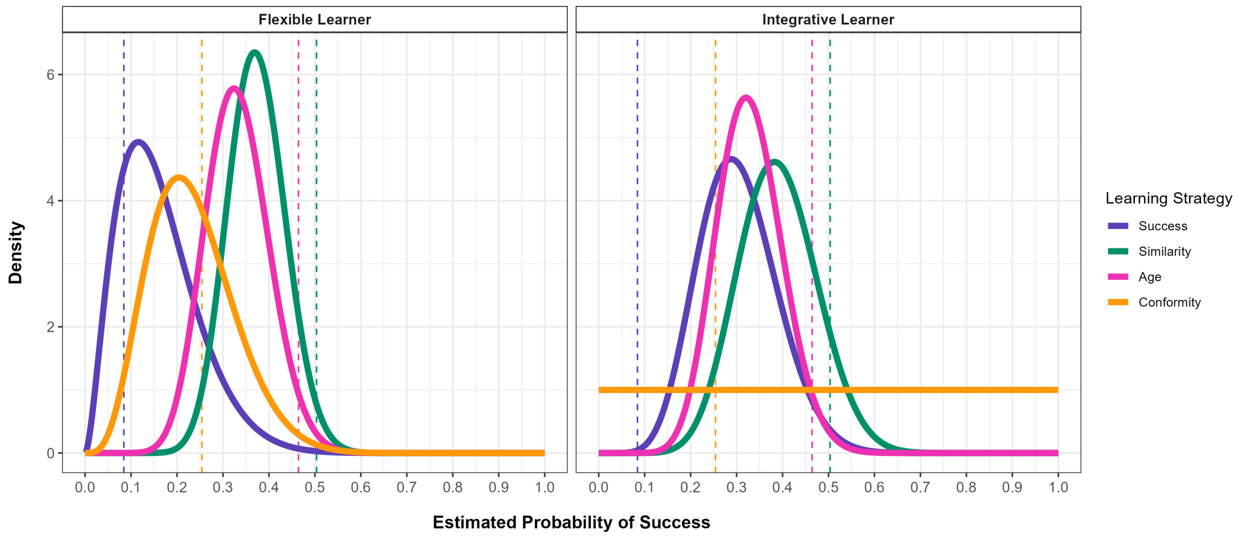
Beta Distributions. Lastly, we examine the Beta distributions for the flexible and integrative learners. Each Beta distribution represents as how successful the respective learning strategy is rated by the flexible learner (Figure 13 and Figure 14,left) and the integrative learner (Figure 13, and and Figure 14, right) as well as how confident the learners are about their estimates. More precisely, the peak of the distribution signals the mean estimated success probability, while the width and height of the distribution signal how confident the estimation is. All distributions start as a uniform distribution where each probability of success is equally likely. The more the distribution moves to the left, the lower the estimated success probability for this learning strategy. The more the distribution moves to the right, the higher the estimated probability of success for the respective learning strategy. The wider and flatter a distribution, the less confident learners are about their estimate. The taller and tighter a distribution, the more confident learners are about their estimate. The dotted lines show the ’real’ success rate for the respective learning strategy (i.e., how often the population with learners using solely this strategy succeeded in social learning).

For the constrained tree (Figure 13), we find again that the flexible and integrative learners agree that all learning strategies have a higher probability of failing than succeeding. Further, both meta-learning types predict the similarity-based strategy to have the highest success probability, while the success-based strategy is rated as least successful. Notably, the estimates for the success-, similarity-, and age-based strategy are closer together for the integrative learner than for the flexible learner. This indicates that the flexible learners are better in distinguishing between strategies than the integrative learners. Further, while the flexible learner is most certain about their estimate for the similarity-based strategy, the integrative learner is most certain about their estimate for the age-based strategy. One explanation could be that the flexible learners are quicker to learn about the decrease in the performance of the age-based strategy when the correlation between age and number of skills decreases. The biggest difference between integrative and flexible learners can be found in their estimation of the conformity-based strategy. The flexible learners rate the conformity-based strategy as less successful than the similarity-, and age-based strategies but more successful than the success-based strategy. As mentioned above, the integrative learners on the other hand do not update their beliefs about the conformity-based strategy. We find that their distribution is still the same as the uniform prior which indicates that they were unable to learn about the probability of success for the conformity-based strategy.

Further, the integrative learners clearly overestimate the success probability of the success-based strategy. While they recognize that it is the least successful strategy, they still estimate its success rate to be at 30%, which is considerably higher than its actual success rate of 8%. The flexible learners are more accurate in their estimates for the success- and conformity-based strategies. For the age- and similarity-based strategy, the flexible and integrative learners slightly underestimate their success rates, with both meta-learning types being about equally accurate.

Figure 13

Constrained Tree: Beta Distributions for Flexible and Integrative Learner

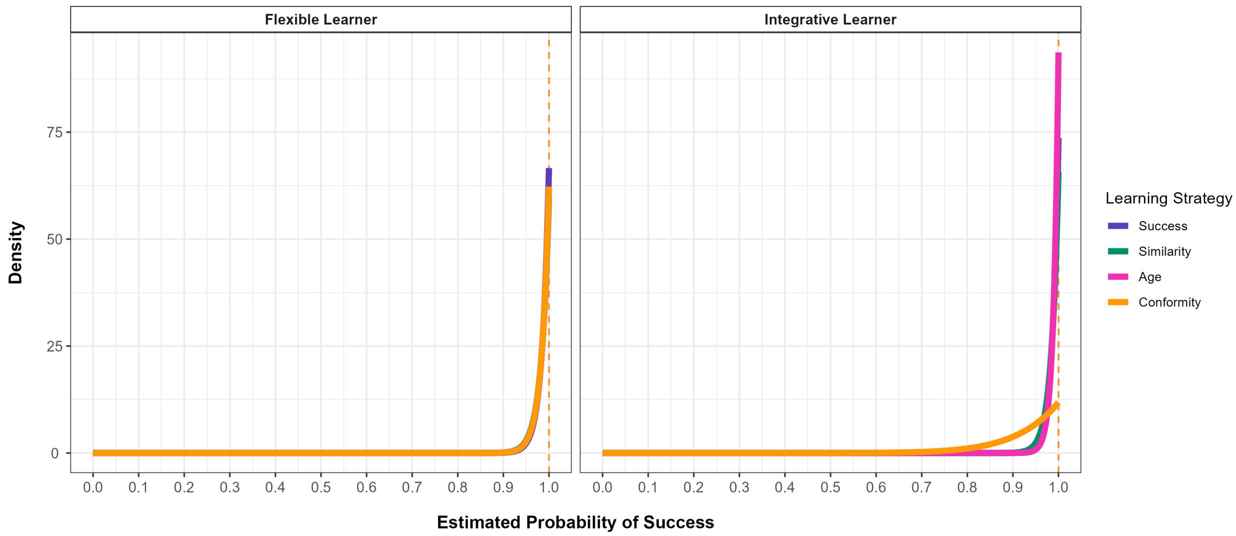


Note. These figures show the Beta distributions for flexible (a) and integrative (b) learners in the constrained tree. Each distribution denotes as how successful the learners rate the respective learning strategy, as well as how confident the learners are in their estimate. The dotted lines indicate the success rate of the respective learning strategy in populations with only this strategy and no meta-learning present (i.e., simulations one to four in Table 1).

For the unconstrained tree (Figure 14), we find that the integrative and flexible learners correctly estimate that the success rates are very high. While the flexible learner shows the same certainty in their estimates for all learning strategies, the integrative learner slightly slightly less certain about their estimate of the conformity-based strategy (for explanation see Integrative learner). Additionally, we can see again that the integrative learners are more certain about their estimates for the age-based strategy than the other strategies, indicating that they put slightly more emphasis on it.

Figure 14

Unconstrained Tree: Beta Distributions for Flexible and Integrative Learner.



Note. These figures show the Beta distributions for flexible (a) and integrative (b) learners in the unconstrained tree. Each distribution denotes as how successful the learners rate the respective learning strategy, as well as how confident the learners are in their estimate. The dotted lines indicate the success rate of the respective learning strategy in populations with only this strategy and no meta-learning present (i.e., simulations one to four in Table 1).

Discussion

Our study provides new insights on how dependencies between skills can influence the performance of social learning strategies and meta-learning types. Our simulation results show that all strategies and meta-learning types perform better when skills are independent from each other. In a setting with independent skills, there is little difference between learning strategies. Yet, in a setting with linearly dependent skills, similarity- and age-based strategies clearly outperform all other strategies, including the flexible and integrative learners. The success-based strategy is least successful in this setting.

The finding that the similarity-based strategy performs best in the constrained tree setting is in line with a recent preprint by Smaldino and Velilla (2024). Similarly to Smaldino and Velilla

(2024), we find that similarity-based social learning is adaptive in certain environments because it allows the learner to find individuals that are most likely to perform behaviors that are useful to the learner. Notably, the operationalization of the similarity-based strategy is up for discussion. For this model, we decided to use the difference in number of skills as proxy for similarity. While this operationalization appears highly realistic for the constrained tree setting, it is debatable for the unconstrained tree as mastering an equal number of skills does not necessarily mean mastering the same skills in this setting. More precisely, two individuals could have the same number of skills while sharing no common skills (except for the base skill). Yet, we decided to go with this approach as we deem it most realistic and previous research (e.g., Morgan et al., 2011) suggests that individuals do not know the exact skills other individuals master but that they can estimate how much another individual knows (e.g., being able to estimate if someone just started bouldering or is very advanced in bouldering).

On the other hand, the finding that there is little to no difference between strategies in the unconstrained tree setting contradicts previous literature that suggests that the success-based strategy performs best for simple tasks (Barkoczi & Galesic, 2016). Yet, in our simulations the success-based strategy only outperforms the other strategies in the first 2000 timesteps.

One possible explanation is that the payoff differences between skills are too small to see a difference between the success-based and the other strategies. The payoff difference between a skill and the skill with the next high skill level ranged between 0.1 and 1, with a mean difference of 0.522 for the simulation with the success-based learners (simulation 1, see Table 1). It is possible that a higher difference in payoff between skills could lead to a bigger difference in total payoff between strategies. Future studies should replicate this study with several payoff structures to explore how the skill payoff structure influences the performance of social learning strategies and meta-learning.

Another possible explanation for this finding is that we did not find an equilibrium for the population development. In our simulations, the skill distribution was bi-modal instead of equally distributed over skills. For the unconstrained tree, most individuals were at the upper end of the distribution (mastering between 35 to 40 skills). This could have artificially increased the payoff for similarity-, age-, and conformity-based learners later in the simulation. When most individuals master almost all skills, there is a high probability that the selection of potential demonstrators consists only of highly skilled demonstrators. Consequently, there is a high probability to choose a very skilled demonstrator, regardless of the learner's strategy. As a result, all strategies are equally likely to learn high payoff skills at the end, thereby reducing the 'advantage' of the success-based learners to learn high payoff skills first in the beginning of the simulation.

In addition, the fact that there is no equilibrium could have impacted the performance in the constrained tree. In the constrained tree setting, most individuals ended up in the lower end of the skill distribution. Very few to none individuals mastered between 20 and 35 skills. As a result, individuals with close to 20 skills were unlikely to find eligible demonstrators. Additionally, if they found a demonstrator, there was a high probability that they failed to learn because the demonstrator was too skilled which means that the probability to exactly select the skill with the next higher skill level was very low. This is akin to when a newbie boulderer goes to the world cup and tries to copy the most successful boulderers. The chance that the newbie can identify a behavior that helps at their skill level, and successfully learn it is very low. On the other hand, there are plenty of people just above the newbie's skill level at the boulder gym, which makes it more likely that the newbie learns by copying their behavior.

We attempted to find an equilibrium by changing the reset rate and the rate of individual learning. Yet, we were unable to find settings that allow the skill distributions to stabilize for both skill trees. Future studies might address this limitation and replicate our study with a stationary skill distribution present.

A third possible explanation is that we do not see differences between strategies because of the variation of outcomes between replications. The high variability in payoff within learning strategies, could make it difficult to recognize differences between them. While the skill distributions have similar shapes across replications, we still find that there are differences in the densities for each number of skills that lead to varying median values between replications (see

Figures 15 - 22 in Appendix).

This variability between replications could be caused by different factors. One important factor is which skills the learner chooses to learn once they selected a demonstrator. While this decision also exist in the constrained tree setting, its impact is even higher in the unconstrained setting as individuals have much more freedom in which skills they can successfully learn. To put it differently, while it does not make a difference in the constrained tree if the learner chooses to attempt a skill that is three or 15 levels above their own skill level because they fail with both choices, it has a high impact for the total payoff which skill the learner attempts in the unconstrained setting as they receive different payoffs based on their choice. These differences in individual decisions accumulate on a population level which in turn could lead to the observed variability in payoffs between replications.

Further factors leading to these differences could be how the skills are distributed at the start of the simulation, the amount of learning attempts per individual (median = 55, IQR[29, 66] learning attempts for the success-based learners in the unconstrained tree), and which and when individuals are reset. As all of these aspects are (to some extent) subject to randomness, we propose that future studies increase the number of replications to receive more reliable estimates and potentially be better able to recognize patterns and differences between populations.

A novel aspect of this study is the introduction of meta-learning in the form of the flexible and integrative learners. While previous literature focused heavily on the combination of individual and social learning (Enquist et al., 2007; Henrich & McElreath, 2003; Laland, 2004; Van Den Berg et al., 2023), there is little research on how different social learning strategies could be combined or even integrated. Our aim was to investigate how individuals learn about social learning strategies and either adapt their use (flexible learners) or integrate them (integrative learners) over time. Our findings for the constrained tree show that both types of meta-learning perform better than the fixed learners with all learning strategies present. Yet, they do not perform better than the populations with only similarity- or age-based learners even though their social learning success rate is almost equally high. Looking at the total payoff and success rates over time, we found that flexible and integrative learners need a warm-up phase of about 2000 timesteps to learn about the strategies while success rates and payoffs for similarity- and age-based learners change less over time (see Figures 7 and 8). This could explain why flexible and integrative learners achieved a lower total payoff than similarity- and age-based learners.

Further, we found that flexible learners in the constrained tree setting tend to be more accurate than integrative learners in their estimation of the learning strategies' success rates. More precisely, the integrative learners overestimate the performance of the success-based strategy, while the flexible learners have a relatively precise estimate for it. This is especially interesting as we do not see notable differences in either total payoff or number of skills between these two meta-learning types. It appears that even though the demonstrator scores of integrative learners were notably influenced by the demonstrator's payoff (criteria for success-based strategy), the scores for similarity and age had enough influence on the total score to lead the decision whom to learn from so that integrative learners learnt successfully in 44% of the attempts.

Conclusion

Our study adds to previous work by investigating how dependencies between skills influence the performance of social learning strategies and how meta-learning allows individuals to apply more than one strategy. Our study finds that the performance of all social learning strategies is influenced by constraints and dependencies between skills. Similarity- and age-based social learning emerged as the most successful strategies in settings with linearly dependent skills. These findings highlight the need and provide a starting point for future studies to account for and examine the impact of skill dependencies on the performance of social learning strategies. In addition, the introduction of our meta-social learning provides a means to further explore how individuals change and adapt strategies over time with the two approaches of strategy switching (flexible learner) and strategy integration (integrative learner).

Data and code availability

Data and code are available at GitHub Repository

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Appendix

Table 2

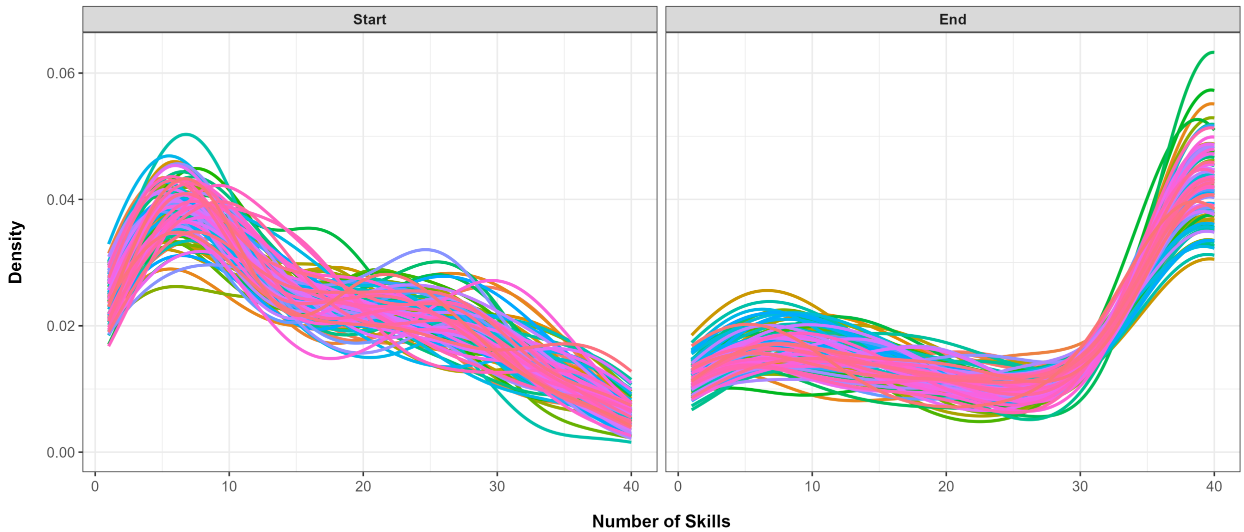
Probabilities for Skill Setup

Skill	Probability
1 - 10	0.05
11 - 30	0.025
31 - 40	0.0125

Note. This table shows the probabilities for each number of skills being selected at the start of the simulation.

Figure 15

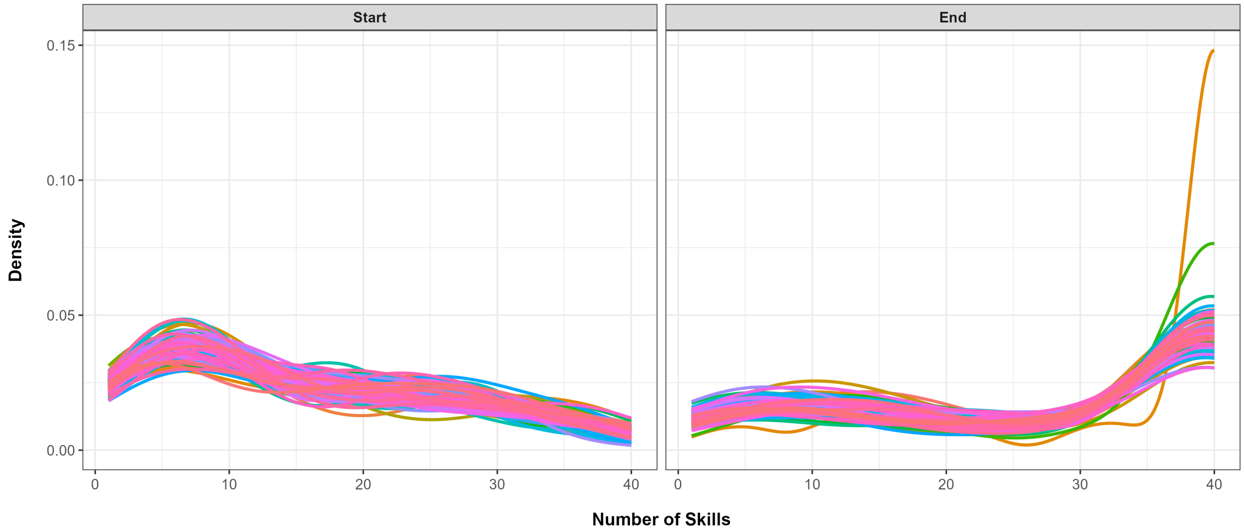
Success-based Learners: Skill Density Distributions By Replication



Note. Theses figures show the density distribution of the number of skills per round/replication in the unconstrained tree at the start (left) and end (right) of a simulation. Each line represents the distribution of skills in one round/replication of the success-based learner simulation.

Figure 16

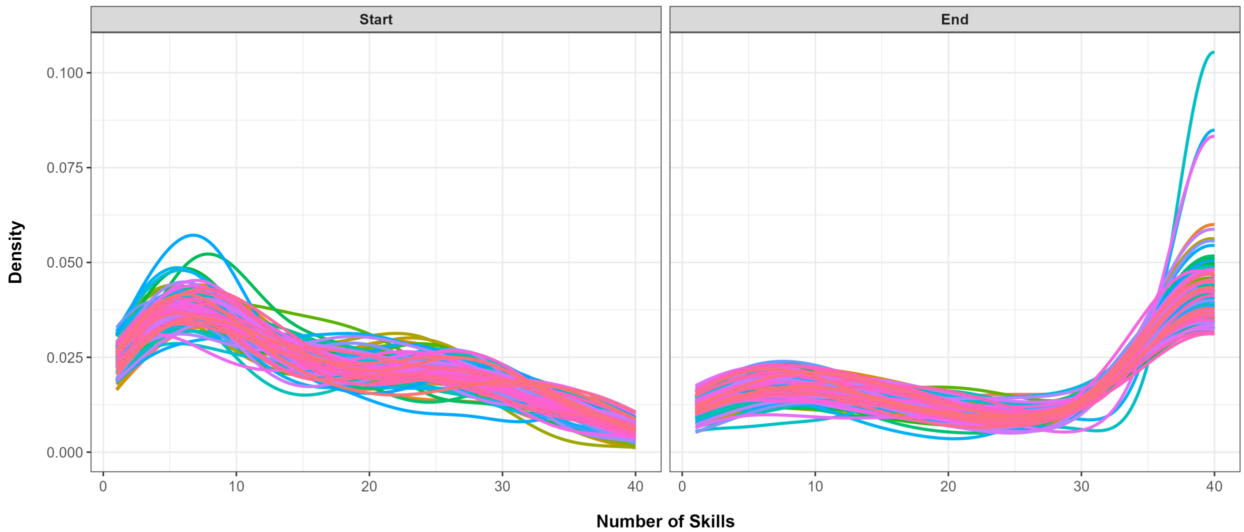
Similarity-based Learners: Skill Density Distributions By Replication



Note. Theses figures show the density distribution of the number of skills per round/replication in the unconstrained tree at the start (left) and end (right) of a simulation. Each line represents the distribution of skills in one round/replication of the similarity-based learner simulation.

Figure 17

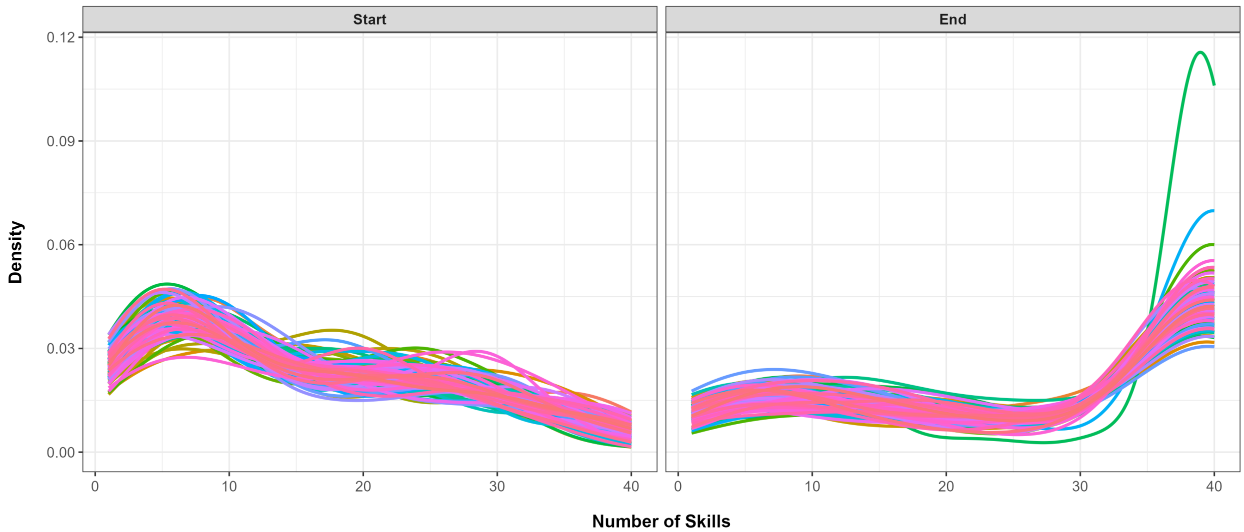
Age-based Learners: Skill Density Distributions By Replication



Note. Theses figures show the density distribution of the number of skills per round/replication in the unconstrained tree at the start (left) and end (right) of a simulation. Each line represents the distribution of skills in one round/replication of the age-based learner simulation.

Figure 18

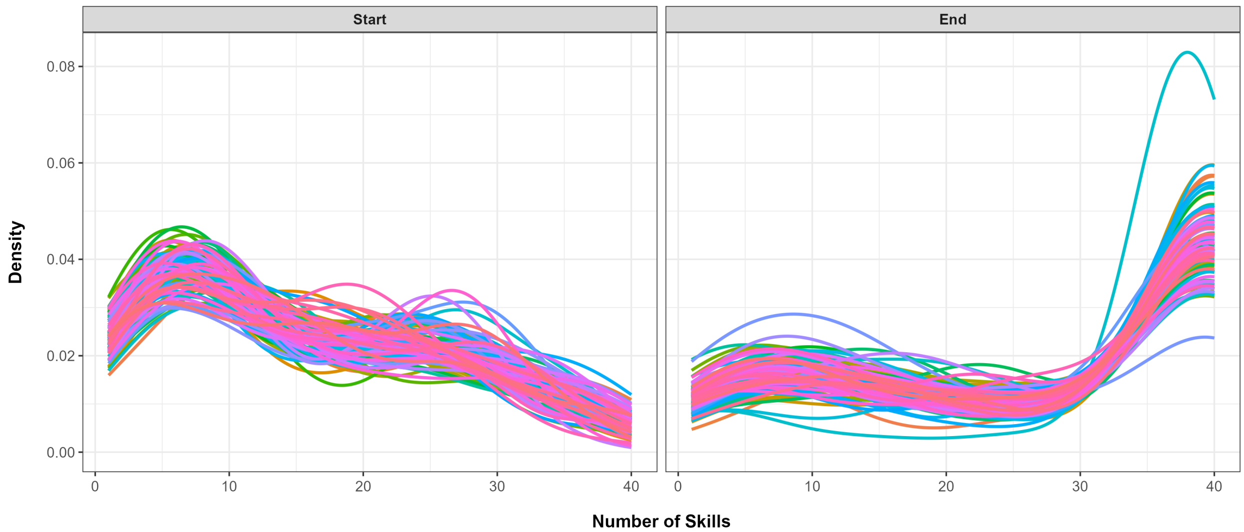
Conformity-based Learners: Skill Density Distributions By Replication



Note. Theses figures show the density distribution of the number of skills per round/replication in the unconstrained tree at the start (left) and end (right) of a simulation. Each line represents the distribution of skills in one round/replication of the conformity-based learner simulation.

Figure 19

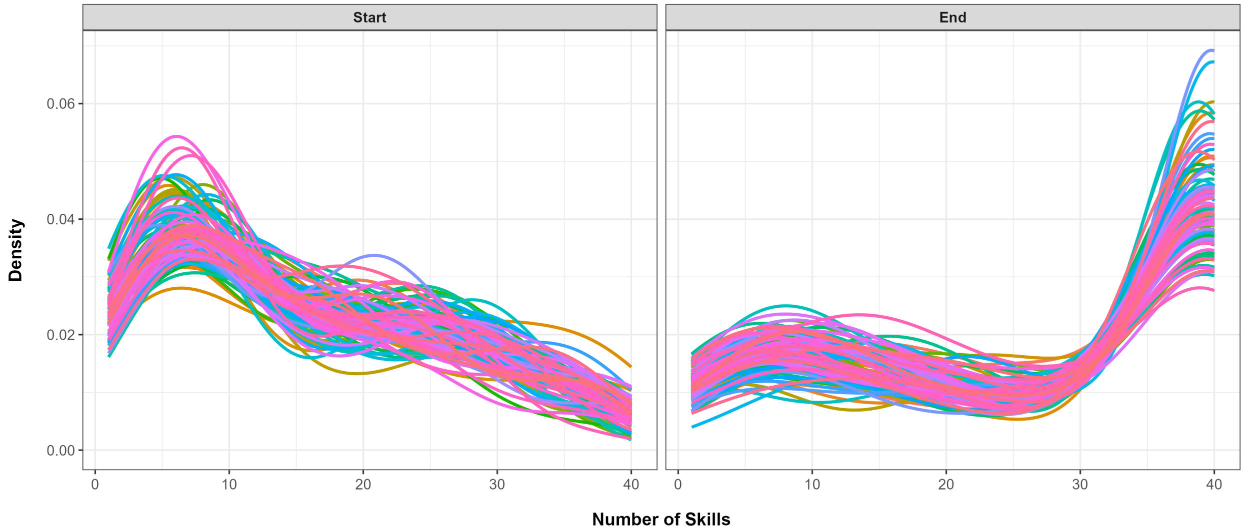
Fixed Learners: Skill Density Distributions By Replication



Note. Theses figures show the density distribution of the number of skills per round/replication in the unconstrained tree at the start (left) and end (right) of a simulation. Each line represents the distribution of skills in one round/replication of the fixed learner simulation.

Figure 20

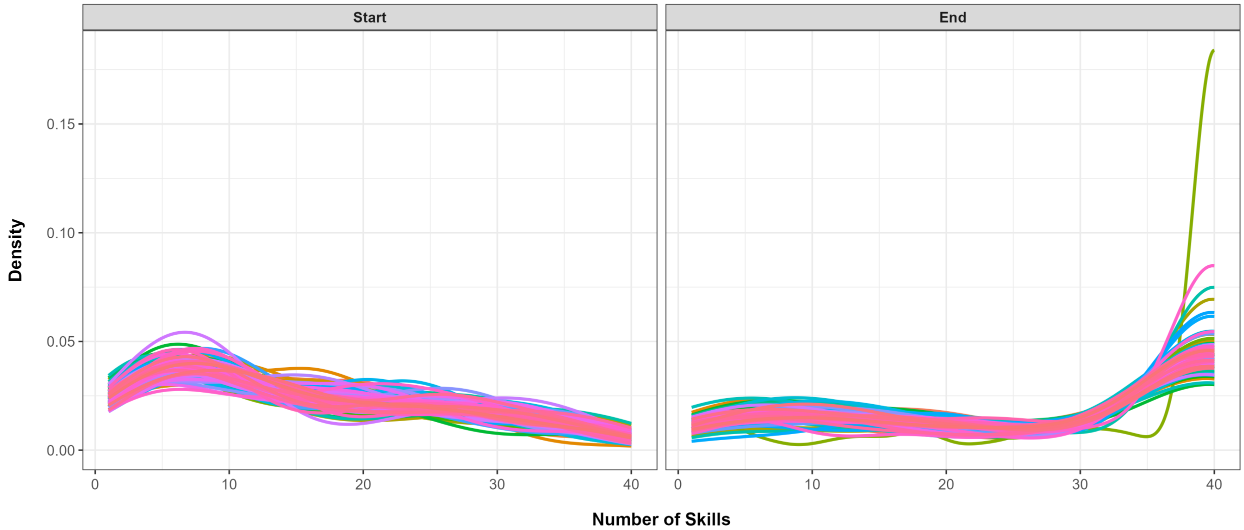
Flexible Learners: Skill Density Distributions By Replication



Note. Theses figures show the density distribution of the number of skills per round/replication in the unconstrained tree at the start (left) and end (right) of a simulation. Each line represents the distribution of skills in one round/replication of the flexible learner simulation.

Figure 21

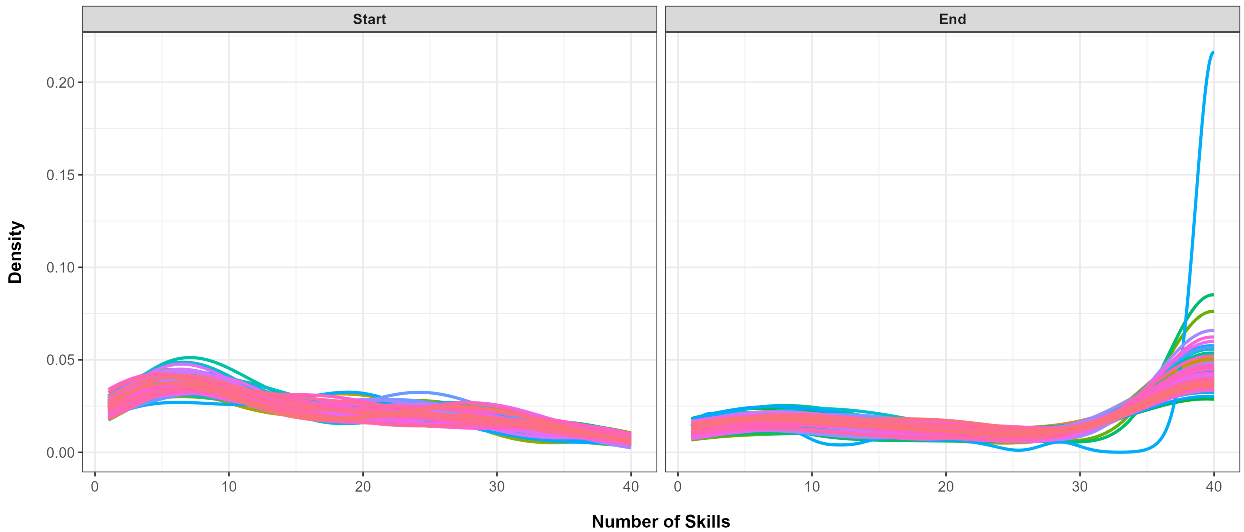
Integrative Learners: Skill Density Distributions By Replication



Note. Theses figures show the density distribution of the number of skills per round/replication in the unconstrained tree at the start (left) and end (right) of a simulation. Each line represents the distribution of skills in one round/replication of the integrative learner simulation.

Figure 22

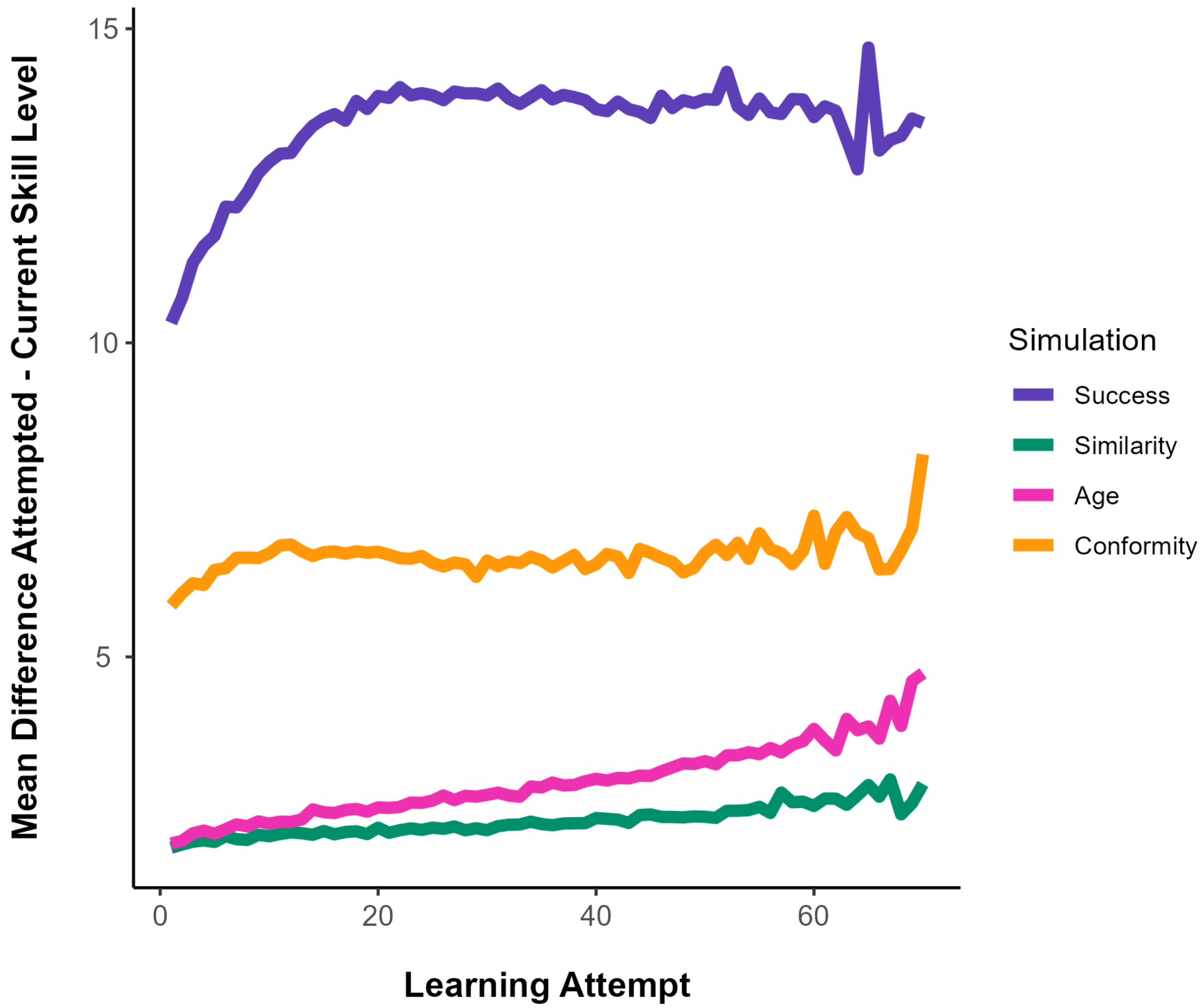
All Learners: Skill Density Distributions By Replication



Note. Theses figures show the density distribution of the number of skills per round/replication in the unconstrained tree at the start (left) and end (right) of a simulation. Each line represents the distribution of skills in one round/replication of the simulation with all learners present.

Figure 23

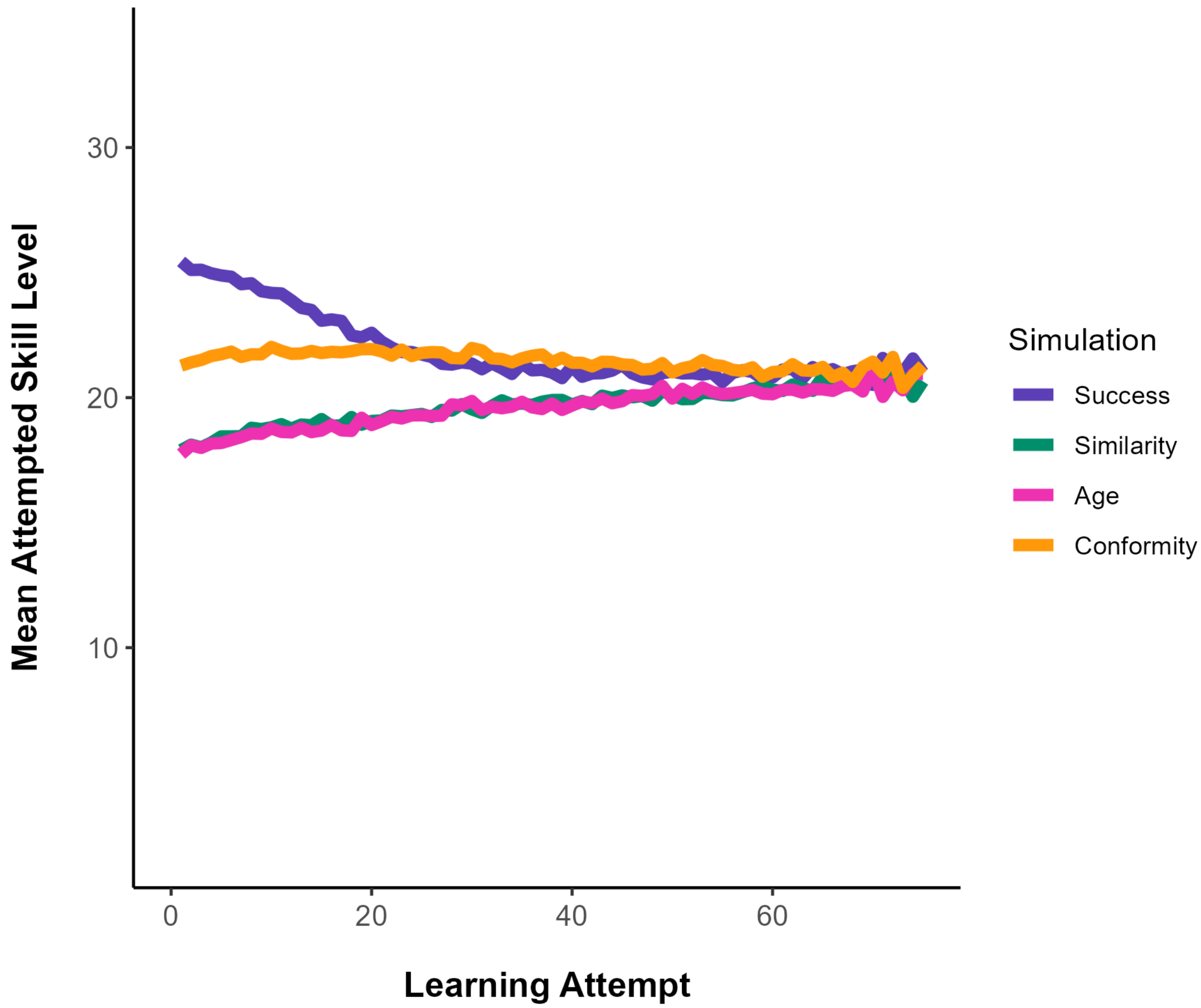
Constrained Tree: Difference Between Attempted And Current Skill by Learning Strategy



Note. This figure shows the mean difference between attempted and current skill level by learning strategy over learning attempts. Learning attempts represent the number of times an individual learnt including the current attempt. The differences between attempted and current skill are averaged across all replications of the respective simulation.

Figure 24

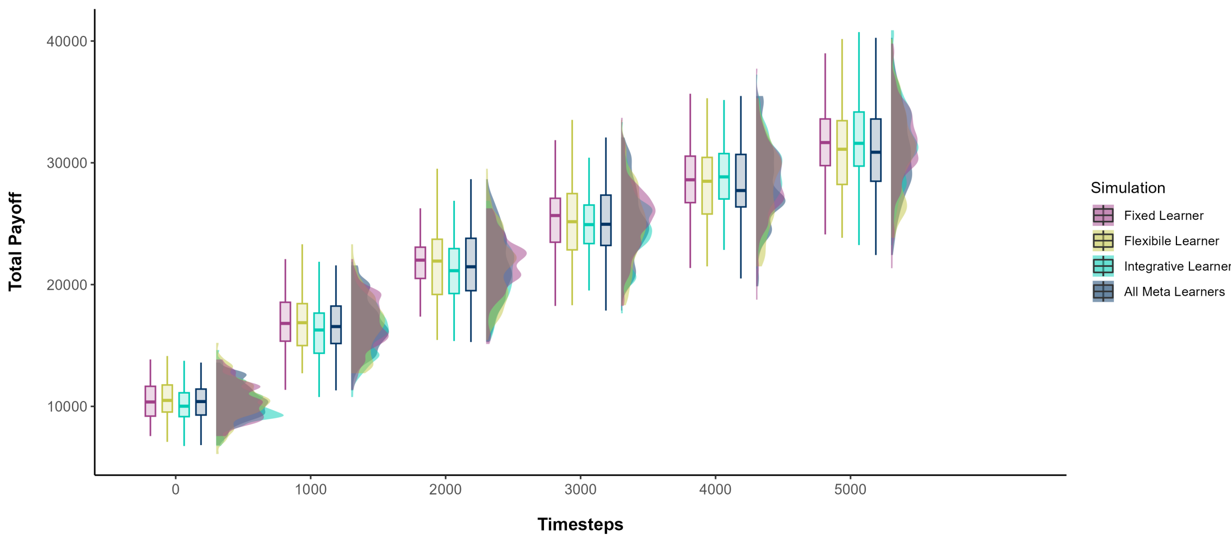
Unconstrained Tree: Differences in Attempted Skill Level by Learning Strategy



Note. This figure shows the mean attempted skill level by learning strategy over learning attempts. Learning attempts represent the number of times an individual learnt including the current attempt. The attempted skills are averaged across all replications of the respective simulation.

Figure 25

Unconstrained Tree: Differences Between Meta-Learning Types in Total Payoff Over Time

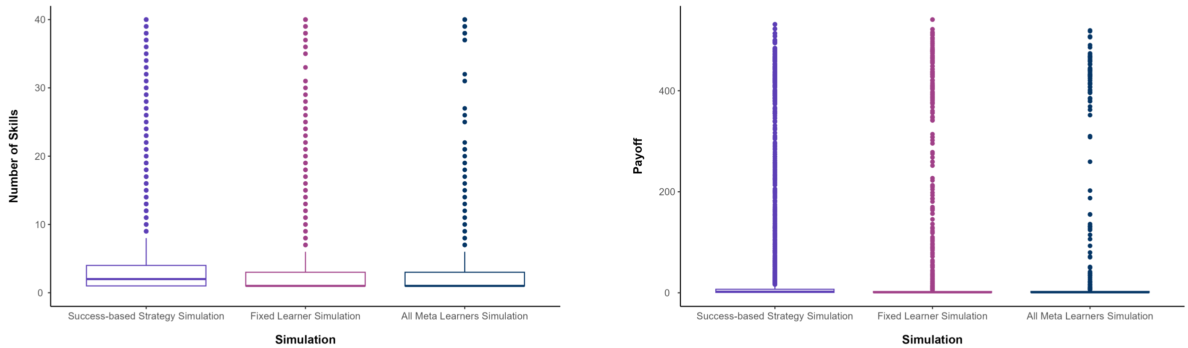


Note. This figure shows the differences in total payoff between populations with different meta-learning types over time. Timestep 0 refers to the start of a simulation, timestep 5000 presents the end of a simulation. Per timestep, the total payoff for each group is represented by a traditional boxplot and a half-density distribution plot (raincloud plot). The boxplot visualizes the median and error range between replications for each group. The half-density distribution additionally shows where densities are clustered and gives (if present) an indication of multi-modality.

Figure 26

Constrained Tree: Performance of Success-based Strategy in Varying Population Compositions

(a) *Number of Skills* (b) *Payoff*

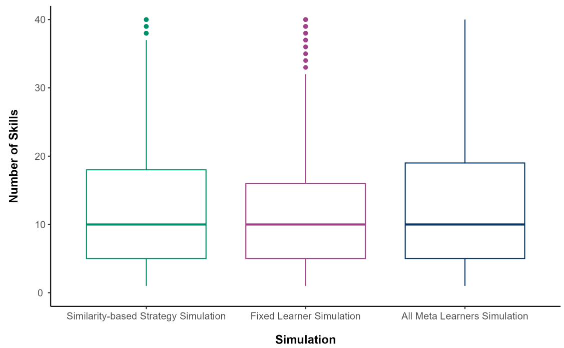


Note. These figures show how the success-based strategy performs in homogenous (only success-based learners) and heterogenous (other learners present) populations. In the success-based learner simulation only learners using the success-based strategy were present. In the fixed learner simulation all learning strategies were present. And in the all meta learners simulation all meta-learning types and learning strategies were present. For the two heterogeneous populations, we show the number of skills and payoffs filtered for the part of the population that solely uses the success-based strategies (n = 10000 in the success-based learner simulation; n = 2515 in the fixed learner simulation, n = 865 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

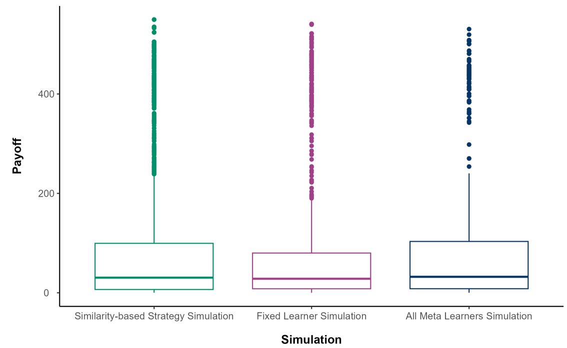
Figure 27

Constrained Tree: Performance of Similarity-based Strategy in Varying Population Compositions

(a) *Number of Skills*



(b) *Payoff*

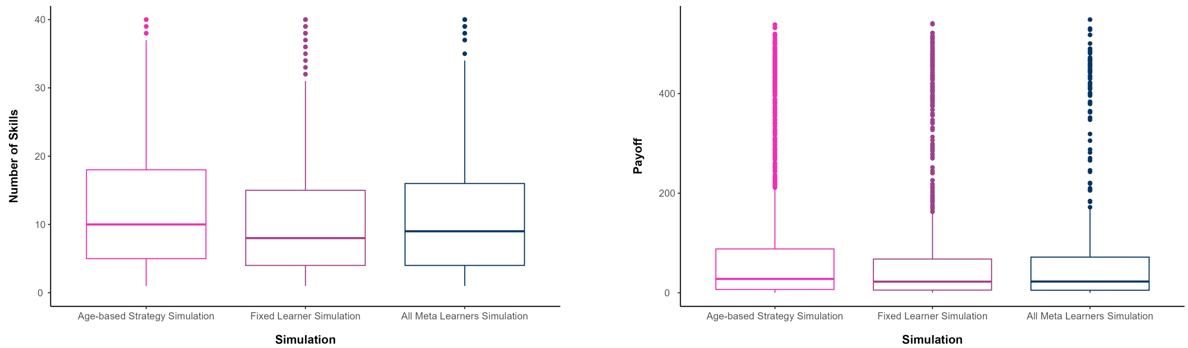


Note. These figures show how the similarity-based strategy performs in homogenous (only similarity-based learners) and heterogenous (other learners present) populations. In the similarity-based learner simulation only learners using the similarity-based strategy were present. In the fixed learner simulation all learning strategies were present. And in the all meta learners simulation all meta-learning types and learning strategies were present. For the two heterogeneous populations, we show the number of skills and payoffs filtered for the part of the population that solely uses the Similarity-based strategies (n = 10000 in the similarity-based learner simulation; n = 2426 in the fixed learner simulation, n = 804 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

Figure 28

Constrained Tree: Performance of Age-based Strategy in Varying Population Compositions

(a) *Number of Skills* (b) *Payoff*

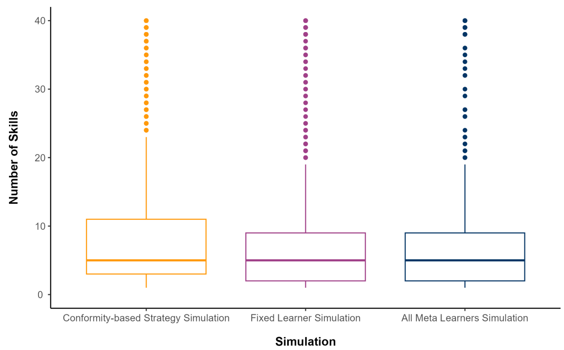


Note. These figures show how the age-based strategy performs in homogenous (only age-based learners) and heterogenous (other learners present) populations. In the age-based learner simulation only learners using the age-based strategy were present. In the fixed learner simulation all learning strategies were present. And in the all meta learners simulation all meta-learning types and learning strategies were present. For the two heterogeneous populations, we show the number of skills and payoffs filtered for the part of the population that solely uses the age-based strategies (n = 10000 in the age-based learner simulation; n = 2550 in the fixed learner simulation, n = 844 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

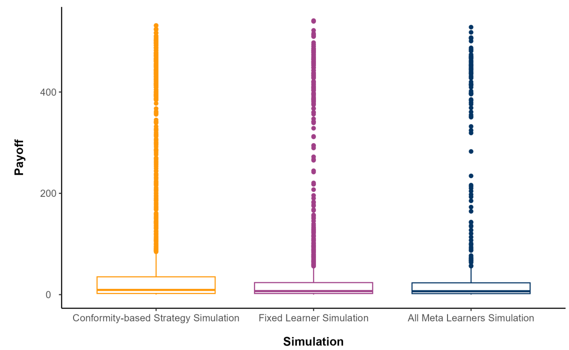
Figure 29

Constrained Tree: Performance of Conformity-based Strategy in Varying Population Compositions

(a) *Number of Skills*



(b) *Payoff*

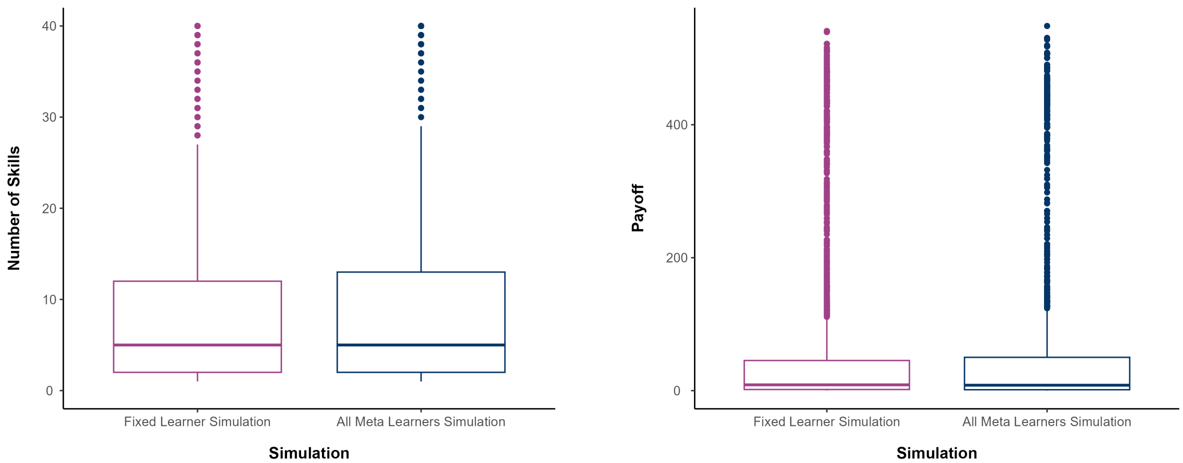


Note. These figures show how the conformity-based strategy performs in homogenous (only conformity-based learners) and heterogenous (other learners present) populations. In the conformity-based learner simulation only learners using the conformity-based strategy were present. In the fixed learner simulation all learning strategies were present. And in the all meta learners simulation all meta-learning types and learning strategies were present. For the two heterogeneous populations, we show the number of skills and payoffs filtered for the part of the population that solely uses the conformity-based strategies (n = 10000 in the conformity-based learner simulation; n = 2509 in the fixed learner simulation, n = 809 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

Figure 30

Constrained Tree: Performance of Fixed Learners in Varying Population Compositions

(a) *Number of Skills* (b) *Payoff*

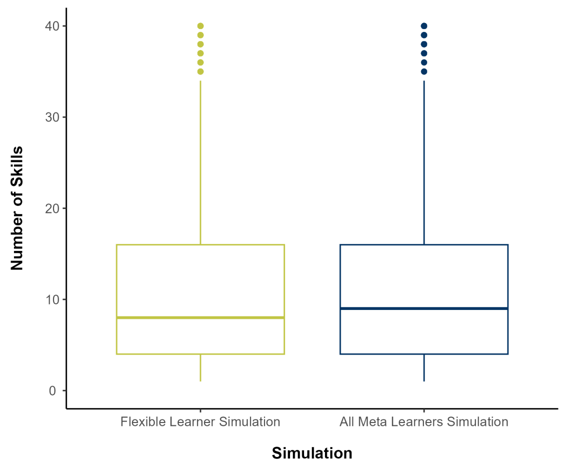


Note. These figures show how the fixed learners perform in homogenous (only fixed learners) and heterogenous (other meta-learning types present) populations. In the fixed learner simulation only learners using fixed meta-learning but all learning strategies were present. In the all meta learners simulation all meta-learning types and learning strategies were present. For the heterogeneous population, we show the number of skills and payoffs filtered for the part of the population that uses the fixed meta-learning (n = 10000 in the fixed learner simulation, n = 3322 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

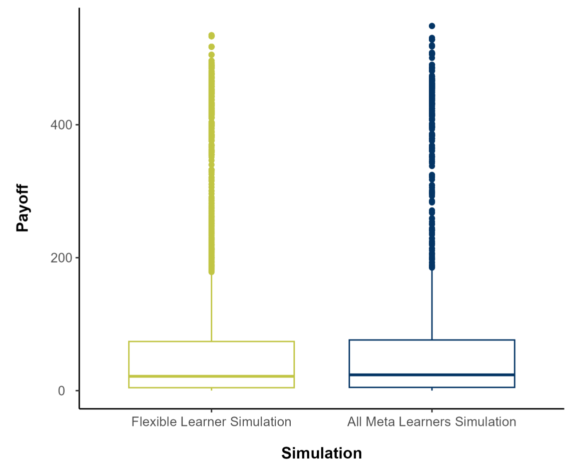
Figure 31

Constrained Tree: Performance of Flexible Learners in Varying Population Compositions

(a) *Number of Skills*



(b) *Payoff*

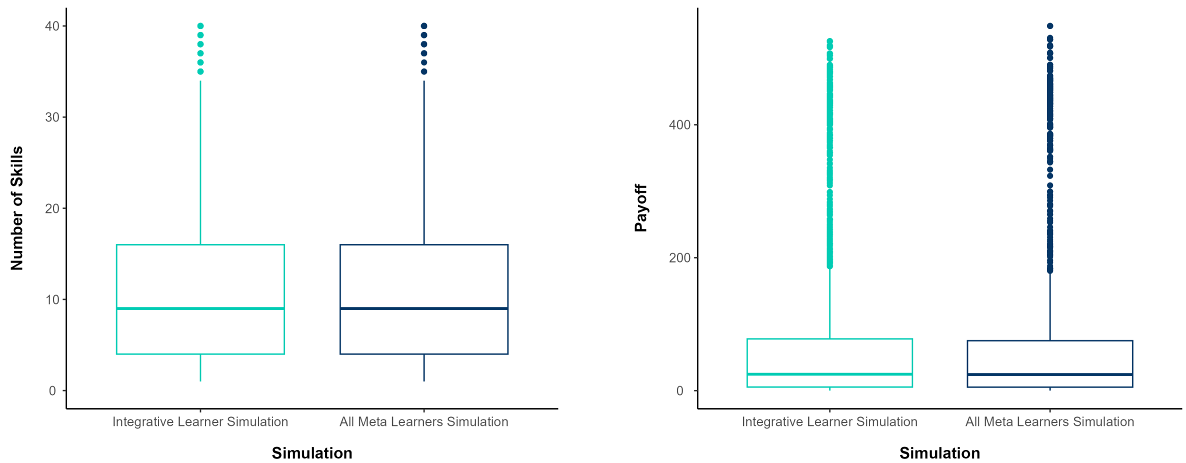


Note. These figures show how the flexible learners perform in homogenous (only flexible learners) and heterogenous (other meta-learning types present) populations. In the flexible learner simulation only learners using flexible meta-learning but all learning strategies were present. In the all meta learners simulation all meta-learning types and learning strategies were present. For the heterogeneous population, we show the number of skills and payoffs filtered for the part of the population that uses the flexible meta-learning (n = 10000 in the flexible learner simulation, n = 3315 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

Figure 32

Constrained Tree: Performance of Integrative Learners in Varying Population Compositions

(a) *Number of Skills* (b) *Payoff*

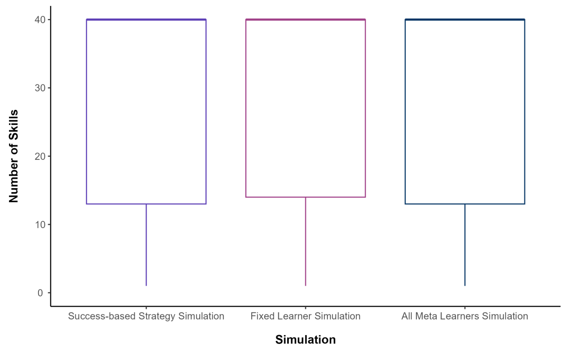


Note. These figures show how the integrative learners perform in homogenous (only integrative learners) and heterogenous (other meta-learning types present) populations. In the integrative learner simulation only learners using integrative meta-learning but all learning strategies were present. In the all meta learners simulation all meta-learning types and learning strategies were present. For the heterogeneous population, we show the number of skills and payoffs filtered for the part of the population that uses the integrative meta-learning (n = 10000 in the integrative learner simulation, n = 3363 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

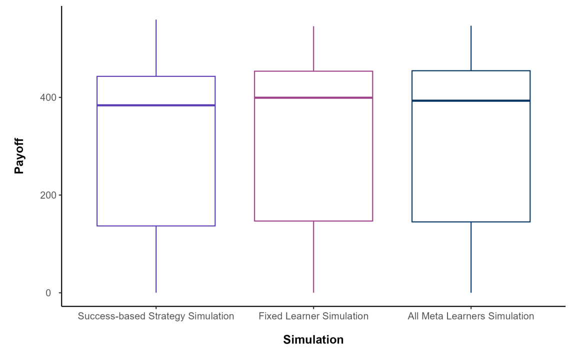
Figure 33

Unconstrained Tree: Performance of Success-based Strategy in Varying Population Compositions

(a) *Number of Skills*



(b) *Payoff*

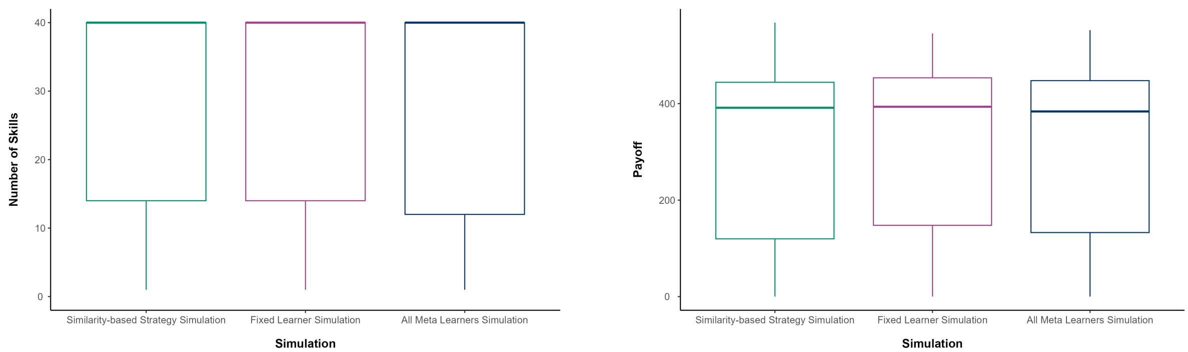


Note. These figures show how the success-based strategy performs in homogenous (only success-based learners) and heterogenous (other learners present) populations. In the success-based learner simulation only learners using the success-based strategy were present. In the fixed learner simulation all learning strategies were present. And in the all meta learners simulation all meta-learning types and learning strategies were present. For the two heterogeneous populations, we show the number of skills and payoffs filtered for the part of the population that solely uses the success-based strategies (n = 10000 in the success-based learner simulation; n = 2515 in the fixed learner simulation, n = 865 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

Figure 34

Unconstrained Tree: Performance of Similarity-based Strategy in Varying Population Compositions

(a) *Number of Skills* (b) *Payoff*

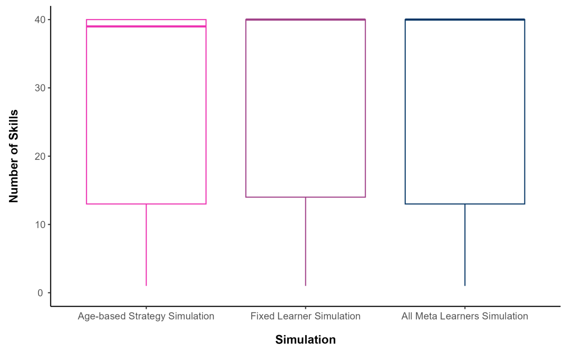


Note. These figures show how the similarity-based strategy performs in homogenous (only similarity-based learners) and heterogenous (other learners present) populations. In the similarity-based learner simulation only learners using the similarity-based strategy were present. In the fixed learner simulation all learning strategies were present. And in the all meta learners simulation all meta-learning types and learning strategies were present. For the two heterogeneous populations, we show the number of skills and payoffs filtered for the part of the population that solely uses the Similarity-based strategies (n = 10000 in the similarity-based learner simulation; n = 2426 in the fixed learner simulation, n = 804 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

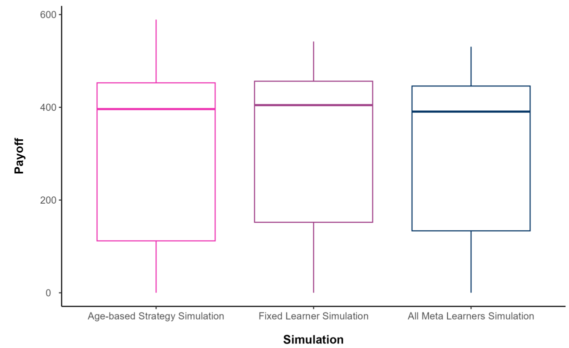
Figure 35

Unconstrained Tree: Performance of Age-based Strategy in Varying Population Compositions

(a) *Number of Skills*



(b) *Payoff*

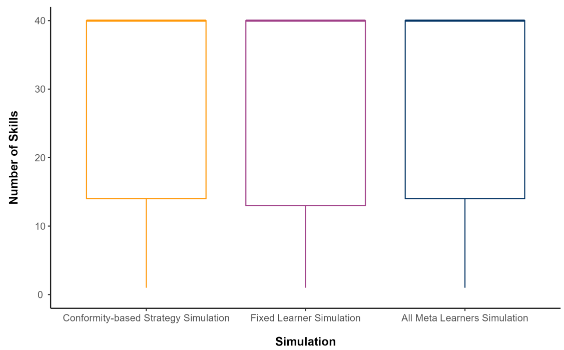


Note. These figures show how the age-based strategy performs in homogenous (only age-based learners) and heterogenous (other learners present) populations. In the age-based learner simulation only learners using the age-based strategy were present. In the fixed learner simulation all learning strategies were present. And in the all meta learners simulation all meta-learning types and learning strategies were present. For the two heterogeneous populations, we show the number of skills and payoffs filtered for the part of the population that solely uses the age-based strategies (n = 10000 in the age-based learner simulation; n = 2550 in the fixed learner simulation, n = 844 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

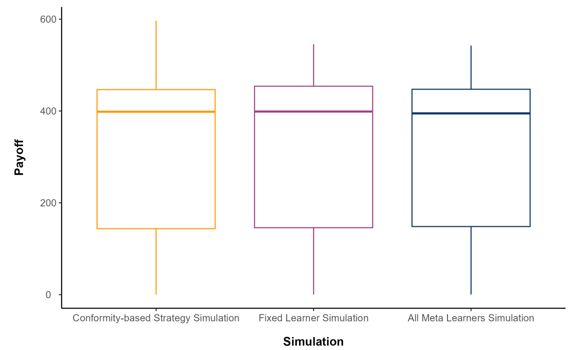
Figure 36

Unconstrained Tree: Performance of Conformity-based Strategy in Varying Population Compositions

(a) *Number of Skills*



(b) *Payoff*

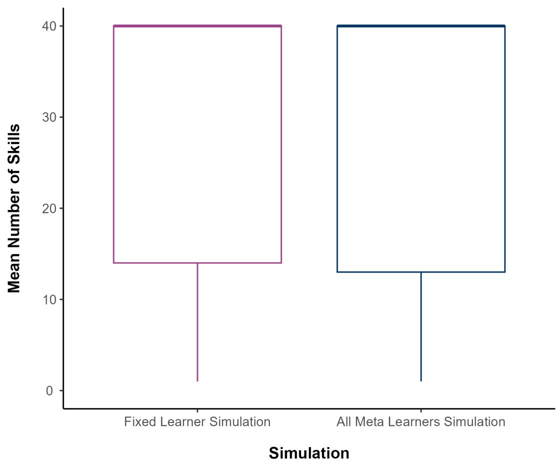


Note. These figures show how the conformity-based strategy performs in homogenous (only conformity-based learners) and heterogenous (other learners present) populations. In the conformity-based learner simulation only learners using the conformity-based strategy were present. In the fixed learner simulation all learning strategies were present. And in the all meta learners simulation all meta-learning types and learning strategies were present. For the two heterogeneous populations, we show the number of skills and payoffs filtered for the part of the population that solely uses the conformity-based strategies (n = 10000 in the conformity-based learner simulation; n = 2509 in the fixed learner simulation, n = 809 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

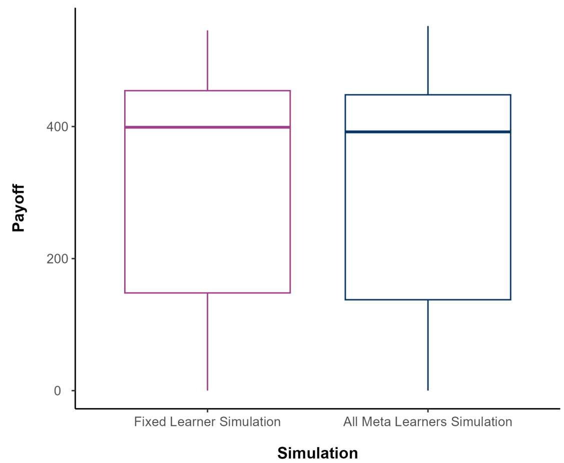
Figure 37

Unconstrained Tree: Performance of Fixed Learners in Varying Population Compositions

(a) *Number of Skills*



(b) *Payoff*

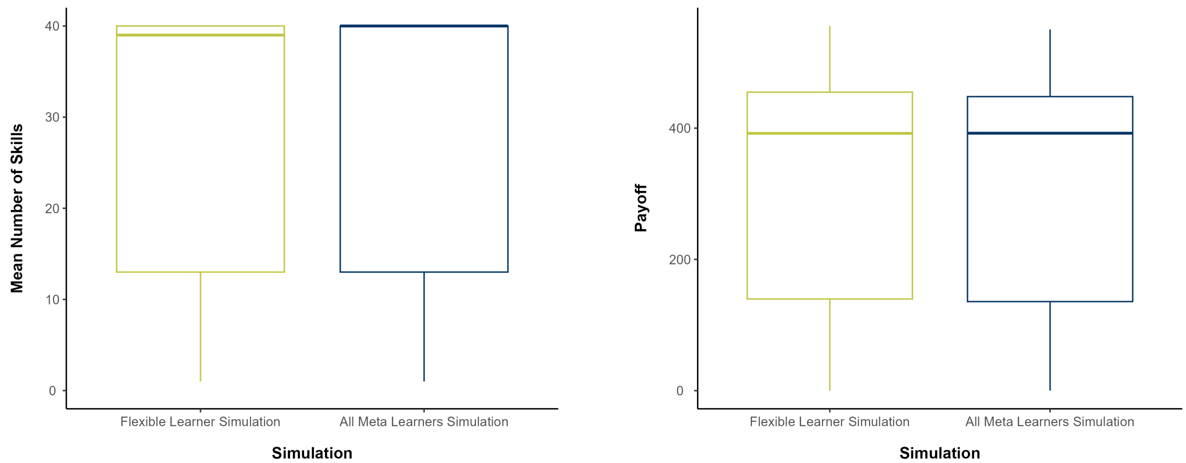


Note. These figures show how the fixed learners perform in homogenous (only fixed learners) and heterogenous (other meta-learning types present) populations. In the fixed learner simulation only learners using fixed meta-learning but all learning strategies were present. In the all meta learners simulation all meta-learning types and learning strategies were present. For the heterogeneous population, we show the number of skills and payoffs filtered for the part of the population that uses the fixed meta-learning (n = 10000 in the fixed learner simulation, n = 3322 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

Figure 38

Unconstrained Tree: Performance of Flexible Learners in Varying Population Compositions

(a) *Number of Skills* (b) *Payoff*

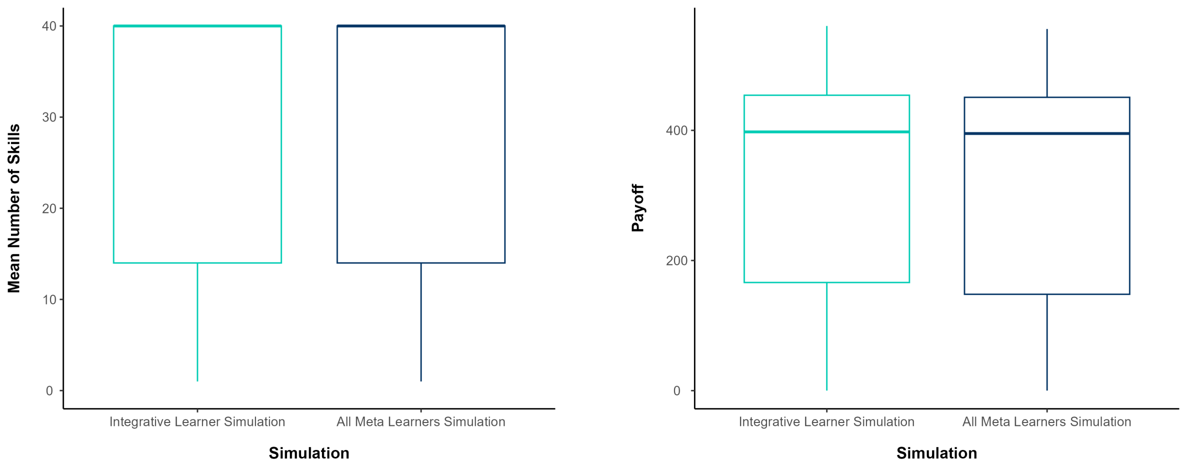


Note. These figures show how the flexible learners perform in homogenous (only flexible learners) and heterogenous (other meta-learning types present) populations. In the flexible learner simulation only learners using flexible meta-learning but all learning strategies were present. In the all meta learners simulation all meta-learning types and learning strategies were present. For the heterogeneous population, we show the number of skills and payoffs filtered for the part of the population that uses the flexible meta-learning (n = 10000 in the flexible learner simulation, n = 3315 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

Figure 39

Unconstrained Tree: Performance of Integrative Learners in Varying Population Compositions

(a) *Number of Skills* (b) *Payoff*

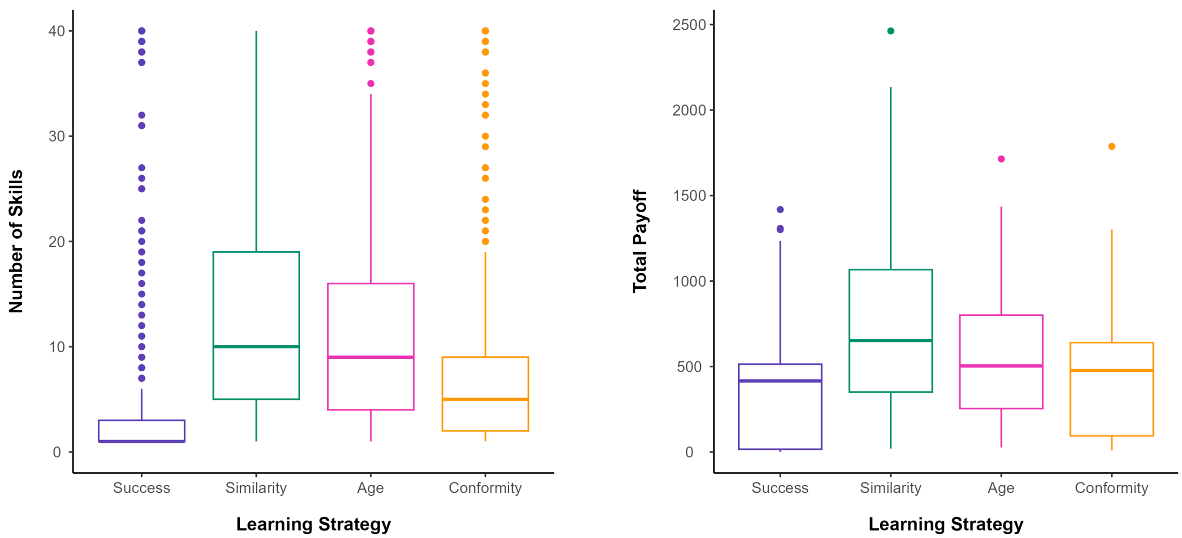


Note. These figures show how the integrative learners perform in homogenous (only integrative learners) and heterogenous (other meta-learning types present) populations. In the integrative learner simulation only learners using integrative meta-learning but all learning strategies were present. In the all meta learners simulation all meta-learning types and learning strategies were present. For the heterogeneous population, we show the number of skills and payoffs filtered for the part of the population that uses the integrative meta-learning (n = 10000 in the integrative learner simulation, n = 3363 in the all meta learner simulation). Please note that due to the differing sample sizes between simulations, we decided to report individual payoffs instead of total payoffs (for a whole population).

Figure 40

Constrained Tree: Performance Differences Between Learning Strategies In Heterogeneous Population

(a) *Number of Skills* (b) *Payoff*

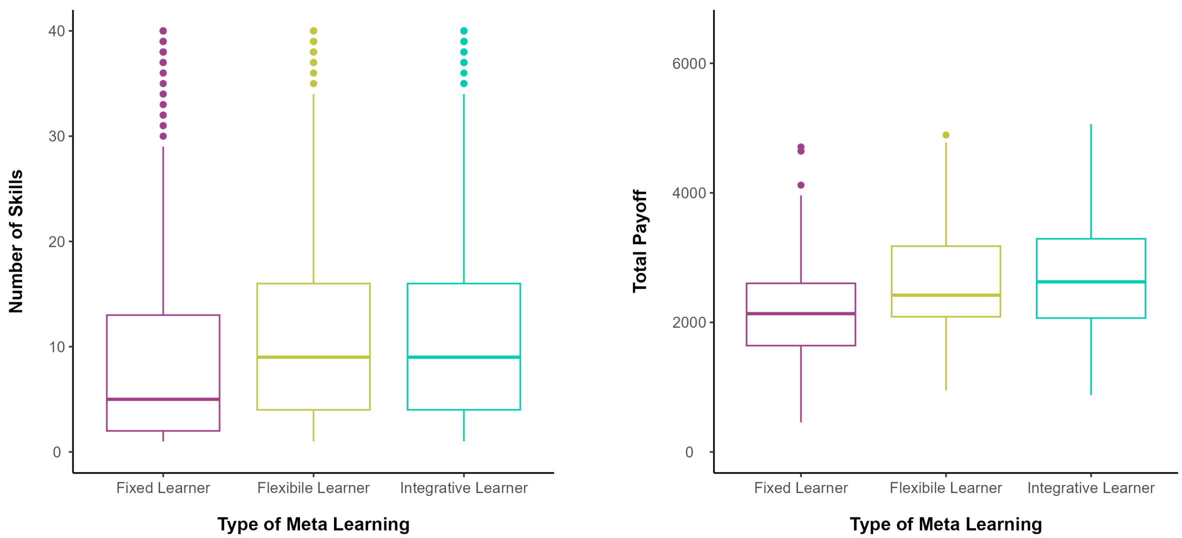


Note. These figures show the number of skills per learning strategy at the end of the simulation. Please note that this is a group comparison which means that we compare the performance of groups (i.e., learning stratgies) within the same population (simulation eight Table 1).

Figure 41

Constrained Tree: Performance Differences Between Meta-Learning Types In Heterogeneous Population

(a) *Number of Skills* (b) *Payoff*

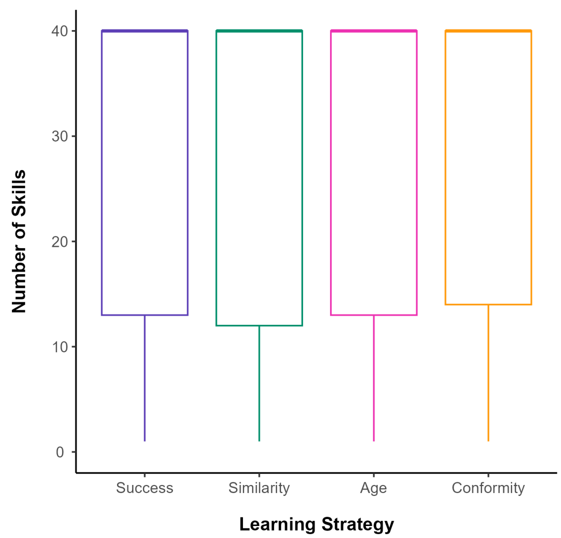


Note. These figures show the number of skills per meta-learning type at the end of the simulation. Please note that this is a group comparison which means that we compare the performance of groups (i.e., meta-learning types) within the same population. For the fixed learners, all learning strategies were present (simulation eight Table 1).

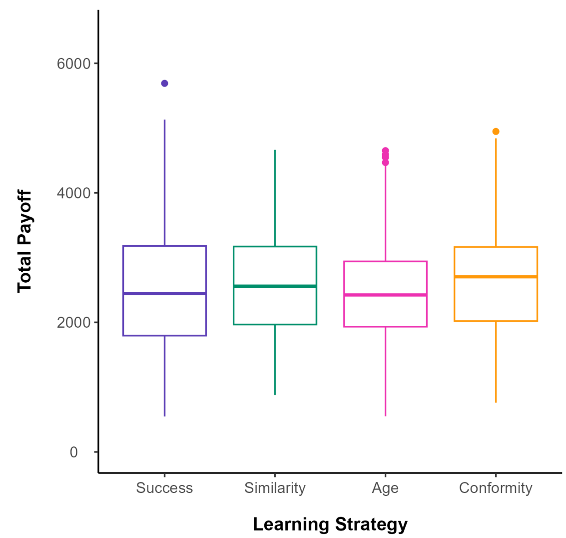
Figure 42

Unconstrained Tree: Performance Differences Between Learning Strategies In Heterogeneous Population

(a) *Number of Skills*



(b) *Payoff*

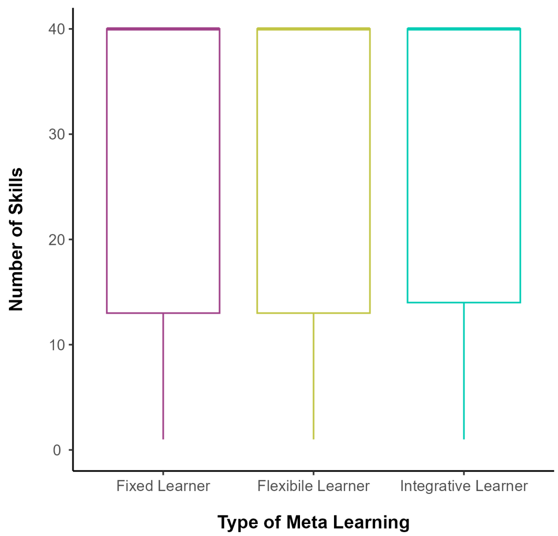


Note. These figures show the number of skills per learning strategy at the end of the simulation. Please note that this is a group comparison which means that we compare the performance of groups (i.e., learning stratgies) within the same population (simulation eight Table 1).

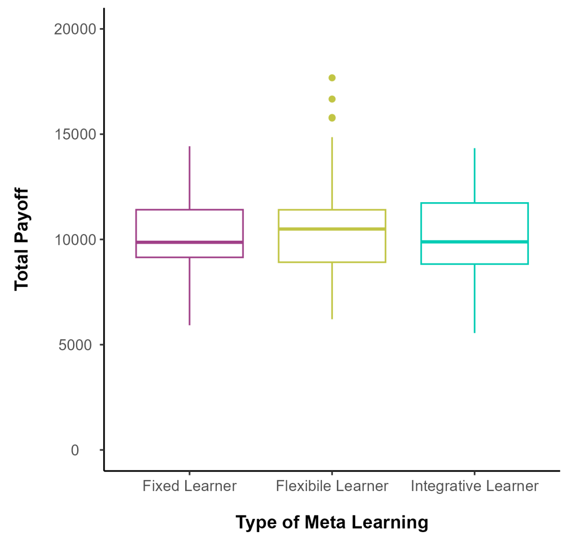
Figure 43

Unconstrained Tree: Performance Differences Between Meta-Learning Types In Heterogeneous Population

(a) *Number of Skills*



(b) *Payoff*



Note. These figures show the number of skills per meta-learning type at the end of the simulation. Please note that this is a group comparison which means that we compare the performance of groups (i.e., meta-learning types) within the same population. For the fixed learners, all learning strategies were present (simulation eight Table 1).