Supplement: Human-AI Delegation in Organizational Routines

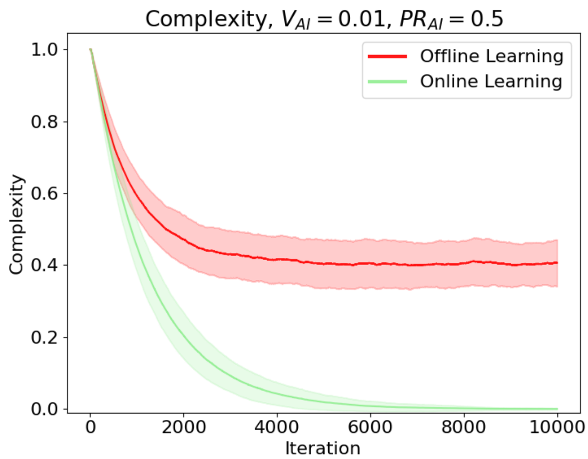
Parameter sensitivity

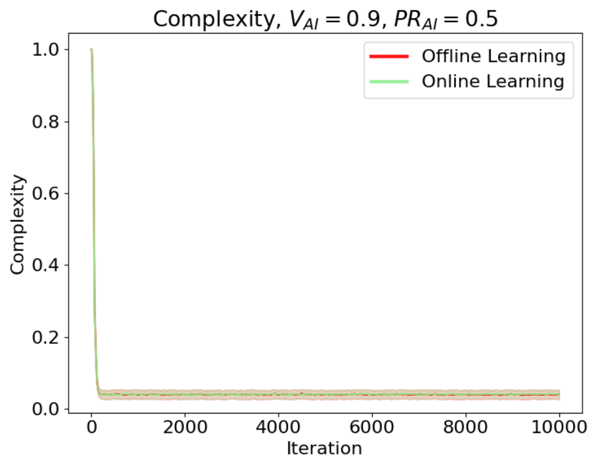
We analyze additional parameter settings to demonstrate the robustness of our findings.

Extremely good and bad initial performance of AI, i.e., large and small V_{AI}

For well-performing AI, complexity drops. For non-learning AI it stabilizes, while for learning AI it quickly drops to 0, as AI is already performing well initially, it is thus also quickly frequently used and it also quickly learns.

For poorly performing AI initially, complexity also rapidly drops as people refrain from delegating to AI. Though AI learns and is occasionally chosen, this happens so rarely that it is not visible within 10000 iterations though eventually AI improves.

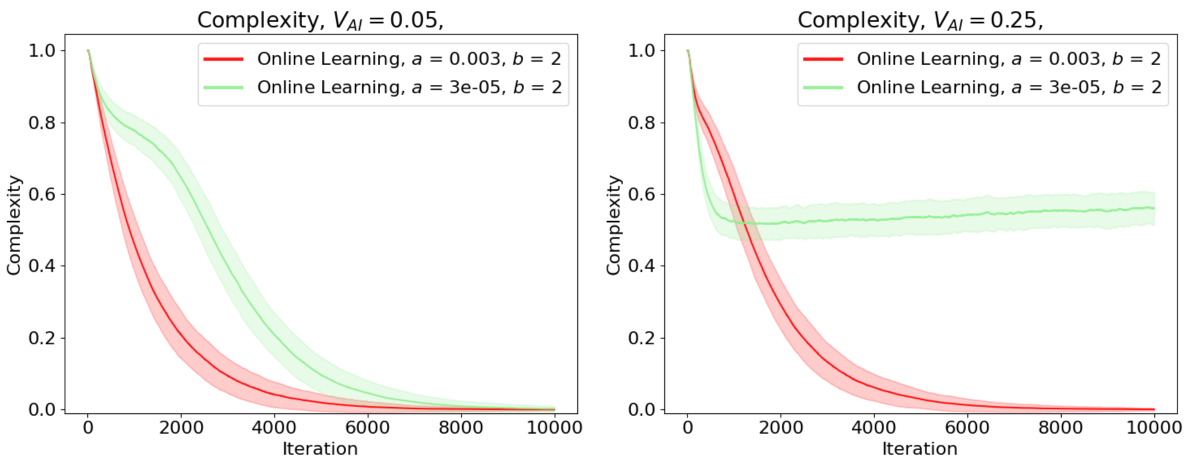




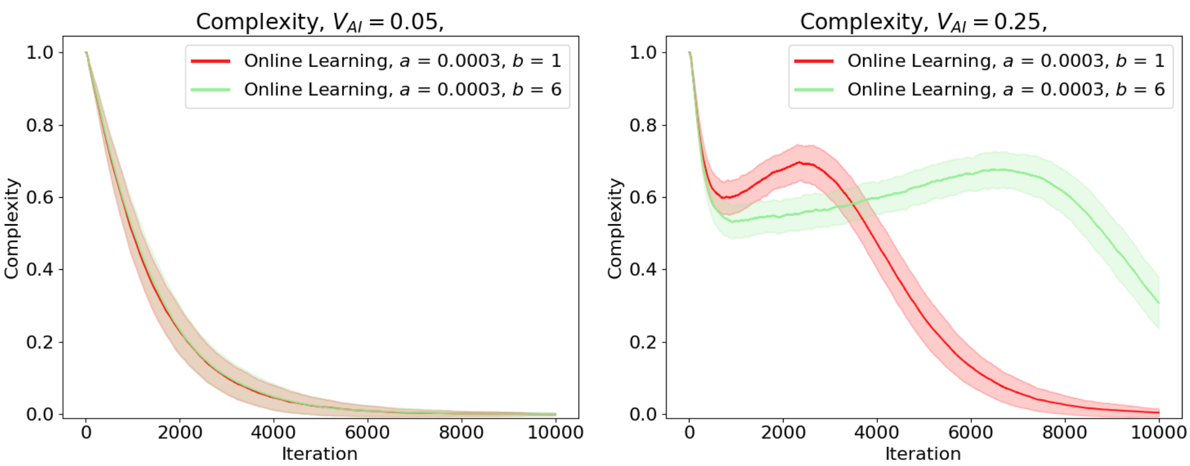
Slow and fast learning, i.e., learning curve parameters a, b

We alter both parameters a and b in our learning curve y=a*(1-x)^b, where y provides the change in accuracy given the current accuracy x and the addition of a single data sample. We see that large differences in learning behavior can have a qualitative impact on routine dynamics. The exponent b can alter the duration of certain phases, i.e., large b leads to much slower learning with growing accuracy, i.e., the closer accuracy gets towards 1 the more learning is reduced with larger b. This is not true for parameter a. Parameter a’s impact is more profound if AI exhibits large initial variation. For slow learning complexity drops quickly, since humans refrain from delegating to AI before slowly increasing again as AI improves. In contrast, for very fast learning (i.e., large a), complexity drops initially equally fast, but then does not seem to rise but rather keeps on decreasing. This can be explained as follows: For slow learning, AI delegations quickly drop from being even between humans and AI and humans mostly perform actions. Then the usage of AI slowly increases from a low level increasing complexity as AI slowly improves. For fast learning, delegation to humans also increases initially for an action, but AI improves so quickly and with such large steps that the complexity shows no visible increase but only a brief slow down in decrease.

Parameter a:

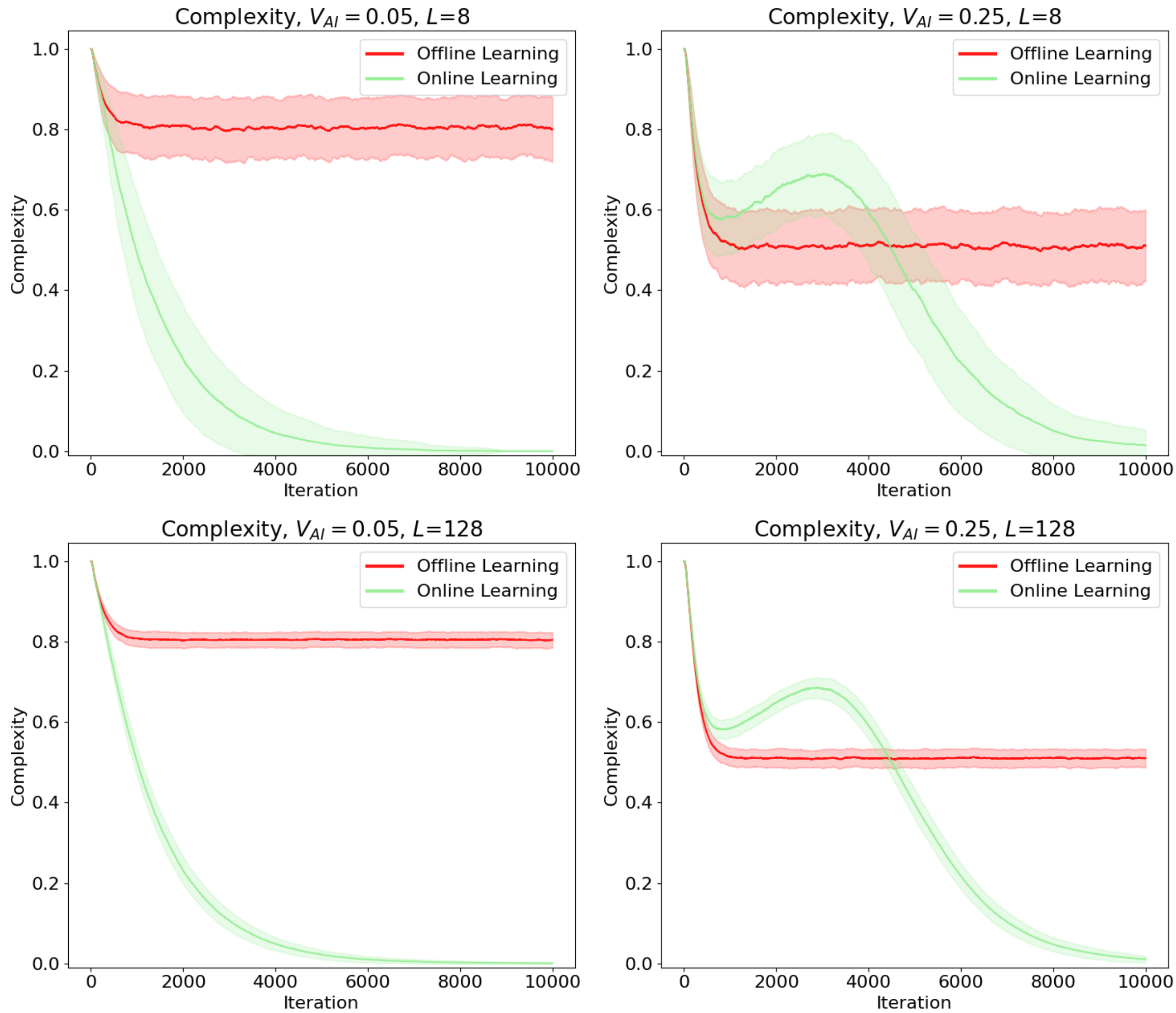


Parameter b:



Number of actions

We varied the number of actions L determining the length of the routine. As can be seen, the length has no impact on the qualitative behavior, i.e., the shapes of the curves, but it has a strong impact on variability.



Model Visualization

We provide model illustrations in Figures 3 and 4.

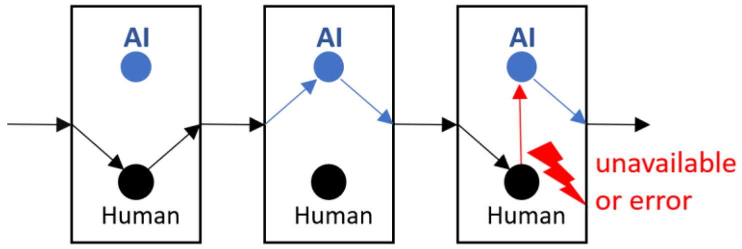


Figure 1: Process: For each step, a human decides if the step is executed by a human only or AI. If there is an issue, a switch from AI to human execution can occur, and vice versa. Successful executions of actions reinforce future choices.

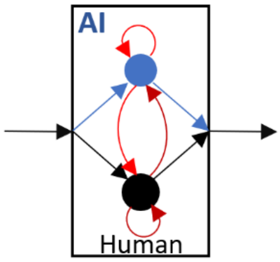


Figure 2: Model with all possible transitions for a single action. Each action is executed until it succeeds. If there is an issue, the step is retried either again by the same agent (i.e., human or AI) or by switching from AI to human, or vice versa.

Simulation Context

We envision a typical hospital routine that includes a number of activities ranging from patient onboarding to the recommendations of treatments.

The routine has three main stages, and each stage entails activities that can be done by humans or AI;

(1) patient onboarding (including registration, assessment of symptoms, quick physical checks),

(2) diagnosis (including assumption about potential disorder, conducting diagnosis techniques, interpreting results) and

(3) treatment recommendations (including evaluating patient context, making assumptions about best possible treatment, making prescriptions).

The routine is shown in Figure 1.

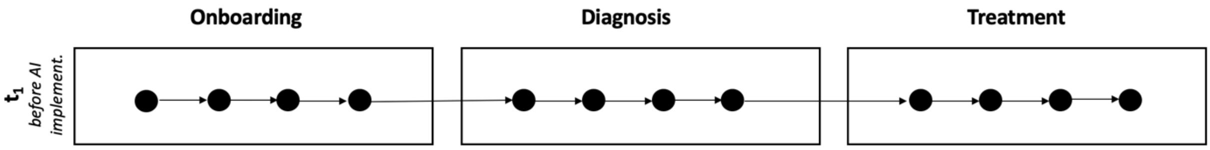


Figure 3: The hospital routine includes a number of activities that span across three main stages: registration, diagnosis and treatment prescription. The black dots entail single steps, the directed graph entails the sequence.

For example, during onboarding, AI can take on the form of a chatbot (Dharwadkar & Deshpande, 2018) that replaces human labor by recording basic information about the patient and, considering the patient's response, posting additional questions that might be useful for the doctor (e.g., when the patient indicates that she was involved in a bike accident, the chatbot collects additional information about the context of the accident and the resulting injuries). A doctor can choose whether to rely on the chatbot or consult a hospital staff. This choice can also have implications for the collected data that can be leveraged by AI. When the conversational agent is used, it can collect data and learn from the dialogue with the human {Li, 2016 #1380}. Conversely, when the AI is not used but interacts with hospital staff, data collection is limited because conversations are not recorded. .

Diagnosis, in turn, can involve the implementation of AI that performs image recognition (Raj et al., 2020) in order to identify a disorder (this can involve a variety of diagnoses, such as the identification of muscle lesions in magnetic resonance imaging scans to detect injuries caused by a bike accident). In medical image analysis, AI applications can be employed that help a doctor better understand AI decisions {van der Velden, 2022 #1382}. For example, sections of an image can be highlighted that are relevant for diagnosis {Sheth, 2020 #1383}Again, a doctor can choose to take AI's prediction into account to derive a diagnosis, or forego it altogether. If the doctor foregoes AI, the AI cannot learn because the doctor's diagnosis cannot be linked to the medical record {Krsnik, 2020 #1385}

Finally, treatment can be complemented with an AI recommendation system (H.-K. Chen, Chen, & Lin, 2021) that suggests effective treatment strategies considering the patient's context (this can include the suggestion of physical exercises to get back in physical shape after the bike accident). In physiotherapy, for example, AI can provide an interactive treatment environment providing feedback based on video analysis and data from wearable sensors {Calvaresi, 2019 #1386}. Again, a human agent, e.g., a doctor, can decide to actually use AI or not. Figure 2 shows the hospital routine at point t_2 after AI was implemented at several stages of the routine.

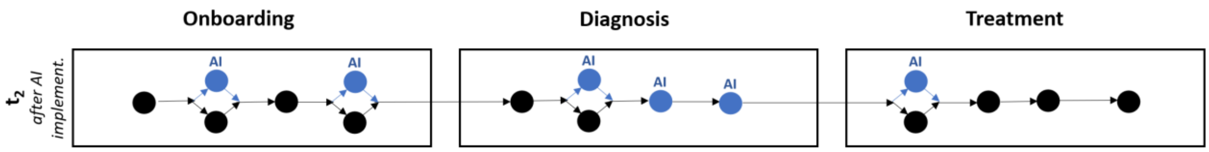


Figure 4: The hospital routine after AI implementation at several stages. Human agents might delegate actions to AI (blue dots) or not (black dots). This scenario is the focus of this paper. In contrast, AI in pure automation does not offer a choice as depicted by the last two blue (AI) dots in diagnosis.