Towards Simulation-Based Preplanning for Experimental Analysis of Nudging

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Abstract. People often make irrational decisions. With digital nudging, decisions made in online environments can be guided beneficially by adapting design elements of the user-interface and thus the user's choice environment. To evaluate the effectiveness of different nudging methods, modeling and simulation can be used. In this paper, we make a step towards preplanning of experiments to analyze nudging methods via simulation. To this end, we provide a model that replicates human behavior based on an experiment, that addresses gaming behavior in a digital environment. In a second step, the model is extended using several nudging methods in order to adapt the gamers' decision-making. Experiments are presented that outline the model's capability to produce plausible results concerning human gaming behavior as well as the effects of nudging methods on decision-making.

Keywords: Digital Nudging, Agent-based Modeling, Loss aversion.

1 Introduction

People often make irrational decisions. This is due to cognitive biases that impact the perception of available information and can thus disadvantage the decision-maker. Those biases can have negative effects in situations as gambling [1, 2], decisions about investment strategies [3] or health behavior [4]. At the same time, if biases are used in a certain way, a decision can also be influenced beneficially. The term *nudging* summarizes methods that change a given decision architecture to generate behavior that is beneficial for the decision-maker or general public. Methods of nudging include, e.g., the provision of defaults and feedback, or structuring complex decisions. Nowadays, nudging is mainly used as a political instrument [5] to maintain health [6], sustainability and energy efficiency [7, 8]. As many decision-making scenarios, such as e-government, e-health or e-commerce, are moving to an online environment [9], nudging has already been adapted to it, too. *Digital nudging* mainly focuses on altering elements of the user interface in order to guide the user's decisions [9]. Before implementing a digital nudge, its effectiveness in encouraging the intended behavior should be ensured to prevent negative consequences. This paper aims at making a step towards an assistance and addresses the following research

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question: "How can simulation be used to preplan experiments to analyze the effects of nudging in digital environments?".

The objective of this kind of early efficacy testing is twofold. First, both offline interventions and digital nudging raise ethical considerations, e.g., restricting people's autonomy or disadvantaging individuals [10, 11]. Undesired side-effects of interventions should therefore be excluded before they are applied to humans. In addition, simulation enables cost- and time-efficient testing of design variants and user-centric design through iterative adjustments, while laboratory experiments are limited to a few interventions and reactions of test persons. Therefore, an experiment is utilized that offers a controlled game-scenario and experimental results of participants' actions in different states in the game. Here, the effects of the cognitive bias *loss aversion* are analyzed in several experiments. This paper introduces a model that in a first step reproduces the human behavior observed in the experiment. Subsequently, nudging is added to the model to encourage beneficial behavior. To adequately represent the human gamers, agent-based modeling (ABM) is used, as it has established in representing humans and cognitive decision-making [12–14].

This paper is structured as follows: Section 2 presents basic elements of human decision-making and digital nudging, as well as relevant contributions of ABM in modeling human behavior. In addition, an experiment is presented that serves as an application example for this paper's model. Section 3 introduces a model of human behavior in a situation of experienced loss aversion using ABM. In Section 4, this model is extended with nudging methods to influence the agents' behavior throughout the game. Finally, Section 5 draws conclusions and gives an outlook on future work.

2 Background

It is frequently assumed that the decision-making of the human brain is a dual-system composed of an automatic and a reflective part [15]. The usage of the automatic part can both facilitate decisions and introduce errors, as the decision results are known to be biased due to heuristics [15, 16]. One of the biases hindering rational choice is loss aversion. Kahneman et al. define loss aversion as follows: "[...] the disutility of giving up an object is greater that the utility associated with acquiring it" [17]. An application of this bias is the endowment effect, which expresses that owning an object (or an option) increases its subjective value to the owner [17, 18]. Therefore, the loss of an object with a certain value has a stronger effect than the gain of an object of the same value. In addition, the status quo bias is closely related to these phenomena, since it implies the tendency of people to maintain their own status and thus the possessed objects (or alternatives) [17]. Many cognitive biases have been identified in decision-making related to information systems, loss aversion is one example [19]. For instance, product sales can be increased with purchase pressure cues (e.g., limited product availability) to enhance the expected loss and thus the likelihood of sale [20]. The order of product placement may influence the user's choice as it anchors the first product displayed and perceives each subsequent product as a gain or loss according to the characteristics of the first product [21].

Heuristics and biases can be used to influence an individual's decision-making towards certain choices [22]. To help people make better decisions, Thaler and Sunstein propose nudges, defined as "[...] any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentive" [23]. In offline scenarios, nudging has been successfully used to influence individual decision-making in several areas such as environment protection [24], retirement saving [25], organ donation [26] as well as healthy eating [27].

Like in offline environments, choices in digital environments can be influenced by nudges as well. Weinmann et al. define this kind of nudges, called "digital nudging", as "[...] the use of user-interface design elements to guide people's behavior in digital choice environments" [9]. In digital environments, the influence on the outcome of a decision can be influenced by tools that concern what decision options are included and how these options are presented [28, 29]. For example, the decoy effect, the scarcity effect or the middle-option bias have been proven [30-32]. The first type describes the fact that the introduction of an unattractive choice raises the attractiveness of the existing options [31]. The second type describes the raise of attractiveness of an option by describing it as scarce [32]. The third type refers to the tendency of people to choose the middle option in a list of choices [30]. Digital nudging is gaining more and more relevance due to the increasing amount of decisions made on screen. In digital environments, any presentation of choices is influenced by the designer's preferences and cannot be designed completely neutral [22]. Therefore, each design decision should be made with a specific goal in mind, e.g., increasing turnover or brand awareness. For instance, correctly set defaults can support customers by simplifying complex decisions and thus lead to faster purchase decisions [33]. Raising awareness for a platforms security settings via digital nudging can increase the user's trust and with it the number of registrations and purchases [34]. To avoid undesired side-effects, it should be considered in the design process of a digital choice environment, e.g., by introducing suitable design principles or processes [22, 33].

Modeling Human Behavior. In contrast to top-down modeling techniques as system dynamics, that models the global system behavior and relationships in terms of differential equations [35], ABM models a system as a collection of autonomous decision-making entities called agents. Human decisions are assumed to be based on different information processing systems and biases affecting decision-making. Therefore, perception and processing of information and external influences have to be implemented. Furthermore, reasoning about the current situation and various goals pursued is needed. Agents can observe and assess their own situation, access their knowledge base and act according to a set of rules [12]. In addition, agents are capable of goal-oriented behavior and interaction with other agents as well as their own environment [36]. Based on this, ABM enables heterogeneous individual attributes, while system dynamics assumes each modeled compartment to be homogeneous and perfectly mixed [37]. Therefore, ABM is used here to model cognitive processes that include both psychological and behavioral theories [13].

The dual-system approach introduced in Section 2.1 can be implemented using the subsumption architecture [38], where the agent defines multiple behaviors simultaneously in a principle of divide and conquer, and uses rules to determine the application of each behavior. This was realized by, e.g., [39, 40] which implement switching between the systems based on situational conditions and properties of the agent. Hence, the reflective system steps into action if these conditions are met. This paper follows a similar course and proposes, that the reflective system is constantly present but is ignored, if the automatic system is triggered by the agent 's perceptions. Therefore, we use different levels of cognition in the agent architecture. The automatic system is represented by simple conditional rules that make the agent react to perceptions, while the reflective system takes a deliberating part that tries to unite the pursued goals and make a rational (best) choice for the agent.

In ABM, the loss aversion is mainly utilized in situations under uncertainty, e.g., in purchasing decisions [41] or in financial markets, where it is used to focus on timing of investment choices [42] or to predict price developments on the market [43]. Although there have been attempts to model agent decision-making in games such as the multi-armed-bandit game [44], existing models utilize a rather uniform use of loss aversion by valuing options solely based on monetary gains and losses. To encounter loss aversion and its negative impact on performance, this paper proposes the use of nudging methods. ABM implementing nudging are mainly found in social issue areas [45, 46]. These models primarily implement nudging based on the influence of the information provided. In health promotion, ABM is mostly implemented using the influence of social networks [47]. The models merely implement a method of influencing behavior. Often, however, a combination of different methods leads to the development of a desired behavior [48]. Furthermore, ABM is underrepresented in the field of nudging, especially in digital contexts.

Loss Aversion: An Experimental Game Setting. The experiment in [18] serves as an application for the model developed in this paper. Here, the effect of loss aversion on performance within the scope of a modified multiarmed bandit game is examined. The general game setting consists of a recurrent choice to click on one of three doors, generating money with each click, that is paid to the participants after the game has finished. The doors have different gains, that result from set distributions centering around 3 cent per click. The gamer's goal is to maximize his earnings within 100 possible clicks without knowing the payoff distributions. Each click on a different door as the current, the gamer loses one of its remaining clicks and thus the possibility to gain money with it. To examine the effect of loss aversion based on options becoming unavailable, the authors conduct several experiments, whereby this paper focuses on two: The *effect of decreased availability* and the *effects of cost saliency on the desire to keep options open*. For each scenario, the best strategy is to stay on one door throughout the entire game, because then each click generates a payoff.

In the first experiment, to integrate the cognitive bias of loss aversion the general game setting presented beforehand (*constant option availability*) is contrasted to the following version of the game: Doors start to shrink if the gamer clicks on one of the remaining doors. If a door is ignored for 15 clicks in a row, it vanishes (*decreased*)

option availability). Here, the authors make use of the scarcity effect described in Section 2.1. Furthermore, doors regain full size if clicked on once before they disappear. Theoretically the participants should increase their knowledge about the different distributions with increasing clicks and thus reduce the number of door switches. Whereas this behavior is shown in the general game setting, the decreased option availability scenario leads to a significantly higher probability of switching. The highest pitch is between 10 and 20 clicks, which is due to a first threat of doors disappearing. With this experiment, the authors show that participants are more interested in alternative options as they are jeopardized to disappear (loss aversion and endowment effect).

The second experiment focuses on the effect of cost saliency on the desire to keep options available. Therefore, the authors add to the constant and decreased option scenario with *implicit switching costs* (gaining no money while switching doors) the juxtaposition of *explicit costs* for switching doors. Here, participants have to pay 3 cent for each switch. The authors describe four scenarios in which reduced and constant option availability is crossed with implicit and explicit costs. The experiment results show, that the existence of explicit costs only marginally decreases switching, especially compared to the effect option availability has on this behavior. Hence, the authors show with their experiment, that the desire to keep options open predominates possible losses in monetary profit [18] (status quo bias).

In the following section we attempt to imitate the participants behavior based on the findings in [18]. Subsequently, we model nudging methods in order to encourage the participants to a better performance by activating the reflective system and thus leading them to a more conscious and thoughtful action (see Sec. 4).

3 Imitating Behavior: Simulating Participants

We start by imitating the participants' behavior as described in Section 2.3. The game is modeled as follows: We represent the participants as agents playing the game. The agent has three doors $Doors = \{d_1, d_2, d_3\}$ with different payoff distributions of which he can choose to click on each round. The agent's goal is to maximize the possible payoff during t = 100 game rounds. One game round corresponds to one click in the original experiment described in Section 2.3. In each round, the agent decides whether to stay at the current door or switch to another and risk a lower payoff due to switching costs. To allow a realistic setting, the agent is not allowed to change doors before receiving a payment for the current door, i.e., he has to click on the same door at least twice in a row.

Agent Behavior. An agent represents a participant in the simulation that tries to unite the conflicting goals of maximizing its own profit and increasing knowledge about the payoff distributions. First, we focus on the behaviors shown by participants in *constant versus decreased option availability* scenarios. Based on the considerations in Section 2.1, the agent is modeled using the dual-system approach (see Fig. 1). Thus, the agent perceives the current status of the game, which is transferred to the

agent's knowledge. Knowledge transfer is represented by dashed lines. The agent then uses the automatic followed by the reflective system to create an action that is then executed. After this, the knowledge base is updated with the currently selected door.



Figure 1. Decision-making using the dual-system approach (left) and decisionmaking in reflective system based on Simulated Annealing (right)

We define the **reflective part** as being rational and conscious in the agents' decision-making. It tries to unite the two opposing goals of maximizing the own profit and further specifying the payoff distributions. We theorize that without the pressure to keep options available, participants can usually make rational choices to maximize profit, meaning that the automatic part of the dual approach can be kept out of focus. As the agents do not know about the different payoffs, this influences the decisionmaking by adding more variability to the doors chosen. At the start of a game, the agent has no concept of the different payoff distributions, which is why the degree of door switching is highest in the first quarter of the game. As knowledge increases, the number of switches rises with it and profit maximization becomes more important. This behavioral nature promotes the use of an adapted algorithm of Simulated Annealing [49] with a cooling temperature temp of $n \subset t$ rounds (see Fig. 1). Based on round t and the actual door $d_{current}$, the algorithm returns the agent's next action d_{next} , which is either the current door or a randomly chosen neighbour of it (d_{new}) (where *current*, *next*, and *new* \in {1,2,3}). Based on the previous knowledge, the agent approximates confidence intervals of the three payoff distributions. If d_{new} has a smaller interval (and thus a safer chance of a specific payoff of 3 cent), the agent switches to that door. Otherwise, he remains on the current door, unless *temp* is still on a high status. In this case, the algorithm provides a probability of switching either way, to find the best possible choice (see Eqn. (1)).

$$e^{\frac{interval(d_{new},t)-interval(d_{current},t)}{temp}}$$
(1)

Additionally, the agent switches doors if he realizes, that the current doors' interval $interval(d_{current},t)$ increased from the previous round. The agent's goal of knowing about the different distributions is achieved by a threshold for switching

 $clicksReached(d_{current}) \in \mathbb{N}$, which allows the agent to switch doors only when this threshold of the number of clicks on the current door is reached, thus if he has collected enough information about the door. This is based on the assumption that an estimate of an interval can only be made on a list of several numbers of a distribution. The algorithm closes with a reduction of the temperature, which decreases the probability to switch in t + 1.

By adding decreased door availability the agent architecture needs to be extended to represent the resulting perceived pressure (see Fig. 1). Therefore, the **automatic part** of the dual-system approach is included. First, the automatic system is triggered by the shrinking status of the currently not clicked doors *statusDoor(d, t)*, which returns the number of rounds, door *d* has not been clicked on in round *t*. If this effect is strong enough, thus if one of the doors is about to be unavailable in the next round, the agent skips the reflective part of decision-making and switches to executing clicking on the endangered door d_{eD} defined by Eqn. (2).

$$d_{eD_t} = argmax_{d \in Door} \left(pressure(d,t) \right), with \ pressure(d,t) = norm \left(\left(\frac{status Door(d,t)}{|Doors|*15} \right)^2 \right)$$
(2)

Otherwise the agent decides for a door according to the reflective system. The pressure causing the automatic action is calculated by Eqn. (3) and returns *thdP*, a threshold defining the turning point of making an informed versus a spontaneous, automatic decision. Because the freedom of choice and flexibility has proven of being more valuable than a high payoff or a good performance [18, 50] and the options most threatened are normally considered the most valuable [32], the pressure of d_{eD} (with $eD \in \{1,2,3\}$) at round *t* is used as the threshold for pressure. The *pressure* \in [0,1] for door d_i is determined by a quadratic function using the number of rounds the door has not been clicked and the number of doors still available. Therefore, the pressure to keep doors open increases with decreasing option availability. If the agent reacts to this pressure, $thdP_t$ is defined by its resistance to the current pressure $resistanceP_t$, that is implemented as a random number in a range between [0, 1].

$$thdP_t = max_{d \in Doors} (pressure(d, t))$$
 (3)

The agent's reaction to explicit cost is implemented as follows: First, in the decreased option scenario the explicit cost component is only included, if the pressure does not exceed a certain value. This value is defined by the merit that $thdP_t$ takes, if one of the available doors is close to disappearing in the next round. Furthermore, cost is modeled as an increasing sensitivity against explicit switching cost. As knowledge about the distributions increases, each decision to switch is weighed more thoroughly against the fix costs. Therefore, we model the probability of being influenced by costs using an exponential function based on the current number of rounds.

Design of Experiment. To evaluate the model, we define four simulation runs using an element of the cartesian product of:

{Decreased availability, Constant availability}× {Implicit cost, Explicit cost}.

Each simulation run is executed using one agent playing the game. Because the model uses random number generators, each of the settings is repeated 100 times. As mentioned in Section 3.1, the door switching is highest in the first quarter of the game. Therefore, we set the cooling temperature of the Simulated Annealing t/4 = 25. Furthermore, the number of clicks *clicksReached(d_{current})* algorithm to that in the reflective system determines the time the agent is capable of switching doors is set to 7, as this is the highest possible number that does not force the agent to let one door close while getting to know about the different distributions (one door closes after 15 rounds not clicked on in row). The cost function is adjusted to the pressure resulting from one door being endangered of closing (not clicked on for 14 rounds). This leads to costs being included in decision-making, if $thdP_t > norm\left(\left(\frac{14}{3*15}\right)^2\right) \approx 0,44.$

Simulation Results and Interpretation. Fig. 2 shows the results of the four defined simulation runs. The line plot on the left shows the comparison between decreased and constant availability with implicit costs, the bar plot on the right contrasts the decrease of switches in the implicit versus explicit cost scenarios. The line plot presents the mean of the defined scenarios throughout the 100 simulation runs, the error bars show the difference to the data set described in [18]. Following the authors' notation, we present the simulation results by means of 10 blocks, whereas each block contains 10 clicks in a row. Throughout the blocks, the distance between the simulated and original data of the constant availability scenario adds up to around 1.5 switches, whereas most blocks overestimate the original data. This is because many restrictions in the agent's decision making can lead to a door change, e.g. if the newly chosen door has a smaller interval or the interval of the current door has become larger, thus decreasing the agent's safety. The biggest difference is seen in the third and fourth block with approximately 0.4 switches. Although the original experiment shows a small rise in the fourth block, too, the previous block is originally defined by a decrease in door switches. On the whole the simulation approximately imitates the original curve's tendencies. The same applies to the decreased door availability scenario. The sum of distances between the mean of the simulation runs and the original experiment amounts to about 1.3 switches. The largest distance is present in the fourth block and is an overestimation of about 0.35 switches. Block 1, 2 and 10 slightly point in the opposite direction as the real data with up to 0.15 switches. From the third to the ninth block the simulation overestimates the experimental findings. This results from the automatic system and the pressure contained therein, as it skips the reflective part completely if the pressure is high enough. In a more advanced game stage the reflective system almost always defines the current door as the best, which leaves the pressure as the only force of switching doors. Basically, there is a distance between the sum of switches in the decreased versus the constant option scenario of about 9 switches.



Figure 2. Switching behavior of agents in decreased vs. constant availability (left) and in implicit vs. explicit scenarios (right)

Adding explicit cost to the scenario of decreased as well as constant availability leads to the resulting bar plot on the right side. The bars represent the percental difference in switching behavior from the implicit to the explicit cost scenario in the two availability options resulting in the simulation. The error bars again show the distance to the original data, which sums up to approximately 8 %. The constant availability option thereby produces a distance of only 1 %. The second scenario of decreased option availability overestimates the effect of cost saliency (see Section 2.3). This may stem from the rather strict definition of a decreasing sensitivity, that leads to the inclusion of costs in the deliberation process.

4 Improving Decisions: Simulation of Nudging

In a second simulation, we aim at manipulating the agents' behavior by using nudging methods. Default is used to influence the automatic system, because it has proven to make a statistically significant difference in human behavior, namely adhering to the default with a higher probability than choosing another option [51]. Furthermore, information is provided to the agent, in order to lead to a more deliberate decision by activating the reflective system. The game is modified as follows: The next door is per default set to the currently chosen door. This is because the best strategy for the agent is to stay on one door throughout the game, as this does not incur any (implicit or explicit) switching costs and thus guarantees the highest possible payoff. If the agent decides for another door, the game answers with the question whether the agent wants to change the door safely and a reminder that this causes costs. Using this, the action the agent is about to execute next is presented as a loss opposed to the expected gain (keeping an option or resetting the shrinking status) (see [29]). With these nudges, the agent is forced to think about his recent decision and may redeliberate, before deciding to actually execute it. This results in better performance as the automatic is slowed down and the reflective part is used more intensively.

Agent Behavior. Compared to the first simulation in Section 3, neither the agent's goals nor its knowledge about the game-specific attributes have changed. The agent's experienced pressure through the shrinking doors $(thdP_t)$ remains unaltered, too, but the probability of being influenced by it is reduced through the effect of nudging methods. For a start, a general probability $p_{newDeliberation} \in [0,1]$ is set, that defines whether the agent is basically willing to deliberate about another door in the first place. This probability decreases in each new decision cycle, in order to represent the falling tendency to overthink a chosen behavior for several times and is reset if the agent executes an action. If the agent is ready to reconsider his decision, the probability to react to the pressure, thus the agent's resistance to it, is increased in each step of redeliberation. For this, a new value *intensityNudge* $\in [0,1]$ is introduced. Each step, the resistance to pressure *resistanceP_t* is increased by using a random number in an interval between 0 and *intensityNudge* (see Eqn. (4)).

resistance
$$P_t$$
 = resistance P_t + resistance P_t * random[0, intensityNudge] (4)

Using this, a nudge is varied in its impact on decision-making. With respect to Fig. 1, a step is added before the actual execution that leads back to the perception and starts a new cycle with an increased resistance to pressure. Hence, using nudging methods the agent experiences a defocusing from the existing pressure.

Design of Experiment. The second experiment consists of two different simulation settings, that focus on decreased option availability. The switching costs can either be implicit or explicit and nudging is used in both scenarios. This leads to the following scenario setups:

{Decreased availability} × {Implicit cost, Explicit cost} × {Nudging methods}.

The probability to start a new decision cycle $p_{newDeliberation}$ is set to 0.5 and in each cycle decreased by steps of 0.1. In order to observe the impact of the nudging methods, the value of *intensityNudge* is varied in steps of 0.1 within range [0.1, 1.0]. As in the first experiment, each simulation scenario is run for 100 times.

Simulation Results and Interpretation. Figure 3 depicts the results of the simulation runs. The upper curve represents the development of the mean of switchings in a scenario with implicit cost. The lower curve shows the results for the explicit cost scenario. The curves have a similar course, whereas the mean difference between the two scenarios is approximately 3 switches. The lower explicit cost curve shows a relatively constant decrease from 6.29 to 5.63 switches. From *intensityNudge* = 0.2 to 0.3 the biggest step implies a decrease of 0.15 which equals. This results from the values of *tdP*, which lie below 0.3 in 60 % of all cases. After this, a constant fall of the curve takes place until *intensityNudge* = 0.7. Up to 1.0 there are hardly any changes in the switching behavior. The value of *thdP* only randomly takes values of this range (only 10 percent of all cases).



Figure 3. Switching behavior of agents in implicit vs. explicit cost under impact of nudging methods

Generally, the agents make 4 switches less in contrast to the same scenario (Decreased availability \times explicit cost), which leads to a gain of about 30 cent (235 without nudging, 263 with nudging). Even if this is compared to the implicit cost scenario without nudging, a profit of about 20 cent can be noted. This implies, that the effect of nudging methods is fully present even at a very low perceived intensity of the nudging methods. In comparison to implicit cost the curve of explicit cost remains very stable along the whole parameter space of *intensityNudge*, which means that the values vary from 8.99 at intensityValue = 0.1 to 8.80 at intensityValue = 1.0. Nevertheless, the overall mean of the number of switches is approximately 8 switches lower than in the experiment (decreased availability × implicit cost) described in Section 3, which leads to a gain of approximately 40 cent. This once again shows how a nudge can influence behavior at a low perceived intensity, even if a new deliberation cycle is only started in about half of all cases. Therefore, this simulation shows how nudging can theoretically defocus the agent from its experienced loss aversion and thus the pressure to keep all options (automatic system) and focuses on deliberating about the best choice (reflective system) and a better performance.

5 Limitations and Future Work

As this work makes a first step towards support for simulation-based preplanning of experiments, there are some limitations that require further investigation. First, this research is exploratory and is built upon assumptions about the impact of nudging methods and the agent's reaction. For this, we used intensity values for nudging and a randomly set resistance of the agent against the perceived pressure caused by decreased option availability. Besides the introduced factors, additional characteristics of individuals such as personality and other biases impact decision-making and susceptibility to manipulation. To calibrate and validate the model in this point, we conduct additional experiments using triangulated perceived data (i.e., personality traits [52–54], cognitive workload [55–57], concentration [58]) and physiological sensor data (i.e., electroencephalography [59, 60], electrocardiogram [61, 62], electrodermal activity [63, 64], eye fixation [65, 66], eye pupil diameter [67, 68]).

Secondly, the use of simulations creates a disadvantage corresponding to one of laboratory experiments. It creates an artificial environment that allows for exclusion of external factors but reduces the generalizability of the model. To adapt the model to other contexts as well as cognitive biases and nudging methods it has to be considered, that cognitive biases differ both in the extent and focus of their influence. For example, biases related to human perception (e.g., framing) manipulate information processing, while other biases directly affect decision-making, e.g., adherence to a decision, although alternative information might suggest a better alternative (loss aversion) [19]. Therefore, for adaption of the model to other contexts, different aspects of the agent's decision-making process need to be improved, for which we lack appropriate data for calibration and validation. Hence, as a next step we plan on conducting the experiments described in this paper in the real world and making use of measuring methods, e.g., as in [69] to improve the existing model.

6 Conclusion

This paper's aim was to make a step into the preplanning of experiments to analyze the effects of digital nudging. To achieve this goal, the accompanying research question focused on the use of simulation. To this end, a model was introduced, that in a first step replicated the behavior of human gamers based on the findings of an experiment described in Section 2.3. Subsequently, the model was extended using several nudging methods for the purpose of guiding gamers towards beneficial behavior, improve their performances. We were able to reproduce the participants behavior in the initial model. Furthermore, simulations with the extended model produced plausible results concerning the influence of nudging on the participants' behavior.

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