Aspirations Levels in Agent-based Models of Decision-Making in Organizational Contexts

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Abstract. Many agent-based models of human decision-making in organizations employ representations and algorithms comprising decision-makers' aspirations. However, aspiration levels usually do not receive much attention in the modeling efforts, nor is agent-based modeling employed to understand better the effects and emergence of aspiration levels in decision-making. This paper elaborates on the relevance of aspiration levels in agent-based models using the widely used hill-climbing algorithms and reinforcement learning as examples. The paper provides a framework for the modeler's multi-faceted design choices when capturing aspiration levels for decision-making with a particular focus on organizational contexts. The framework builds on the ODD+D protocol, which has been proposed explicitly for agent-based models with human decision-makers. The framework also allows deriving potential contributions of the agent-based modeling approach to understanding the effects of aspiration levels in organizations. These may, for example, include the dynamic interactions between individual and organizational aspirations, the adaptation to environmental changes, or the relevance of decision-makers' cognitive capabilities.

Keywords: Aspiration Level, Hill-Climbing, ODD+D Protocol, Reinforcement Learning, Satisficing, Target Setting, Uncertainty

1 Introduction

An aspiration level refers to the level of outcome that will satisfy the individual or organization; hence, in decision-making, alternatives that at least promise to attain the aspiration level are acceptable. Dating back to Cyert and March's "Behavioral Theory of the Firm" [1], there is a large body of research in organizational sciences on the role of aspiration levels in decision-making. For example, it was argued that aspiration levels reflect uncertainty as a counterpart to rational expectations and risk in more traditional schools of economic thought [2, 3]. Prior research has also discussed aspiration levels as representations of organizational targets and the adaptation of aspiration levels in environmental turbulence (for overviews, [3-6]).

Regarding aspiration levels in agent-based models of decision-making in organizational contexts, the situation appears somewhat mixed. First, it is worth mentioning that various highly influential papers on organizational evolution employ computational models that explicitly stress and even study the role of aspiration levels (e.g., [7-9]). Second, many agent-based models of decision-making *within* organizations comprise aspiration levels, though often implicitly or "hidden." However, interestingly, the if and how of aspiration levels in agent-based modeling are not necessarily linked to the various foundations in prior research. Moreover, although agent-based models may appear "predestined" due to their inherent micro-to-macro perspective, they are rarely employed in research on the role of the various decision-makers' aspirations levels for organizational outcomes.

This paper addresses the link – or the missing thereof – between research on aspiration levels in organizational sciences on the one hand and aspiration levels employed in agent-based computational models of organizational decision-making on the other. It advocates reflecting the foundations of aspiration levels in agent-based models of organizational decision-making.

For this, the paper puts forward the following course of argumentation. Section 2 outlines major strands of prior research on aspiration levels in organizational decision-making. Then, Section 3 argues that, in agent-based models of organizational decision-making, aspiration levels are ubiquitous, often hidden, and potentially critical for the simulation results pertained. Building on the ODD+D protocol [10], Section 4 proposes a framework that captures the main modeling choices related to aspiration levels in agent-based models of organizational decision-making.

2 Aspiration Levels in Organizational Decision-Making: A Brief Overview

This section briefly highlights some strands of research on aspiration levels in organizational decision-making, particularly relevant to this paper's focus: Agent-based models allow linking the micro- with the macro-level and, thus, mitigate the well-known micro-macro-divide in organizational sciences [11, 12]: the micro-level primarily refers to individuals, including their cognition, decisions, and actions; the macro-level refers to, for instance, organizational structure or strategy. For example, agent-based models allow bridging between individuals' decision-makers (micro-level), the controls employed in organizations for affecting decision-making, and the patterns (e.g., in terms of performance) obtained at the aggregate level of the organization [13].

Against this background, at least two strands of research on aspiration levels are of interest here: (1) their role in individual decision-making of boundedly rational decision-makers (micro-level) and (2) their relevance at an organizational (or macro) level of decision-making as capturing, for example, an organization's targets.

2.1 Aspiration Levels in Individual Decision-Making

Aspiration levels play a prominent role in the idea of bounded rationality of decision-makers and satisficing behavior, as introduced by Simon [14-16]. According to Simon, satisficing means a sequential search for options until a satisfactory level of utility is achieved. The aspiration level captures what the decision-maker regards as satisfactory. Satisficing is based on three building blocks: (1) a sequential procedure capturing which options are discovered and evaluated first, second, and so on; (2) the aspiration level, which gives the level of outcome that is regarded satisfactory and against which options' outcome is evaluated; (3) a stopping rule, saying that the search stops when the decision-maker has found a first satisfactory option. These three elements, in principle, correspond to building blocks identified in the heuristics of decision-making: search rules, stopping rules, and decision rules [17, 18]. The aspiration level may be subject to adaptation, as Simon argues:

> "The aspiration level, which defines a satisfactory alternative, may change from point to point in this sequence of trials. A vague principle would be that as the individual, in his exploration of alternatives, finds it *easy* to discover satisfactory alternatives, his aspiration level rises; as he finds it *difficult* to discover satisfactory alternatives, his aspiration level falls…" [14] (p. 111, emphasis in original).

Simon's satisficing stimulated a large body of further research in various domains, from psychology and economics to multi-agent systems (e.g., [19-23]), and provided a basis for Selten's "aspiration adaption theory" [24].

Considerable empirical support exists that satisficing – with aspiration levels as an essential "ingredient" – captures key elements of human decision-making (e.g., [25, 26]). However, the initial setting and update of aspiration levels give rise to questions [22, 27]. In this vein, it is also worth mentioning that empirical research on aspiration levels in organizations predominantly does not directly measure aspirations (with few exceptions, e.g., [2, 28]). Instead, aspirations often are measured via proxies: e.g., the performance of comparable firms as a kind of social comparison or past performance (for overviews, [5, 6]). Indirect measurements may also allow disentangling individual decision-makers' aspirations from organizational aspirations and internal (self) from external (social) reference points [6].

2.2 Aspiration Levels in Organizations

According to Selten [24], organizations often employ "aspirations on risk related goal variables" (p. 210) when probabilities are not available or, at least not at a reasonable cost, i.e., in situations of uncertainty. Aspiration levels serve as organizational goals and may be adapted based on experience [2].

Here, organizational members' expectations of future states in relation to aspirations come into play. Evidence suggests that aspirations and expectations may show some "overlap" depending on whose decision-making behavior is studied. Lant and Shapira [3] find that expectations play a significant role for economists in shaping their further thinking about goals and actions; in contrast, the distinction between controllable and uncontrollable factors appears particularly relevant for managers. Managers' belief in the controllability of factors shapes their propensity to react to performance feedback (i.e., deviation from aspiration levels); at the same time, managers' tendency to take risks shapes the perceived control of outcomes.

Moreover, individual decision-makers may not necessarily adopt the aspirations of the overall organization. Conflicts among individual and organizational aspirations may, for example, be motivated by career considerations and reflected in risk aversion and overweighting of certainty (certainty effect) [29].

Prior research has yielded numerous results on the formation of aspirations. Lant [2] finds that a history-dependent process captures the formation of aspiration levels in organizations (e.g., [7]), meaning that more experience than predictions of the future shape aspirations (i.e., goals). Moreover, there is evidence that contingent factors affect aspiration levels. For example, in stable environments, aspiration levels may adjust to rational expectations based on learning [2].

These findings may be particularly relevant for agent-based models of organizational decision-making, as they indicate that aspiration levels may evolve based on learning and complex interactions.

3 On the Relevance of Aspiration Levels in Agent-based Models

This section aims at highlighting the two-fold relevance of aspiration levels in agent-based models of organizational decision-making – first, for their *ubiquity* and second, for their considerable *effects* on simulation results. For this, the following employs *two examples*: hill-climbing algorithms and reinforcement learning. These examples are chosen for their fundamental character and prevalence in agent-based modeling.

3.1 Aspiration Levels in Prominent Algorithms in Agent-based Models

Many agent-based models of organizational decision-making comprise backward-looking search behavior and experiential learning. To capture this, greedy algorithms, particularly hill-climbing algorithms, prevail (e.g., [30]). According to Cormen et al. [31], a "greedy algorithm always makes the choice that looks best at the moment" in terms of "a locally optimal choice in the hope that this choice will lead to a globally optimal solution" (p. 414). With the metaphor of seeking the highest summit, a hill-climbing algorithm requires that the outcome ("altitude") increases by moving in the landscape. In other words: the "*built-in*" or *implicit* aspiration level in hill-climbing algorithms is an improvement greater than zero.

While hill-climbing algorithms show some correspondence to the marginal principle known in more traditional schools of economic thought, several traits of hill-climbing received attention in the context of decision-making of boundedly rational agents. Among these is the peril of inertia of adaptive search, i.e., getting stuck in local maxima, ridges, or plateaus in a landscape or myopia of search since no moves of short-term decline in favor of a long-term higher outcome would happen (e.g., [32]). Moreover, some cognitive biases suggest that decision-makers eventually favor performance declines, raising questions about whether hill-climbing algorithms appropriately capture managerial search behavior [33].

However, aspiration levels also *explicitly* show up in familiar algorithms in agent-based models. A prominent example is learning based on reinforcement [34]: an agent learns by comparing the past outcome of an action to an aspiration level. Should the outcome meet the aspiration level, the probability of choosing this action in the future increases and vice versa. Aspiration levels in reinforcement learning have drawn considerable attention in various domains (for an overview, [4]).

These examples may underpin that aspiration levels play a considerable role in agent-based modeling. However, the question of how a particular aspiration level is reasoned may not, in any case, be straightforward. For example, when hill-climbing serves to capture managerial search behavior: Is it reasonable to assume that a change "only" has to provide *some* increase in outcome in an organization? Would it not be more realistic to assume that a specific hurdle rate remarkably greater than zero has to be attained – may it, for example, be due to stakeholders' expectations (e.g., investors, public) or requirements of superiors? Or should an aspiration level reflect the individual decision-makers' aspirations, including some "insurance" against unforeseeable costs of change, including eventual contingent effects of biases against risk?

Hence, for agent-based models in organizational contexts, questions refer to whose aspirations are captured, what the aspirations should reflect, why a certain level is set, or how it evolves. Section 3.2 argues that being clear on these questions is essential as the aspiration level may considerably affect a model's results.

3.2 Effects of Aspirations Levels in Agent-based Models: Examples

While agent-based modeling is the preferred means of Generative Social Science [35] for explaining a macroscopic pattern, it is well noticed that a model's parametrization could be of critical relevance, which also applies to aspiration levels. Even switching from "greater than or equal to" (≥) to "greater than" (>) may affect the emerging macro pattern considerably. The same holds for the level of aspiration for which – subject to the respective model – "tipping points" may exist: Even a slight deviation beyond a certain level may result in a particular macro pattern showing up.

The following provides an example from organizational decision-making: It has been argued that tighter coordination among decision-makers may be related to higher interdependencies between the various decisions within an organization. Hence, the macro pattern to be explained is that tighter coordination predominates when intra-organizational complexity is high.

Figure 1 shows results from an agent-based model where artificial organizations search on NK fitness landscapes [34, 35] for superior performance (fitness). The organizations have decomposed their overall decision problem into equal-sized sub-problems, each assigned to one subordinate decision-maker (manager). From time to time, the headquarters may change the predominant mode of coordination based on *reinforcement learning* out of three modes of coordination possible: (1) full decision-making autonomy at the subordinate level, i.e., in fact, no coordination, (2) sequential planning as a kind of lateral coordination across subordinate managers, and (3) hierarchy via the headquarters.[1] The reinforcement learning mechanism includes the aspiration level. In particular, when the headquarters observes that the performance differ-

[1] The organizations all start with full autonomy of local decision-makers, i.e., no coordination, and in period 20 the coordination modes are randomly chosen with equal probability of 1/3 each. For the rationale behind this initialization of the simulation experiments see [34].

ence obtained with the current coordination mode in the last T^* periods equals or is above an aspiration level α, the probability of keeping that mode increases and vice versa (for a description in more detail and further references, see [36, 37]).

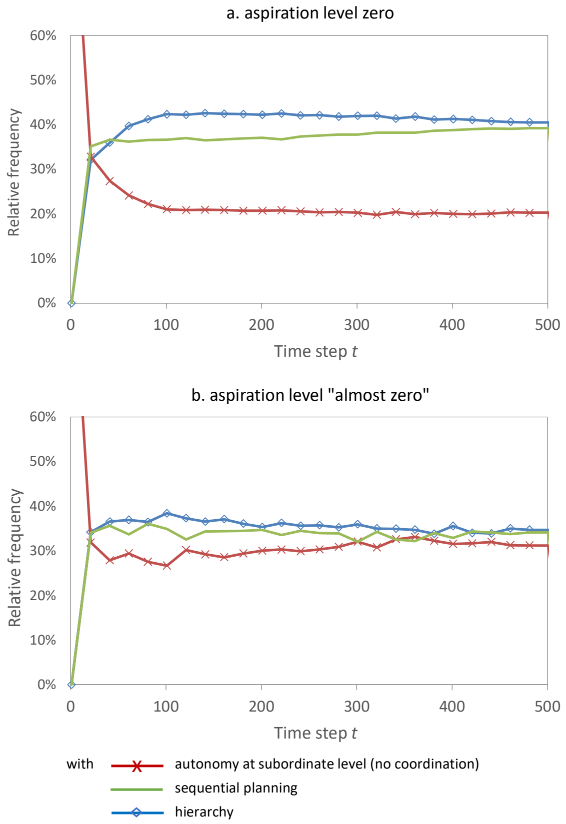

Fig 1. Emergence of coordination modes via reinforcement learning for aspiration levels of (a) zero (α=0) and (b) "almost zero" ($\alpha=10^{-10}$) in a highly complex task environment (i.e., N=12; K=11). For each scenario, 2,500 simulations were run, with 10 runs on 250 fitness landscapes.

The two plots in Figure 1 show results obtained for an aspiration level α equaling zero versus "almost zero" – in each case, fixed for the entire observation period. The model produces the macro-pattern as the theory predicts (i.e., tighter coordination predominating for this level of complexity) when the aspiration level equals zero. However, no clear pattern shows up for the "almost zero" aspiration level. In short, the "non-emergence" of the pattern is caused by the interference of the decision problem's complexity and the negative feedback from aspiration levels greater than zero.[2]

[2] In particular, in a highly complex task environment, for organizations with decentralized decision-making by boundedly rational agents it is rather difficult to find solutions that increase performance – at least, after the first performance increases are obtained. Hence, an

For the argumentation in this paper, the relevant point is that a slight change in the aspiration level may remarkably change the model's results. This may highlight the relevance of sound design and parametrization of the aspiration levels in agent-based models, as the next section seeks to outline.

4 Towards a Framework for Modeling Aspiration Levels

With aspiration levels' ubiquity and efficacy on results in agent-based models of organizational decision-making, it may be worth making deliberate design choices on aspiration levels employed in agent-based models. This section outlines a framework that may help capture aspiration levels in an agent-based model. To this end, we build on the ODD+D protocol suggested by Müller et al. [10] to extend the ODD protocol [38, 39] for agent-based models with human decision-making agents. The ODD+D protocol comprises ten patterned design concepts intending to capture design choices related to typical features of agent-based models.

4.1 Aspiration Levels in the Design Concepts of the ODD+D Protocol

This section briefly introduces the major design choices on aspiration levels referring to the ODD+D protocol, as summarized in Table 1:

As indicated in Section 2, there is a large body of theoretical and empirical research on aspiration levels, and the first design concept suggests clarifying the respective foundations.

The design concept "*2. Individual decision-making*" appears particularly relevant for modeling aspiration models: It captures which agents' aspirations are modeled and for which decisions they apply. As outlined in Section 2, aspiration levels may refer to individual decision-makers' desires or the organization's goals, which stakeholders outside the organization may eventually define or affect.

Moreover, the second design concept also captures how the aspiration levels enter *decision-making rules*. For example, the modeler may consider whether decision-making agents follow a hill-climbing algorithm or a satisficing approach, as mentioned in Section 2.1 (for an algorithmic representation, see [40]).

This design concept also relates to the *formation and adaptation* of aspiration levels. Aspiration levels may be fixed for the entire observation period or subject to adaptation which could also be worth observing as a model's output (see concept "*10. Observation*"). As for the *computational representation,* the adaptation could be based, for example, on the exponentially weighted moving average of past performance [7], the average of expectations [41] or by comparing prior expectations with prior experience [9]. The adaptation of aspiration levels could be relevant for individual decision-makers and collectives, e.g., at the organizational level [42].

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aspiration level even slightly higher than zero means that the organizations likely receive a negative feedback (i.e., due to not meeting the aspiration level) regardless of which coordination mode is implemented. Hence, no pattern can show up, as the coordination modes have similar probabilities – and frequencies accordingly – of being implemented.

Table 1. Framework of design choices on aspiration levels in agent-based models of organizational decision-making based on the ODD+D protocol.

Design concept	Design choices for aspiration levels
1. Theoretical and empirical background	Which general concepts underlie the modeling of aspiration levels (e.g., Selten's (1998) aspiration adaptation theory; for overviews of concepts and empirical findings, see Lant 1992, Mezias 1988, Washburn and Bromiley 2012, Bromiley and Harris 2014)?
2. Individual decision-making	For which subjects and objects of decision-making are which aspiration levels relevant? How do aspiration levels enter decision-making rules (e.g., like in hill-climbing algorithms or according to Simon's satisficing [Wall 2023])? How are aspiration levels computationally represented? Are aspirations levels fixed, or are they adapted (e.g., to environmental changes or performance achievements), and if so, how? (for overviews, see Lant 1992, Washburn and Bromiley 2012)
3. Learning	Do agents learn in terms of adapting the adaptation rules for aspiration levels (e.g., more/less speedy adaptations, Greve 2002)
4. Sensing	How do decision-makers achieve knowledge of aspiration levels reflecting organizational targets? How do decision-makers receive information on whether aspiration levels are achieved? How precise is this information? Is there ambiguity in the interpretation of achievements (Joseph and Gaba 2015)?
5. Prediction	Do aspiration levels reflect decision-makers' predictions and/or preferences about future states, and, if so, how are predictions formed? Do aspiration levels reflect decision-makers' internal models, including data and memory employed for forming aspirations?
6. Interaction	Do agents communicate their aspiration levels to other agents? How does information about other agents' aspiration levels affect an agent's aspiration levels? Are there coordination networks/mechanims to coordinate agents' aspiration levels, e.g., aspiration levels of individual decision-maker (internal / self) versus aspirations reflecting an organization's goals (external / social)?
7. Collectives	Are there aspiration levels of collectives relevant beyond overall organizational targets (for example, departmental goals or social norms)? How are collectives, including their aspirations, structured, and are collectives predefined, or do they emerge?
8. Heterogeneity	Is there heterogeneity across decision-making agents regarding aspiration levels, especially concerning design concepts 2, 3, 4, and 5 (see above)?
9. Stochasticity	Are aspiration levels subject to stochasticity and, if so, for which causes (e.g., imperfect communication processes within an organization, incomplete adoption of organizational aspirations by individuals)? Which statistical properties and temporal structure do stochastic components show?
10. Observation	If aspiration levels are subject to adaptation, should they be observed as model outputs (data)? If so, which temporal structure of observed data is of interest (data points vs. time series)?

The design concept *"3. Learning"* reflects agents' learning on the adaptation rules of aspiration levels. For example, the organization (collective agent) may learn that, in the past, the adaptation for aspiration levels was too slow or fast [8] and update the adaptation rule accordingly.

Closely related are the design concepts "*4. Sensing*" and "*5. Prediction*," broadly referring to the *cognitive capabilities* of the agents whose aspiration levels are to be modeled. These concepts capture, for example, the precision of (perceived) performance feedback, including individual biases in reaction to positive and negative deviations from aspiration levels or eventual ambiguous interpretations of performance achievements [42], the memory of past achievements, or mental models about future desired states. As outlined in Section 2, the professional background (economists vs. managers) may shape how far aspirations differ from (rational) expectations, and with increasing knowledge due to experience, differences may vanish [3]. This could be captured in an agent-based model. Hence, design choices regarding "4. Sensing" and "5. Prediction" also may be relevant for the concept "*9. Stochasticity*" of aspiration levels in an agent-based model (Table 1).

The design concept *"6. Interactions"* captures – direct or indirect – interactions among agents, including communication and coordination networks, and may be particularly relevant for modeling aspiration levels in organizational contexts. For example, modeling choices may refer to how agents at higher hierarchical levels in the organization communicate their aspirations to lower-level agents and how far this may lead to adjustments of aspirations on the side of the subordinate agents, as mentioned in Section 2.2. Moreover, decision-making agents' aspirations may also be affected by organizational targets and arrangements like incentive schemes which reflect important intra-organizational coordination mechanisms.

In this vein, the design choices for "*7. Collectives*" may specify aspirations of collectives, e.g., departmental goals or based on social norms, that may affect agents' decision-making – may they be individuals or collectives on their own. Since the potential heterogeneity of agents is among the key properties of agent-based modeling, agents may be heterogeneous regarding aspirations levels and their adaptation as captured by the design concept "*8. Heterogeneity*".

4.2 Studying Aspiration Levels with Agent-based Modelling

The preceding considerations may provide a rough framework for guiding the design choices when the modeler wishes to reflect aspiration levels in an agent-based model explicitly. However, further efforts to extend and refine the framework appear worthwhile. As such, there is an extensive and ongoing body of research on aspiration levels in organizational sciences, and reflecting the results of these research efforts in the framework would further contribute to specifying sound modeling choices.

The framework introduced also indicates the potential of agent-based modeling for advancing the understanding of aspiration levels in organizational decision-making.

For example, agent-based models could help study the interactions between individuals' and the organization's aspirations, where interactions may evolve due to performance achievement when organizations adapt to environmental turbulence.

While it is well noticed in organizational sciences that dynamic adjustments of aspirations are of particular relevance, studying adjustments poses considerable challenges for empirical research [42]. Agent-based modeling could contribute to this strand of research by deriving testable hypotheses.

Decision-makers' cognitive capabilities could pose another promising application of agent-based modeling to understand aspiration levels in organizational decision-making. As illustrated before, the setting, communication, or perception of aspiration levels in an organization and evaluating actual performance against aspirations involve information processing. Hence, how decision-makers' cognitive capabilities, in conjunction with aspiration levels, affect decision-making could be studied using the particular strengths of agent-based modeling.

5 Conclusion

This paper advocates fostering the foundation of aspiration levels in agent-based models of decision-making with a particular focus on organizational contexts. For this, the paper outlines a framework of design choices for capturing aspiration levels according to their multi-faceted nature in agent-based models building on the ODD+D protocol. On the one hand, this research endeavor is motivated by the ubiquity and (potentially crucial) effects of aspiration levels in prominent algorithms employed in agent-based models for organizational contexts. On the other hand, the proposed framework of design choices may highlight the potential contributions of agent-based modeling to advance the understanding of aspiration levels in organizational decision-making.

However, the outlined framework requires further refinements and extensions in the conceptualization. Moreover, the framework next awaits extensive applications and evaluation in agent-based models that seek to understand aspiration levels in organizational decision-making.

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