Agent-Based Simulation of Strain and Motivation in Human Work Performance

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***Abstract*—Even though the relevance of the "human factor" on the performance of work processes is well known, the design and optimization of such processes, e.g., in factories, often strongly focuses on machines. Especially intrinsic mental states such as *strain* and *motivation* can influence the human workers' performance and thus the organizational outcome. This paper is based on a previous agent-based model of human work processes and extends this model using Atkinson's theory of achievement motivation. The combination of the job demands-resources model with a more advanced motivation theory allows for a more sophisticated and realistic modeling of task selection based on its difficulty, individual competencies, and perceived attractiveness. Experiments are presented, to demonstrate the model's capability to simulate human work performance and the mutual influences between job demands, resources, personal resources, as well as the intrinsic mental states of strain and motivation.**

***Keywords*–Human Work Performance; Agent-based Modeling; Job Demands-Resources Model; Strain; Achievement Motivation.**

I. INTRODUCTION

In previous work, the relevance and impact of the "human factor" on the performance of work processes has been outlined and a model for the simulation of human work performance based on strain and motivation has been proposed [1]. This is relevant, as peoples' workplaces are constantly changing, especially as digitalization progresses, and as we believe that this digital revolution should be oriented towards employees' needs. Yet, people often subordinate to IT systems and thus disempower themselves [2]. For example, a scheduling system in a call center distributes incoming calls without considering individual needs of the call center agents. Consequences are not only physical but also psychological strains like burn-out.

Digital transformation should not be rejected in general as it has the potential to make work processes more efficient. Current approaches for designing and optimizing work processes, e.g., the production of goods in a factory, often make use of simulation and focus on machine processes. Examples are predictive maintenance or throughput time optimization. Here, downtimes of machines or queuing strategies are analyzed to identify optimal process configurations. In reality, however, human workers can also influence the performance of such production processes, e.g., due to unavailability, distraction, or overload. Existing frameworks for the analysis of industrial service provision processes often neglect the human factor and only allow for the modeling and simulation of machines in production lines.

In a production plant, human workers may be assigned a series of orders with different difficulties to be processed during the working day. The workers' performance can be measured by the ratio of completed orders in relation to the total number of orders. While machines do not show performance fluctuations when being confronted with an immense workload or time pressure, human workers tend to be susceptible to such influences. Intrinsic processes of motivation and strain are driving factors influencing their performance [3]. Still, during the planning and implementation of work processes, human beings are often only considered as workforces without individual intrinsic needs, even though their significance and importance are well known, e.g., modeling of humans in Business Process Model and Notation (BPMN). To achieve a more adequate integration of humans into these processes as well as to increase performance and organizational outcome, individuals and their intrinsic needs must be represented individually and realistically.

Based on these considerations, the authors of this article have developed an agent-based model of human work performance by utilizing the Job Demands-Resources model (JDR model), which includes motivation and strain as intrinsic mental states [1]. They investigated the agents' performance in a simple work context in which orders of various difficulties need to be completed in a limited time. In different simulation experiments, plausible results were generated that confirm the mutual influence of motivation and strain.

This paper adapts the previous model and presents two main extensions that focus on the definition of motivation by using Atkinson's motivation theory [4] as well as on the impact of strain on the duration of order processing using a Performance Moderator Function (PMF) [5]. This allows for a more sophisticated and realistic modeling of individual task selection based on the tasks' difficulty, individual competencies, and the subjectively perceived attractiveness of tasks. To model workers and their behavior, Agent-Based Modeling (ABM) and especially the Belief-Desire-Intention (BDI) architecture of practical reasoning [6] are used, which are established in modeling of human cognitive decision-making [7]–[10].

The article is structured as follows. In Section II, related work on the field of modeling strain and motivation in ABM is presented and discussed. In this regard, the concept of performance motivation is introduced, which serves as a theoretical basis for extending motivation in the proposed model. Furthermore, the flexible Job Demands-Resources model is introduced, which is well-established in psychology and investigates factors in the working environment that may lead to burn-out, especially focusing on those factors causing a stressful situation and mental effort for the worker [11]. Subsequently, an extended agent-based model of work performance is introduced in Section III. In Section IV, the results of simulation experiments are discussed to analyze the model's adequacy to represent human work performance. Finally, Section V provides a summary as well as an outlook on future work.

II. Background

There are several frameworks for modeling and optimizing industrial processes, e.g., Enterprise Dynamics or Anylogic [12], which strongly focus on functionalities of machines in manufacturing. These frameworks lack in the representation of human resources such that the "human factor" cannot be considered properly when measuring the overall performance. However, other areas, e.g., the representation of social networks, lay emphasis on an adequate representation of human beings. Here, agent-based models that utilize sociological and psychological behavioral theories are well-established [13]–[15]. This article introduces an extended agent-based model of human work performance including the intrinsic processes of strain and motivation, which in future work could be used to represent workers in existing frameworks. In the following, we discuss existing work on agent-based models including stress and motivation formation and present the psychological JDR model, that serves as the basis for our implementation.

A. Modeling and Simulation of Strain

In ABM, various approaches exist that include psychological strain in behavioral development. Silverman's generic agent architecture contains a working memory (BDI decision logic) and four subsystems: Physiological System, Emotive System, Cognitive System and Motor/Expressive System [16]. In the strictly modularized approach, the calculation of an integrated stress value is part of the Physiological System, which is defined as a function of exhaustion, time pressure, and event strain. Fatigue is represented via available physiological resources and time pressure results from perceived stimuli. Event strain is the result of negative emotions of the Emotive System [17]. Based on these variables, different coping strategies are initiated using a PMF. Silverman proposes an inverted-U shaped PMF, which was first introduced by Janis & Mann and has since been replicated and validated several times. Depending on the integrated stress value, different coping strategies are chosen: Unconflicted Adherence and Change, Vigilance, Defensive Avoidance, and Panic. This PMF is characterized by an activating effect of stress on performance in addition to the limiting effects [5]. Duggirala et al. apply this conceptual model in an agent-based simulation of strain at work [18]. They selected the variables *task arrival volume*, *pending tasks*, and *work hours* to calculate the integrated strain value and to determine the coping strategies. However, by choosing work hours for determining exhaustion, they have missed Silverman's consideration of individual resources.

Ashlock and Cage also simulate strain at work using an agent-based model and a strain factor consisting of individual strain tolerance and number of stressors [19]. Still, strain is difficult to quantify and validate, especially using static mathematical formulas that are limited to a number of variables. For this reason, Morris et al. investigated system dynamics of strain to model agents by representing strain as causal loop diagram and stock-flow diagram [20]. In the BDI extension BRIDGE, strain is, similar to Silverman's approach, part of the implicit behavior and only influences the deficiency needs and overrules selected intentions [21]. Another broad research field, in whose models strain is also considered, (e.g., [22]), is crowd simulation. Strain influences behavior generation mainly reactively, but this is due to the frequent application context of emergency evacuations, where deliberative behavior is less important.

Most models include two aspects: Firstly, the models focus on stimuli during the genesis of strain and secondly in doing so, they neglect the consideration of resources that can significantly reduce the amount of strain generated. Such models do not recognize strain as the result of intrinsic processes although psychology has already sufficiently shown the degree to which cognitive processes occur regarding strain for a long time (e.g., [23]).

B. Modeling and Simulation of Motivation

In ABM, when considering motivation as part of the decision-making process, models can be distinguished by the motivations' directionality, i.e., whether motivation is caused by external factors or if it is merely generated intrinsically by the individual. Maslow's hierarchy of needs as an intrinsically oriented motivation theory, e.g., is implemented by Spaiser and Sumpter [24] as well as Silverman [16]. In these models, the agent's actions focus primarily on covering deficiency and growth needs, and mostly neglect environmental influences on motivation development. As mentioned above, the BRIDGE architecture also uses this theory to define an agent's goals and desires [21]. Using Vroom's extrinsically oriented expectation theory, the agent's decision making is modeled on the basis of its expected subjective value of a future event in his environment [25] [26].

Following Atkinson's concept of achievement motivation [4], behavior is aimed at the self-assessment of a competency, in confrontation with a standard of quality that one wishes to achieve or exceed [27, p.59]. Achievement motivation is affected both by external tendencies T_{ex} (e.g., striving for reward or avoiding punishment) and internal tendencies T_i, which result from the conflict of hope for success $T_s = M_s \cdot W_s \cdot A_s$ and fear of failure $T_f = M_f \cdot W_f \cdot A_f$, where

- $M_s(M_f)$ represents the success (failure) motive (stable disposition of a person, describing the capability to experience pride when having success (M_s) and shame when being unsuccessful (M_f)),
- $W_s(W_f)$ is the subjective expectancy of success (failure) (a person's expectancy that an action leads to an anticipated goal (or not); this variable changes due to experience), with $W_s + W_f = 1$, and
- $A_s(A_f)$ is the incentive of a success (failure) (a person's pride exceeds with difficulty of a given task) [27, pp. 59].

Individuals with a motive profile of $M_s > M_f$ are *success-oriented*, which means that they tend to look for goals that they want to achieve. These are achieved by minimizing the difference between the current status and the goal status. In contrast to this, a motive profile of $M_s < M_f$ means that these individuals are *failure-oriented*. They tend to avoid failure by maximizing the distance between the current status and the goal status [28]. Atkinson also states that the incentive for success can be described as $A_s = 1 - W_s$ (cf. [4, p. 94]) and, thus, solely depends on the subjective expectancy of success. This is based on the assumption that accomplishing a task that appears to be very difficult and, therefore, probably not achievable is perceived more attractive than an easily accomplishable task [4, p. 94]. A similar thought applies to the incentive for failure A_f. If an individual defines a task as easy to accomplish with a high value of W_s, the shame and embarrassment felt by the individual is also high in case the accomplishment of this task fails. Therefore, the incentive of failure can be described as $A_f = -W_s$. This leads to an adaption of the resulting tendency to $T_r = (M_s - M_f) \cdot (P_s - P_s^2)$. Among other things, e.g., the persistence in completing a task [29] [4, pp. 110], achievement motivation can be used to explain the selection of tasks of various degrees of difficulty [4, p. 99].

Achievement motivation has, so far, only been used in a few agent-based models. For instance, Merrick and Shafi (2013) investigated the effect of the three motive profiles of achievement, power, and affiliation motivation in situations of several mixed motive games. The authors demonstrate that the perception of the agents differs from each other according to their current motive profile composition [30]. Di Pietrantonio et al. developed an agent-based model of organizational work performance based on both the workers' abilities as well as their motivational needs [32]. Therefore, they also make use of the *Three Needs Theory* [31], which includes the motive profiles of achievement, affiliation, and power motivation. The authors investigate the effect of different motive profile distributions and the workers' own abilities while working in teams on the overall performance, which is defined as the number of completed tasks after a specific number of time steps [32]. To the authors' knowledge, Atkinson's achievement motivation model is only sparsely used in ABM. Among just a few others, Merrick [33] uses this motivation theory. She utilizes an experiment from human psychology and simulates it with agents to prove the suitability of the concept for use in an agent-based model.

The introduced approaches for ABM of motivation mainly rely on subjectively perceived environmental factors and largely neglect the mutual influence of intrinsic factors, e.g., between perceived strain and motivation, although the relation between these factors has already been described, e.g., by Dignum et al. [21].

A well-known model that both considers stressors (stimuli), resources, and the influence of motivation, is the JDR model by Demerouti et al. [11]. The JDR model is an empirically evaluated model that has been flexibly used in a variety of scenarios such as to predict job burn-out [34], organizational commitment [35], connectedness [36], and work engagement [37]. The model consists of two processes: a health impairment process and a motivational process (see Figure 1). The health impairment process is concerned with how job demands affect individual strain. Job demands can be stressors like workload, emotional demands, or organizational changes [38].

As part of the motivational process, job resources are main predictors for motivation and engagement. While job demands consume energetic resources and cause strain, job resources fulfil basic psychological needs and generate motivation. Thus, job demands and resources initiate two different processes but these processes are not independent because job resources can buffer the impact of job demands on strain and job demands can reduce the generation of motivation through job resources (see Figure 1). Due to these moderation effects, there is also a direct relationship between strain and motivation. By using the model, predictions can be made about employee well-being, job-performance, and respectively the aggregated performance of a company.

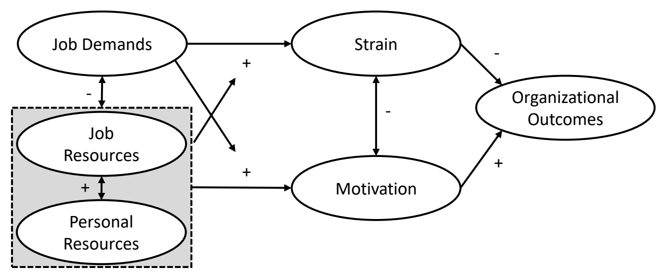


Figure 1. Job Demands-Resources Model [39].

The model was extended several times by the authors, in particular to include job crafting and self-undermining, and was transferred into a theory based on several meta-analyses [3], [40]. In this work, one of the first extensions of the model is used to significantly reduce the complexity of the simulation and to focus on the prediction of job performance [39].

III. An Agent-Based Model of Work Performance

In this section, an extended agent-based model of human work performance is introduced that combines the BDI architecture and the JDR model presented in Section II. The workers are modeled based on the BDI architecture of practical reasoning [6], which organizes goals (desires), information about the environment and the own conditions (beliefs), and action-oriented measures (intentions) into mental states. To this end, we also make use of the JDR model presented in Section II. By utilizing both models, a strict modularization is achieved, which can be easily extended and exchanged by other theories and models.

Figure 2 shows the basic concept of the agent-based model of human work performance. Following the JDR model, the agent's environment consists of sets of $JobDemands$, $JobResources$, and $PersonalResources$ that impact internal processes forming $strain$ (α) and $motivation$ (ζ). These, in turn, determine the agent's action as well as the corresponding duration of the action and, thus, the organizational outcomes. Here, this is equal to the individual performance.

Referring to the factory example introduced in Section I, the agent is confronted with a set of $Orders$ that is composed of the two sets $UnfinishedOrders$ and $FinishedOrders$ (Equation (1)). Initially, $|Orders|$ is equal to $|UnfinishedOrders|$. If an order $i \in UnfinishedOrders$ is completed, it is deleted from this set and added to $FinishedOrders$. Each of the orders has a certain difficulty $diff_i \in \mathbb{N}$, which is defined within a range of set difficulties. The difficulty of an order expresses how much time is required to execute it. As job demands represent stressors like workload (see Section II), $difficulties$ is introduced, which represents the agent's workload on one working day. It is composed of the sum of difficulties $diff_i$ for each $i \in UnfinishedOrders$ (Equation (2)).

$$Orders = FinishedOrders \bigcup UnfinishedOrders \tag{1}$$

$$difficulties = \sum_{i=1}^{|UnfinishedOrders|} diff_i \tag{2}$$

A working day is defined by a number of time steps $totalTime \in \mathbb{N}$, where $t \in \mathbb{N}$ represents the current time that has already elapsed. At each time step, the $remainingTime$ to complete all $UnfinishedOrders$ is computed (Equation (3)). The difficulty level corresponds to the minimum number of time units required to process an order and depends on the agent's $skillRank \in \mathbb{N}$, i.e., its work-related know-how. A lower value of $skillRank$ means that less time units are needed to complete one difficulty level. The $skillRank$ together with the overall $remainingTime$ to complete all orders form the agent's set of $JobResources$.

The agent's set of $PersonalResources$ is comprised of its general motives $motiveSuccess \in \mathbb{N}$ and $motiveFailure \in \mathbb{N}$ as well as its own $selfEfficacy \in \mathbb{R}$. The motives are based on Atkinson's achievement motivation model introduced in Section II, that is used as the underlying motivation theory. $selfEfficacy$ represents the subjectively perceived competence to perform actions effectively [41] [42]. The agent's $PersonalResources$ can be gathered from an input of empirical data (see Section V).

$$remainingTime = totalTime - t \tag{3}$$

Job demands initiate a health impairment process that affects the agent's individual strain. Job resources, on the other hand, have a moderating effect on strain and buffer the impact of the job demands. $strain$ (Figure 2, Function α) represents the experienced pressure as the ratio between the unfinished orders $difficulties$ and the $remainingTime$ to complete them (Equation (4)).

$$\alpha\colon strain = \frac{difficulties}{remainingTime} \tag{4}$$

$Motivation$ is formed in a process that is influenced by job resources, job demands, and personal resources. Based on the achievement motivation introduced in Section II, we require the two motives $motiveSuccess$ and $motiveFailure$ as well as the subjective probability of success to define motivation for this model. In [1], motivation is defined as the general and objective probability that "represents whether the agent is able to perform the open orders in the given time based on its own $skillRank$ at time t". As this definition does not yet take into account individual motives and subjective probabilities, it is used to represent the objective probability of success at time t $objProb_t$ (Figure 2, Function β) (see Equation (5)). As $objProb_t$ represents a probability, its value is normalized to the interval [0,1]. A higher value of this variable implies that the agent is objectively capable of completing the whole set of unfinished orders in the remaining time.

$$\beta\colon objProb_t = \frac{remainingTime}{skillRank_t \cdot difficulties} \tag{5}$$

The subjective probability of success for a specific order difficulty $subjProbS_{diff} \in$ [0,1], on the one hand, is composed of a general and objective probability $objProb_t$. The subjective component of $subjProbS$ is introduced by the agent's $selfEfficacy \in$ [0,1], which defines the agent's own conviction of being able to complete tasks of high complexity [42]. Nicholls [43] states that this reflects Atkinson's assumption that the "degree of difficulty can be inferred from the subjective probability of success" [28, p.362]. Furthermore, the influence of $selfEfficacy$ on an agent's performance reduces with increasing task complexity [41]. Thus, the agent's $subjProbS$ is represented by the decay of $selfEfficacy$ based on the objective probability to complete all remaining orders and referring to the level of difficulty of the respective order (see Equation (6)).

$$subjProbS_{diff} = selfEfficacy^{(1-objProb_t)\cdot diff} \tag{6}$$

Consequently, the subjective probability of success is used to define $motivation$ (Figure 2, Function ζ) for each remaining order difficulty $diff$ as follows:

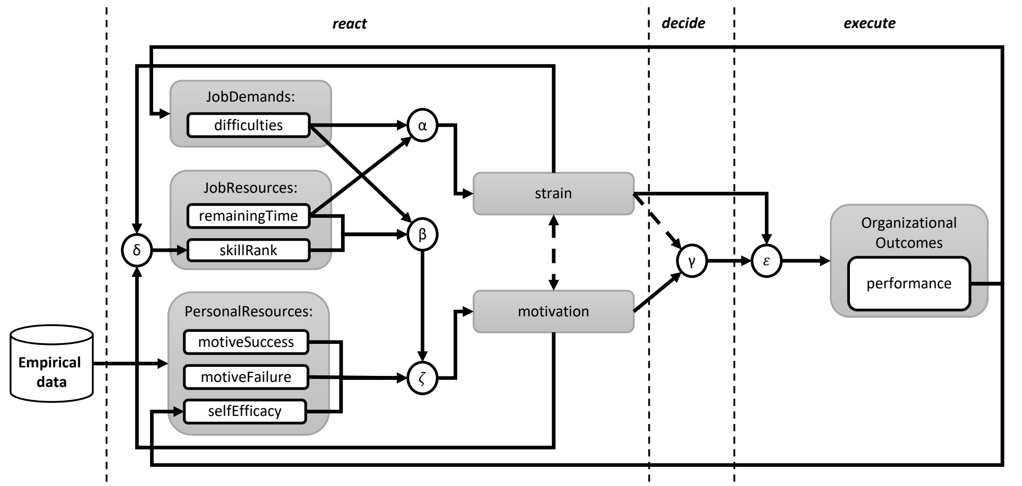
$$\begin{aligned}\zeta\colon motivation_{diff} = (&motiveSuccess - motiveFailure)\cdot \\ &(subjProbS_{diff} - subjProbS^2_{diff})\end{aligned} \tag{7}$$

For the purpose of simplicity, we neglect the external tendency T_{ex} for now, since we assume a controlled environment without an external reaction as reward or punishment to the work done. As the next task to accomplish (Figure 2, Function γ), the agent always selects the difficulty of available orders for which the highest motivation value $motivation_{diff}$ exists (see Equation (8)).

$$\gamma\colon \arg\max_{diff} motivation_{diff} \tag{8}$$

$Strain$ and $motivation$ represent an agent's set of $IntrinsicStates$. Both values are normalized to $[0,1]$, relative to the minimal and maximal possible values of the variables.

To calculate the agent's productivity, and the time the agent needs to complete a task, an inverted-U shaped PMF



Algorithm: **BDI ControlCycle**

```
1   B := initializeBeliefs (input)
2   D := initializeDesires (input)
3   I := {}
4   action := none
5   repeat
6       B := brf (B, D, action)
7       I := decide (B, D, action)
8       action := selectIntention (I)
9       execute (action, B)
10  end repeat
```

Figure 2. Job demands-Resources Model as Agent-Based Model (left) and Algorithm (right).

(Figure 2, Function ε) is introduced following Silverman's approach described in Section II. It considers both the limiting effect and the activating effect of stress on performance. Depending on the current strain value, the agent can behave according to five different coping strategies (see Figure 3), which determine the number of ticks required to complete an order.

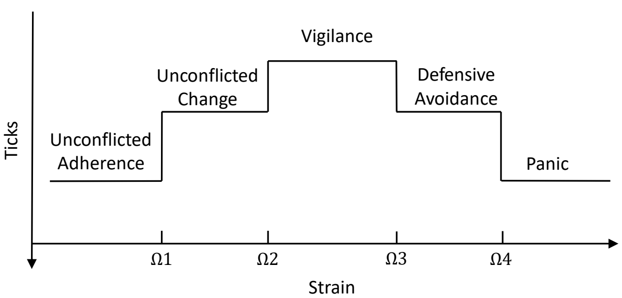


Figure 3. Performance Moderator Function: Inverted-U shaped [17]

The strain thresholds $\Omega1$ to $\Omega4$ are derived from Silverman's work [17]. The required number of ticks ($ticks$) is calculated using following Function ε depending on the default number of ticks ($ticks_{def}$), which an agent at least needs to fulfil a given order:

$$\varepsilon\colon ticks = \begin{cases} ticks_{def} \cdot 1.3, & strain \in [0.0, 0.1] \\ ticks_{def} \cdot 1.15, & strain \in]0.1, 0.25] \\ ticks_{def}, & strain \in]0.25, 0.75] \\ ticks_{def} \cdot 1.15, & strain \in]0.75, 0.9] \\ ticks_{def} \cdot 1.3, & strain \in]0.9, 1.0] \end{cases} . \quad (9)$$

Following the example introduced in Section I, $performance$ is measured using the ratio of $FinishedOrders$ to the overall number of $Orders$ (Equation (10)).

$$performance = \frac{|FinishedOrders|}{|Orders|} \quad (10)$$

The algorithm in Figure 2 shows the BDI control cycle that determines the agent's behavior formation process. First, the internal states as well as a variable determining the next action to perform are initially set (lines 1-4). Based on the general BDI architecture, the agent's behavior in our model is formed by passing various phases that consider and construct the mental states. These can be divided into *react*, *decide*, and *execute* (see [44]). In *react* (*belief-revision-function (brf)*), the agent processes perceived information and updates its beliefs (B) about the current situation and intrinsic states. In *decide*, based on the updated beliefs and the agent's desires (D), the agent updates its intentions (I). Considering these, an action to perform next is chosen, before it is carried out in *execute*.

The agent's beliefs B are composed of the four sets $JobDemands$, $JobResources$, $PersonalResources$, and $IntrinsicStates$ (see Equation (11)). Based on the beliefs B that are generated and updated in *react*, the agent decides for an unfinished order to proceed with next, to reach its sole desire, i.e., completing all orders.

$$\begin{aligned} B = {} & JobDemands \bigcup JobResources \bigcup \\ & PersonalResources \bigcup IntrinsicStates \\ \Rightarrow B = {} & \{difficulties, remainingTime, skillRank, \\ & motiveSuccess, motiveFailure, \\ & selfEfficacy, strain, motivation\} \end{aligned} \quad (11)$$

In the *decide* phase, the agent decides for a difficulty $diff$ of orders it wants to process next. For this, the agent computes motivation values for each remaining difficulty and decides for a difficulty with the highest motivation and, thus, for the intention I to commit to (see Figure 2, Function γ). Consequently, *decide* is only processed if the current order has been completed in the preceding time step. The chosen difficulty (I) is used to pick the next order ($action$) to complete, which is then performed in *execute*. Starting from the initial value, the $skillRank$ adapts in dependence to the values of $motivation$ and $strain$ (decrease or increase of value) and to the current order's difficulty (strength of decrease or increase of value) (Figure 2, Function δ). Furthermore, based on the expected time needed to complete an order in comparison to the actual time that it takes for the agent, the value of $selfEfficacy$ is modified. If the agent is performing as expected (defined by thresholds $\Omega 2$ and $\Omega 3$) the value is slightly increased and if the productivity strongly deviates it is slightly decreased, so if strain is transcending the thresholds $\Omega 1$ and $\Omega 4$ (see, e.g., [42]). After each time step t, the $performance$ is used to update the orders' difficulties.

IV. Simulating Work Performance: Experiments and Results

In this section, the agent-based model of work performance is evaluated based on a case study and compared to previous simulation results from [1]. First, the main findings from the initial paper are presented. Then, the simulation setup for this article's model is defined and the additional model input variables are specified. Finally, the findings are presented and the assumptions derived from these are discussed.

This article's model presents an extension of the agent-based model of work performance defined in [1]. The authors specified the agent's initial $skillRank$, the $difficultyRange$, which represents the range of difficulties, orders in the experiment can have and the available $timeCapacity$ (see Table I). Furthermore, the number of $Orders$ is set to 20 and the maximum value of the agent's $skillRank$ is fixed at 10. After 30 replications of each defined experiment, Figure 4 shows the results separated by the variation of $timeCapacity$, whereas the x-axis depicts the initial input value of the variable $skillRank$. The y-axis shows the performance of the agent. The boxplots' colors represent the orders' $difficultyRange$, darkgrey represents a range of 1-3, lightgrey for 1-5, and white for a range of 3-5.

TABLE I.
SCENARIO SPECIFICATION ORIGINAL EXPERIMENT [1].

timeCapacity		*difficultyRange*		*skillRank*
smallTimeCapacity		1-3		1
suitableTimeCapacity	×	1-5	×	5
highTimeCapacity		3-5		10

The authors discuss three main findings as well as several observations from the experiment results:

1) An increasing $timeCapacity$ leads to increased performance: In a scenario with a $high$ $timeCapacity$, the agent is capable to complete all or a majority of orders in the given time, without considering the respective $skillRank$.
2) A low $skillRank$ does not equal a high performance: The performance is represented via the ratio of finished orders. Agents with a $skillRank$ of 1 tend to choose orders of a high difficulty and, thus, finish less orders in summary because of the adaption in $skillRank$ after a bad performance and the respective $strain$ and $motivation$.
3) A $difficultyRange$ of 3-5 leads to the worst performance: Thus, the mean performance throughout the simulation runs is 0.52, whereas ranges 1-3 and 1-5 lead to mean values of 0.69 and 0.63. This leads to the conclusion that a balanced order compilation is more purposeful as it, on the one hand, demands the worker enough to keep his interest and, on the other hand, allows for phases of lower concentration while completing orders of a low difficulty level [45].

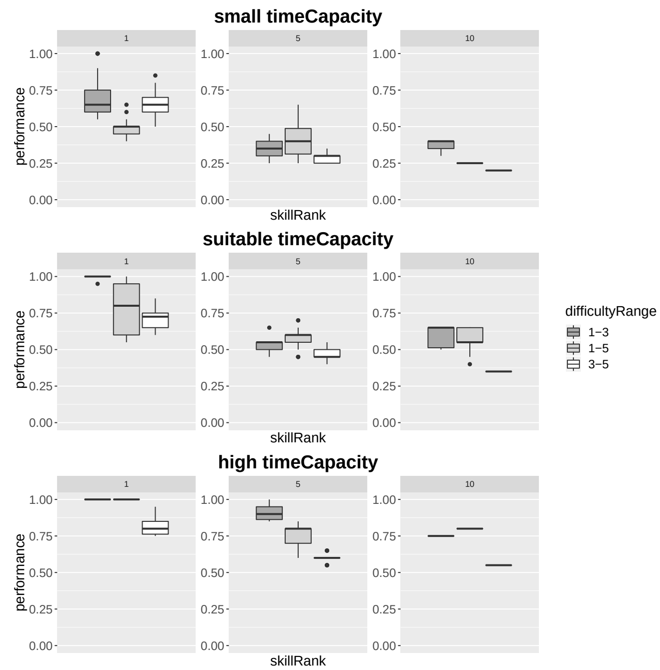


Figure 4. Experimental results in the original experiment [1]. Performance depending on $timeCapacity$, $skillRank$, $difficultyRange$.

Furthermore, the authors address some exceptions to their main findings, namely:

- In $small$ $timeCapacity$ and $skillRank = 1$ the performance is worse for the order difficulties in a range of 1-5 as for 3-5,
- in $small$ $timeCapacity$ and $skillRank = 5$ as well as in $suitable$ $timeCapacity$ and $skillRank = 5$ or 10 the performance is worse for the order difficulties in a range of 1-3 as for 1-5 and
- a $skillRank$ of 10 leads to extreme performance measures without outliers.

The first two exceptions are explained by the way $strain$ and $motivation$ as well as choosing a next order difficulty are defined in the model. In both exceptions, the agent chooses high difficulties first which, caused by the progressing time, leads to increasing $strain$ and decreasing $motivation$ and ultimately to less finished orders. The third exception is due to a low $motivation$ value resulting from the high $skillRank$ as well as the restriction of the model to generate a higher $skillRank$ than 10. With decreasing $remainingTime$, the $strain$ value increases and the $skillRank$ is not allowed to improve.

A. Simulation Setup

In this article, the agent-based model of work performance from [1] is extended by making use of a specific motivation theory, the achievement motivation defined by Atkinson as well as the effect of $strain$ on the ticks needed to complete an order (see Section III). To be able to compare the simulation outcomes of the extended model and the basic model, further variable specifications need to be mentioned.

The adapted model in Section III introduces the set of $PersonalResources$ as an additional input of the JDR model. The set composes of the variables $motiveSuccess$, $motiveFailure$ and $selfEfficacy$. To include these parameters, the scenario specification in Table I needs to be adapted. Following [46], a possible way to obtain these person-specific motives is a questionnaire containing of 10 items, which can take values of 1 to 5 each. Here, five items refer to the motive for success and five belong to the motive for failure. Thus, $motiveSuccess$ and $motiveFailure$ each can take values in the interval [0,20]. In the scenarios defined in this experiment, these variables vary in steps of five, leading to a set of [5, 10, 15, 20]. Equally, the value for $selfEfficacy$ can be derived with a questionnaire (see e.g., [47]), and in this model can take values between 0.25 to 1.0 in steps of 0.25. Accordingly, 1728 experiments are defined ($timeCapacity$ (3) $\times$ $difficultyRange$ (3) $\times$ $skillRank$ (3) $\times$ $motiveSuccess$ (4) $\times$ $motiveFailure$ (4) $\times$ $selfEfficacy$ (4) = 1728). Additionally, the value of $ticks_{def}$, that is needed in PMF (see Equation (9)) to determine the productivity, is set to the agent's current $skillRank$, as this variable was defined as the number of ticks needed to complete one difficulty of an order. Because the model includes stochastic processes each experiment is repeated 30 times.

B. Simulation Results and Discussion

The simulation results in Figure 5 show the experimental results separated by $timeCapacity$. As in Figure 4, the x-axis shows the initial input of $skillRank$ and the y-axis shows the output of the agent's performance. The boxplots separate by color in the three available difficulty ranges 1-3 (darkgrey), 1-5 (lightgrey) and 3-5 (white). The overall tendencies described earlier in this section remain for the adapted model presented here, too: With an increasing $timeCapacity$ the agent's performance increases. Hence, the mean performance value increases for $skillRank$ of 10 and $difficultyRange$ of 3-5 from 0.16 in $small\ timeCapacity$ to 0.47 in a scenario with a $high\ timeCapacity$. Second to that, the $difficultyRange$ of 3-5 leads to the worst performances of a mean value of 0.42, whereas ranges of 1-3 and 1-5 lead to performance means of 0.73 and 0.64.

Besides these general tendencies, the experiment output shows some deviations from the initial paper. As stated above, the $difficultyRange$ affects the performance in a way that high difficulties (3-5) lead to the worst performances. In contrast to the findings in [1], this effect is present in each scenario separated by $timeCapacity$ and $skillRank$. A reason can be found in the definition of $motivation$ of the original model that is ultimately dependent on the input parameters (e.g., $remainingTime$). Based on that calculation of $motivation$, in some scenarios the agent always chooses the highest difficulty available. In comparison, $motivation$ here is extended by the personal motive profile of the agent. Agents with a higher $motiveSuccess$ as $motiveFailure$ tend to decide for orders with a medium probability of success (e.g., in a range of 1-5 the difficulty 3 is predominantly chosen), whereas an agent with a higher value of $motiveFailure$ than $motiveSuccess$ results in choosing border options (difficulties that are very likely or very unlikely to complete successfully). This leads to a higher distribution in the choice for options for each of the defined $difficultyRanges$ and thus to a decrease in performance from the ranges 1-3 over 1-5 to 3-5.

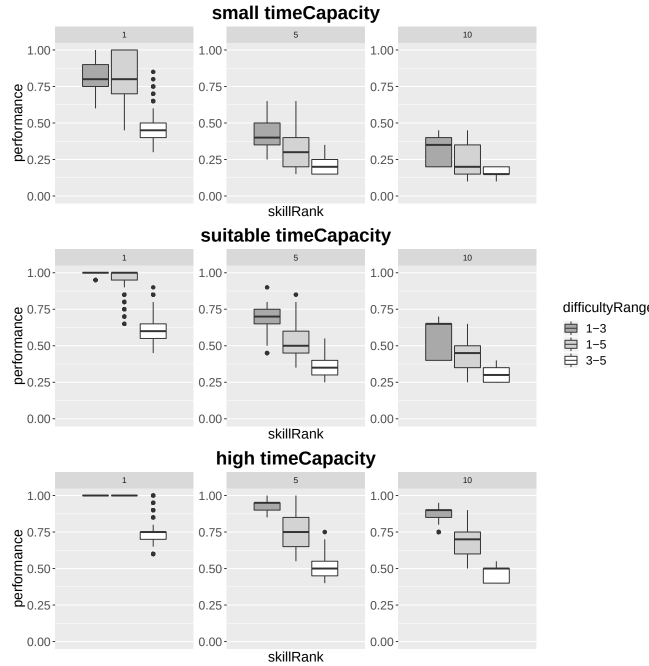


Figure 5. Performance depending on $timeCapacity$, $skillRank$, $difficultyRange$.

Finally, a $skillRank$ of 10 produces a less uniform picture than in the original experiments. The values of the minimal and maximal performances of these agents span a wider value range of at a maximum 0.3 in a $suitable\ timeCapacity$ and $difficultyRange$ of 1-3. Overall, a $skillRank$ of 10 still produces the worst performances in each scenario, but especially in $high\ timeCapacity$, the comparison of the resulting performance of the current model and the one in [1] shows an increase of performance of 0.2 at a maximum. As is defined in the scenario specification at the beginning of this section, the maximum $skillRank$ is set to 10. Therefore, this value can not deteriorate due to the agent's poor performance. On the contrary, the skill of an agent can be improved based on a decreased $strain$ and increased $motivation$ value. Furthermore, the presence of different motive profile distributions leads to a higher spread in a choice for difficulties. Additionally, agents with an equally distributed motive profile randomly choose one of the orders, regardless of the respective difficulties [4, p.99]. As each of these decisions influences the agent's overall performance, due to the adapting variables $strain$ and $motivation$, the observed behavior can be explained.

To investigate the effect of different motivation profile distributions, Figure 6 shows the agent's performance (on the y-axis) separated by the available $timeCapacity$ (x-axis). The expressions *HighLow*, *HighHigh*, *MediumMedium*, *LowLow* and *LowHigh* refer to the composition of the agent's motive profile in the sequential order $motiveSuccess$ followed by $motiveFailure$. *HighLow* means that the agent under investigation has a high value of $motiveSuccess$ (here: 20), while $motiveFailure$ has a low value, e.g., of 5 (cf. Table II). The two motive profiles *HighHigh* as well as *LowLow* are not completely equally distributed. This is based on the fact that equal values completely negate the effect of the respective other, which leads to a complete random selection of

TABLE II.
SPECIFICATION OF MOTIVE PROFILES.

Motive profile	$motiveSuccess$	$motiveFailure$
HighLow	20	5
HighHigh	20	15
MediumMedium	10	10
LowLow	5	10
LowHigh	5	20

difficulties. Therefore, in deviation from the experiments in, e.g., [33] or [48] a fifth motive profile *MediumMedium* was added, that represents this equally distributed motive profile. A profile defined as *HighHigh* is thus characterized as having a maximum value of $motiveSuccess$ and the second highest value of $motiveFailure$. For the corresponding profile *LowLow* the value of $motiveFailure$ is set to the higher value in comparison to $motiveSuccess$.

Throughout the simulation runs, a motive profile of *HighLow* shows the best performance results with an overall mean of 0.63. An agent's best performance can be found at $high\ timeCapacity$ with a mean value of 0.79 and a maximum of 1. In all scenarios, this motive profile is capable of reaching a maximum performance by completing all available orders. An agent with a high $motiveSuccess$ and a low $motiveFailure$ tends to choose a medium order difficulty (with a medium probability of success), which could lead to a relatively constant value of $strain$, since the progressing time is neither very large nor very small. This, in turn, influences the time needed for the next order defined by the PMF.

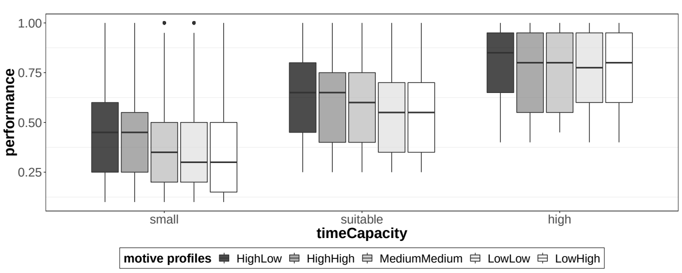


Figure 6. Performance depending on motivation profiles.

In contrast to this, the profile *LowLow* produces the worst performance with a mean of 0.58. Compared to the motive profile *LowHigh*, which is often at a similar level, the mean value only slightly differs from it with a distance of 0.01 at $high\ timeCapacity$ (*LowLow*: 0.76 and *LowHigh*: 0.77). *LowHigh* leads to extreme decisions due to the high proportion of $motiveFailure$. Hence, in situations with time pressure, the $strain$ value either increases because the agent decides for a difficult order that demands a long processing time or slightly decreases because the agent chooses the other extreme with an easy and less time consuming order. This may explain the wider output space for this profile in $small\ timeCapacity$ in contrast to *LowLow*. On the other hand, in a scenario with enough time ($high\ timeCapacity$) an agent with a *LowLow* profile chooses order difficulties more randomly, which can lead to less finished orders. For the profile *LowHigh* the agent more probably relies on an order difficulty of 3, as with decreasing time the subjective probability of success might shift to this difficulty as time progresses (see Equation (6)).

An agent that has a high $motiveSuccess$ as well as $motiveFailure$ possesses the second-highest performances throughout the presented scenarios, whereas the mean performance values duplicate those of *HighLow* in a small as well as suitable $timeCapacity$. With such a profile, the agent chooses more randomly but with a shift towards the kind of decision-making of *HighLow* due to $motiveFailure = 15$ rather than 20 (as it is the case in *MediumMedium*).

The motive profile *MediumMedium* neglects the impact of the two motives as they neutralize the impact of each other (see Equation (7)). This agent chooses a difficulty based on a random manner. This leads to a medium overall performance of 0.60 and a mean of 0.78 in $high\ timeCapacity$. Here, the performance is just as high as with a profile of *HighHigh*.

V. Conclusion and Future Work

In this article, an extended agent-based model of human work performance is presented that makes use of the JDR model and was based upon the model presented in [1]. A decision-behavior based on the general BDI architecture was introduced and adapted to the processes defined in the JDR model including a representation of strain and motivation as well as the mutual influences of job resources, job demands, personal resources and intrinsic mental states. The motivation is based upon a theoretical foundation of Atkinson's achievement motivation and extended the definition of the original model mentioned before. Within several experiments, the impacts of the input variables $timeCapacity$, $skillRank$, and $difficultyRange$ on the overall performance of the agents were analyzed. Furthermore, the impact of different motive profiles was investigated. The experimental results revealed that the model is capable of producing realistic working performance including intrinsic processes of strain and motivation. The extension of the original model by achievement motivation and PMF allows for a more sophisticated and realistic representation of performance. Hence, different motive profile distributions lead to a decision behavior similar to empirical findings in literature [4, p.99].

In future work, we plan on conducting empirical experiments with workers in a controlled working environment (see, e.g., [49]). In these experiments, we aim at identifying stressors and resources and measure individual reactions like strain, especially by biosignals (see, e.g., [49] [50] [51]). Additionally, Atkinson's achievement motivation relies on three general determinants, whereas one of them (incentives A_s and A_f) can be fully represented by the probability of success. The motive of success as well as the motive of failure can be measures by using a *revised Achievement Motive Scale (AMS-R)* [46]. Furthermore, the general self-efficacy of a person can be measured using the *Allgemeine Selbstwirksamkeitskurzskala (ASKU) (General Self-efficacy Short scale)* [47]. To measure the individually perceived workload of human test persons, the *NASA-TLX* test could be used [52]. By using these measurement scales, the subjectively perceived situation of the respective test person can be included in the model.

Furthermore, we need to improve the existing model in several respects. The model shows the best results for orders within difficulty range 1-3. As discussed in Sec. IV-A, a varied order difficulty should lead to best performances, due to a balanced ratio of exertion and relaxation [45]. To receive a more realistic representation, the effects of missing challenges could be included. A difficulty range of 1-3 would thus theoretically lead to a worse performance than a range of 1-5. The agents' performance should be measured by showing how much of the workload has been completed. Thus, not only the proportion of finished orders, but the difficulties of the finished orders should be taken into account, too. Additionally, the effect of $motivation$ as well as the motive profiles on persistence could be investigated [4, pp.110ff] [29]. In this context, the effect of orders that are not fully or incorrectly made could be examined. Furthermore, working in teams should be included in the model. This could result in improved organizational outcomes as poor performances of some members may be offset by good performances of others by the interaction.

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