Simulating Strain and Motivation in Human Work Performance: An Agent-Based Modeling Approach Using the Job Demands-Resources Model

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***Abstract*—Even though the relevance of the "human factor" for 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 as *strain* and *motivation* can influence the human workers' performance and thus the organizational outcome. This paper proposes an agent-based model of human work processes with respect to these intrinsic states. To this end, the well-established job demands-resources model is utilized. Experiments are presented that outline the model's capability to produce plausible results concerning the human work performance and the mutual influences between job demands, resources, and the intrinsic mental states of strain and motivation.**

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

I. Introduction

Peoples' workplaces are constantly changing, especially as digitalization progresses. This digital revolution should be oriented towards employees' needs. Yet, people often subordinate to IT systems and thus disempower themselves [1]. For example, a scheduling system in a call center distributes calls without considering inidividual needs. The consequences are not only physical but also psychological strains like burn-out.

Digital change should not be rejected generally, as it has potentials for making 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 such as 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, distractions, 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 to the total number of orders. While machines usually do not show performance fluctuations when being confronted with an immense workload or time pressure, human workers are often susceptible to such influences. Intrinsic processes of motivation and strain are driving factors influencing their performance [2]. Still, human beings are often only considered as workforces without individual intrinsic needs during the planning and implementation of work processes, 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 increase performance and organizational outcome, individuals and their intrinsic needs must be represented individually and realistically within a computer system.

This paper aims at modeling human work performance formation. Here, a special focus lies on representing the intrinsic processes of strain and motivation. For modeling workers, Agent-Based Modeling (ABM) and especially the Belief-Desire-Intention (BDI) architecture of practical reasoning [3] is proposed, as it has established in modeling of human cognitive decision-making and behaviors [4]–[7]. Therefore, in Section II, related work on the field of modeling strain and motivation in ABM is discussed. Furthermore, the flexible Job Demands-Resources model (JDR 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 [8]. Subsequently, an agent-based model of work performance is introduced in Section III. In Section IV, several experiments are conducted 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 work processes, e.g., Enterprise Dynamics or Anylogic [9], which focus strongly on the processes and functionalities of machines. These frameworks often neglect to represent human resources sufficiently, so that the "human factor" can not 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 the human being. Here, agent-based models that utilize sociological and psychological behavioral theories have been established [10]–[12]. This paper introduces an agent-based model of human work performance including the intrinsic processes of strain and motivation, that 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.

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. An integrated strain value is calculated as a function of the event strain, time pressure and exhaustion, on the basis of which different coping strategies are initiated [13]. Duggirala et al. apply this conceptual model in an agent-based simulation of strain at work [14]. 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 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 [15]. Nevertheless, 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. have investigated system dynamics of strain to model agents by representing strain as causal loop diagram, and stock-flow diagram [16]. 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 [17]. A broad field of research is crowd simulation, in whose models strain is also considered, (e.g., [18]). Strain influences behavior generation mainly reactively, but this is due to the frequent application context of emergency evacuations, where deliberative behavior is less important.

However, 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., [19]).

In ABM regarding 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 [20] as well as Silverman [13]. In these models, the agent's actions focus primarily on covering deficiency and growth needs, and mostly neglect environmental influences on motivation development. As already mentioned above, the BRIDGE architecture also uses this theory to define an agent's goals and desires [17]. 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 [21], [22]. These models 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 recognised (see, e.g., [17]).

A well-known model that both considers stressors (stimuli), resources, and the influence of motivation, is the JDR model by Demerouti et al. [8]. The JDR model is an empirically evaluated model, that has been used flexibly in a variety of scenarios, such as to predict job burn-out [23], organizational commitment [24], connectedness [25], and work engagement [26]. The model consists of two essential 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.

During the motivational process, job resources are main predictors for motivation and engagement. Whereas job demands consume energetic resources and in this way cause strain, job resources fulfil basic psychological needs and therefore 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. The model was extended several times by the authors, in particular to include personal resources and job crafting, and was maturated into a theory based on several meta-analyses [2]. Nevertheless, this paper uses the original model to reduce the complexity of the simulation significantly and focus on the prediction of job performance [28].

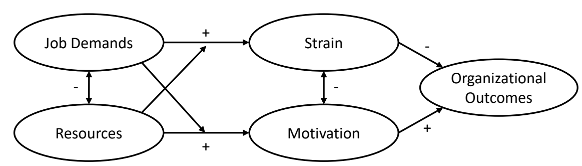


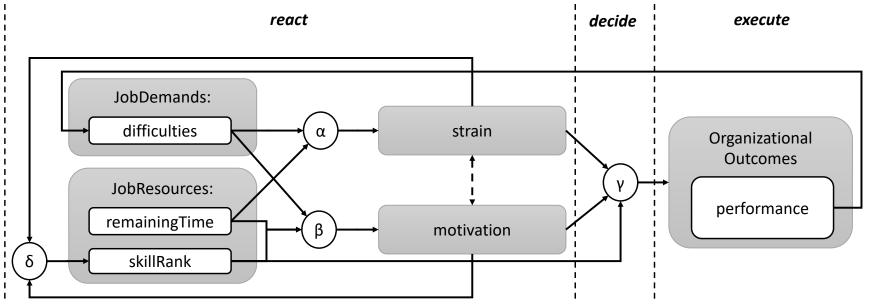
Figure 1. Job Demands-Resources Model [27].

III. An Agent-Based Model of Work Performance

In this section, an agent-based model of human work performance is introduced that coombines the BDI architecture and the JDR model presented in Section II. The workers are modeled based on the BDI architecture of practical reasoning [3]. It organizes goals (desires), information about the environment and the own conditions (beliefs), and action-oriented measures (intentions) into mental states. To this end, we make use of the JDR model presented in Section II. By utilizing both models a strict modularization is made, which can be easily extended and exchanged against further 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 $JobDemands$ and $JobResources$, that impact internal processes forming $strain$ (α) and $motivation$ (β). These, in turn, determine the agent's action and thus the organizational outcomes (here: equal to individual performance).

Referring to the factory example introduced in Section I, the agent is confronted with a set of $Orders$, that are composed of the two sets $UnfinishedOrders$ and $FinishedOrders$ (Equation 1). Initially, $|Orders|$ is equal to $|UnfinishedOrders|$. If

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Algorithm: BDI Control Cycle

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

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 the order. Because job demands represent stressors as workload (see Section II) the variable $difficulties$ is introduced, which represents the agent's workload on one working dayand is composed of the sum of difficulties $diff_i$ for each $i \in UnfinishedOrders$ (Equation 2).

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

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

One working day is defined by a number of time steps $totalTime \in \mathbb{N}$, whereas the running variable $t \in \mathbb{N}$ 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 $skillRank \in \mathbb{N}$, thus 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 $JobResources$.

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

Considering the JDR model, job demands initate 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. Therefore, $strain$ (Figure 2, Function α) represents the experienced pressure as the ratio between the unfinished orders $difficulties$ and the $remainingTime$ to complete them (Equation 4). $Motivation$ is formed in a process that is mainly influenced by job resources. Here, job demands reduce the generation of this variable. Hence, $motivation$ (Figure 2, Function β) implies the capabilities of the agent and represents whether the agent is able to perform the open orders in the given time based on its own $skillRank$ at time t (see Equation 5). If the $motivation$ value is high, the agent is confident to complete the whole set of unfinished orders in the remaining time. $Strain$ and $motivation$ represent the agent's set of $IntrinsicStates$. Both values are normalized to $[0, 1]$ relative to the minimal and maximal possible values of the variables.

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

$$motivation = \frac{remainingTime}{skillRank_t * difficulties} \tag{5}$$

Following the example introduced in Section I, $performance$ is measured using the ratio of $FinishedOrders$ to the overall number of $Orders$ (Equation 6).

$$performance = \frac{|FinishedOrders|}{|Orders|} \tag{6}$$

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 initally 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 build the mental states. These can be divided into *react*, *decide*, and *execute* (see [29]). 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 three sets $JobDemands$, $JobResources$, and $IntrinsicStates$ (see Equation 7). 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 (completing all orders).

$$\begin{aligned} B &= JobDemands \bigcup JobResources \bigcup IntrinsicStates \\ &\Rightarrow B = \{difficulties, remainingTime, skillRank, \\ &\qquad strain, motivation\} \end{aligned} \tag{7}$$

In the *decide* phase, best choices for both values of $strain$ and $motivation$ are defined. Hereby, a mapping of $UnfinishedOrders$' difficulties $diff_i$ to the respective values takes place, whereas a high $motivation$ value leads to a choice of a high difficulty. A high value of $strain$ generates a low difficulty as the best possible choice. These best choices serve as boundaries to decide for the intention I to commit to, which is done on a random basis (see Figure 2, Function γ). Consequently, *decide* is only processed if the current order has been completed in the preceding time step. The

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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). 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. Therefore, first the simulation setup is defined and the model input variables are specified. Subsequently, the findings are presented and the assumptions derived from these are discussed.

A. Simulation Setup

In order to simulate human work performance, the variables introduced in Section III are specified. The number of orders $|Orders|$ is set to 20 and one agent is simulated at a time. Because it is theorized that the workers abilities do not vanish completely due to an immense workload, the $skillRank$ cannot exceed a maximum of 10. Equally, the skills of an agent can not decrease infinitely and the maximum decrease of the $skillRank$ is to 1, so that at least one time unit is needed to complete one difficulty level of an order. Each ten time units, the values of $strain$, $motivation$, and $skillRank$ are updated.

To test the impacts of input variables on performance, 27 scenarios are defined and the output behavior of the model is analyzed (see Figure 3). Each scenario is defined by an element of the cartesian product of $timeCapacity$, $difficultyRange$, and $skillRank$ (see Table I). The agent's inital $skillRank$ is varied between a minimal (1), medium (5), and maximum value (10). The orders' $difficultyRange$ encompasses the range 1-5 (complete difficulty range), 1-3 (low difficulty), and 3-5 (high difficulty).

TABLE I.
SCENARIO SPECIFICATION.

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

$TimeCapacity$ is defined by a $small$, $suitable$, and $high\ timeCapacity$ and depicts the time available to perform the set of $Orders$. The three values of $small$ (405) and $high\ timeCapacity$ (135) to complete the orders center around a suitable amount of time units (270). The reference value of 270 time units arises from the time an agent persistently having a $skillRank$ of 5 would need to complete all orders with difficulty range from 1-5. Because the model makes use of random number generators, it is repeated 30 times to neglect possible effects.

B. Simulation Results and Discussion

The diagrams of Figure 3 show the experimental results seperated by the variation of $timeCapacity$. The x-axis depicts the initial input value of the variable $skillRank$. The y-axis shows the performance of the agent, thus, the ratio of finished orders compared to the overall number of orders. 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. In the following, three main observations regarding the work performance are discussed.

First, the results show that with increasing $timeCapacity$, the agent is able to finish all or a majority of orders. Where $small\ timeCapacity$ shows a minimum performance value of 0.2, this value increases to 0.55 in $high\ timeCapacity$, so that even an agent with a $skillRank$ of 10 is capable of completing half of the orders. Theoretically, an agent with $skillRank$ of 1 should be able to complete the whole set of orders even in the $small\ timeCapacity$ scenarios. Nevertheless, this mainly occurs in a $high\ timeCapacity$ scenario. The simulation output does not reveal the difficulties of the finished orders. Agents with a small $skillRank$ tend to choose orders with a high difficulty due to a high $motivation$ value. Thus, the agent may finish these high difficulty orders but has a worse performance due to an overall smaller number of finished orders. Agents with a $skillRank$ of 10, on the other hand, tend to start with low difficulty orders which is why the number of finished orders differs less than expected from that of the remaining $skillRanks$. With increasing time capacity the choosing behavior becomes less important, because the agent still has enough time left to finish the remaining orders of small difficulty.

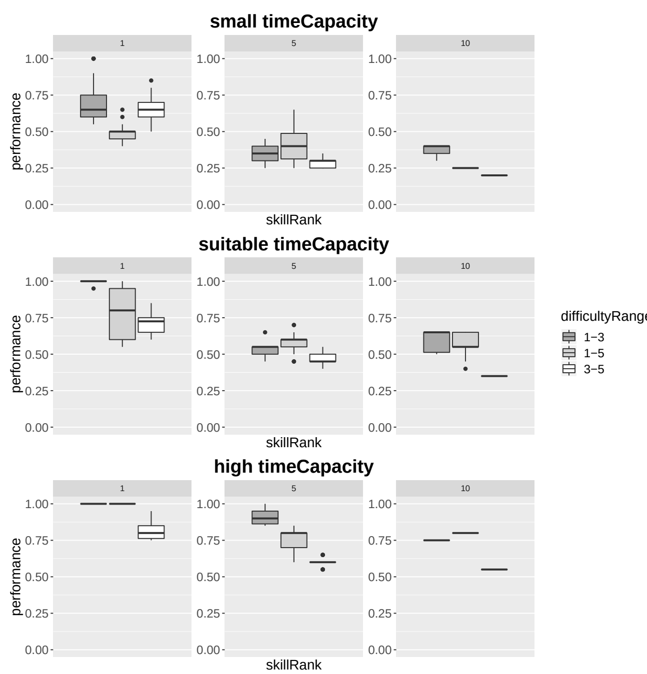

Figure 3. Performance depending on $timeCapacity$, $skillRank$, and $difficultyRange$.

The second trend observed is the influence of the $difficultyRange$ of orders on performance. The results indicate that a range of 3-5 leads to the worst performance. Thus, the performance mean throughout the simulation runs is 0.52, whereas ranges 1-3 and 1-5 lead to mean values of 0.69 and 0.63. Transferred to working life, a constant execution of difficult orders that afford a high level of exertion and concentration may lead to a low performance due to a heavy

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strain load. 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 [30].

Nevertheless, there are exceptions to this observation, as it can be observed in *small* $timeCapacity$ with $skillRank$ of 1 and 5 as well as in the suitable time capacity scenario with $skillRanks$ 5 and 10. A first exception is a worse performance for order difficulty range 1-5 than for 3-5 (*small* $timeCapacity$ and $skillRank = 1$). This can be traced back to the fact that the agent starts the simulation with a low level of $strain$ as well as a high $motivation$ value, due to the wider range of 1-5 and thus a smaller value of $difficulties$. In contrast, a second exception intimates a worse performance for range 1-3 than for 1-5 (*small* $timeCapacity$ and $skillRank = 5$; *suitable* $timeCapacity$ and $skillRank = 5$ or 10). The agents in these scenarios start with a relatively low $motivation$ due to the comparably high value of $skillRank$. However, the $difficulties$ absolutely define which order is chosen first. Therefore, 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 range of order difficulties should thus be adapted to the available time as well as the agent's skills in order to reach the best results.

A third tendency refers to the influence of the input $skillRank$ on performance. In contrary to the remaining values, a $skillRank$ of 10 tends to lead to extreme performance values without any outliers. Especially concering $difficultyRange$ 3-5, the agent is not capable of completing more than 20% of the existing orders. This 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. This covers findings in psychology that investigate the connection between high strain at the workplace to burn-out and thus a low job performance [31].

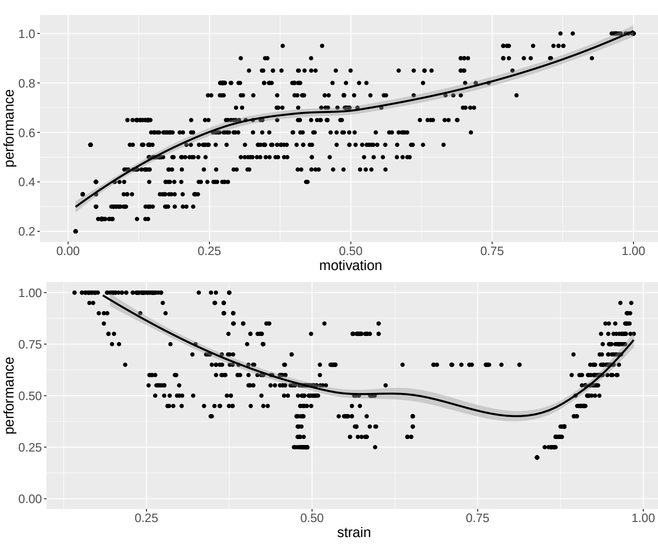

Figure 4. Performance depending on $motivation$ and $strain$.

The diagrams in Figure 4 depict the impact of the values of $motivation$ and $strain$ (x-axis) on the agent's performance (y-axis). The data points represent the mean value of the variables $motivation$ and $strain$ throughout one simulation run (x-axis), whereas performance refers to the status at the end of a simulation run (y-axis). The diagrams undermine the aforementioned tendecies. With increasing mean $motivation$ throughout the simulation runs, the agent's performance increases almost lineary. Each scenario with a mean $motivation$ value of 1.0 leads to a perfect performance, whereas a value $<= 0.25$ results in a mean performance of 0.42 and a best value of 0.75. The agent's $strain$ value shows a u-shaped impact on performance. A low $strain$ level ($<= 0.25$) leads to a high performance mean of 0.99. Subsequently, the curve drops to a minimal mean performance of 0.2 at a $strain$ level of 0.84, before it starts to increase again to a mean value of 0.86 at a $strain$ level of 0.98. The upswing of the curve at higher $strain$ values is rather unexpected, since there is a linear calculation of the variable. Once again, the diagram does not show us the difficulties of unfinished orders, but the proportion of finished orders in comparison to all orders. Hence, if the agent is heavily strained during the entire simulation run, its $skillRank$ probably rises fast to the highest possible value and remains there for the rest of the run. This causes the agent to favor low difficulty orders, which increases the value of $motivation$ and performance.

V. Conclusion and Future Work

In this paper, an agent-based model of human work performance was presented that makes use of the JDR model. 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, and intrinsic mental states. Within several experiments, the impacts of the input variables $timeCapacity$, $skillRank$, and $difficultyRange$ on the overall performance of the agents were analyzed. The experimental results revealed that the model is capable of producing realistic working performance including intrinsic processes of strain and motivation. However, the model lacks reliable empirical studies to validate the model and the underlying relationships.

In future work, we plan on conducting empirical experiments with workers in a controlled working environment (see, e.g., [32]). During these experiments, we aim at identifying stressors and resources and measure individual reactions like strain, especially by biosignals. Furthermore, we need to improve the existing model in several respects. As mentioned in Sec. IV-A, a $skillRank$ of 10 leads to performance measures that indicate burn-out developing processes. In order to investigate at which point the agent is no longer able to perform, further experiments with more detailed parameter steps have to be executed. Hereby, possible intervention strategies to countermeasure this development could be tested. The model shows the best results for orders within difficulty range 1-3. As has been discussed in Sec. IV-A, a varied order difficulty should lead to best performances, due to a balanced ratio of exertion and relaxation. In order 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. Furthermore, working in teams should be included in the model. This could result in better organizational outcomes, as by the interaction, poor performances of some members may be offset by good performances of others.

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