Micromechanisms of Simulated Work: Translating Task-Level Demands into Organizational Strain

Veronika Kurchyna[1,2,4], Ye Eun Bae[1], Thomas Ellwart[3], Marco Schulz[1,2], Julia Birke[3], Johanna T. Paul[3], Jan Ole Berndt[1], and Ingo Timm[1,2]

[1] German Research Center for Artificial Intelligence, Cognitive Social Simulation
[2] Trier University, Business Informatics and AI I, Trier, Germany
[3] Trier University, Business Psychology
[4] Corresponding Author: veronika.kurchyna@dfki.de

Abstract. While Organizational Psychology typically emphasizes job-level characteristics, a social simulation perspective suggests that integrating empirically validated micromechanisms via feedback loops can significantly reinforce process resilience at a granular level. We introduce a prototypical process model integrating psychological constructs with empirical data. By addressing shortcomings identified during the modelling phase, it proposes an interdisciplinary research agenda, focusing on task-level measurements, team-level constructs, and the practical application of these findings. Beyond identifying mental health state as a key variable in operational resilience, the simulation results reveals significant potential for optimization by enhancing working conditions and reorganizing workflows to account for individual variability.

Keywords: Work process · Process simulation · Job demands · Job strains · Organizational Psychology · Social Simulation

1 Introduction

Human actors are central to sociotechnical systems, yet analytical approaches often treat human performance as an opaque variable. While Industrial and Organizational Psychology shows how job characteristics and human capabilities interact [2, 3], and how they influence process outcomes and psychological reactions [1], it usually remains at the job-level, overlooking the underlying task structure. Underrepresentation of task's characteristics can be problematic in complex or high-variability environments, especially where a fine-grained understanding of performance deviations is critical for diagnosing root causes of inefficient work and preventing cascading failures. Enhancing and maintaining resilience in workplaces thus requires knowledge of structural dependencies, process flows and an awareness of the psychological factors that function as vulnerabilities or buffers.

Process modelling offers an avenue for simulating work system resilience by embedding psychological insights into complex, temporally dynamic systems where interactions, feedback loops, and cascading effects can be explored. Since it is tasks—not jobs—that form the actual building blocks of sociotechnical workflows, micro-level (task-level) is important for both simulation and the design of sociotechnical systems [4]. To accurately predict work system resilience, simulations need to incorporate task characteristics, human capabilities, and their emotional, behavioural and emotional responses.

Despite the limited availability of methods tailored to task-specific approaches, Organizational Psychology can contribute validated measurement instruments, statistically grounded stress–strain relationships and theoretical models as basis, offering a foundation for future research. By embedding these constructs into process simulations, we can investigate the complex interplay between job demands and strains in order to mitigate potential bottlenecks in the process. The aims of the current study includes:

1. Present a prototype model based on Zeiner-Fink [5], wherein the Task Execution Reliability Model (TERM) of Leva et al. [6] is extended by adding a mental health indicator which is based on the findings on workplace mental health by Dettmers et al. [7].
2. Examine the observations made with currently available data and identify questions that lack sufficient empirical support.
3. Propose an interdisciplinary research agenda between simulation sciences and occupational psychology to move from high-level examinations towards explainable micromechanisms in short-term process analytics.

2 Psychological Background

Understanding sociotechnical processes requires analysis grounded in established psychological theories explaining how individuals and groups experience and respond to the conditions under which work is carried out. Psychological research demonstrates that human performance and health at work systematically fluctuate as a function of job demands, resources, and individuals' capacities to cope with these demands [3, 1]. This section outlines the key concepts and underlying framework of job demands, individual capabilities, and strain reactions used to assess and explain psychological impairment and mental health in the workplace, based on ISO 10075 [8] and Parker and Grote's study [1]. Based on these concepts and framework, a production process involving multiple roles is analysed and examined, with its structure introduced in the following section on concept.

At the individual level, theory distinguishes between demands placed on workers and their emotional response, termed strain reactions. *Psychological demands* refer to all identifiable external influences that affect individuals and have a psychological impact on them (e.g. work intensity, social support in the workplace, or the duration, timing and distribution of working hours). Demands should therefore be understood in a value-neutral manner. Some demands are categorised as stressors, meaning that they tend to increase the likelihood of negative strain reactions (e.g. monotony or psychological exhaustion). Others, however, may function as resources enabling activation like engagement and motivation. This duality of job demands is fundamental for capturing the human variability in process simulations. It enables the dynamic interplay of multiple job- or task-related factors and individual resilience, beyond the simplistic assumption that all kinds of demands are detrimental. For instance, autonomy, can mitigate the negative effect of work intensity, meaning that workers can better cope with intensive work when they have the feeling of autonomy and thus maintain their work performance [9].

There are different measurement approaches to quantify and evaluate job demands: Subjective Measures such as ISTA [10], WDQ [11] or FGBU [12] quantify job demands through the workers' self-reports while Objective Measures like TAG-MA [13] or TBS [14] apply standardises observation-interviews through experts to quantify the work place demands [13].

Psychological strain is the immediate impact of work demands on an individual (manifesting through physical and psychological changes). Strain reactions encompass emotions, cognitions and behaviours and may take both functional and dysfunctional forms. Dysfunctional strains describe experiences of stress and other indicators of health impairment. Functional strains take the form of activation/positive stimulation, which reflects that not all demands lead to detrimental outcomes. Appropriate levels of challenge can have energizing, constructive, or motivational effects on individuals [15]. For psychological strain reactions there are multiple measures: Objective Measures use physiological data like heart rate or health data while Subjective Measures capture different strain facets like psychological stress, monotony and exhaustion using self-report scales [16].

Earlier models postulate a complex relationship between demands and strain, while more recent models additionally incorporate individual capabilities to account for variability in responses. These individual characteristics include psychological factors (e.g. skills and experience) and conditions like health, age, and current state. Similar to demands, individual capabilities can both serve as a resource in dealing with demands and describe dysfunctional conditions. These capabilities can be assessed using instruments that capture work-related behaviour and experience (e.g. AVEM [17]) or through job crafting scales [18].

A major limitation for applying these measures in simulation models is that psychological constructs are typically measured at the job-level, without considering task-level aspects. Instruments such as the Work Design Questionnaire (WDQ) assess various job demands, both job stressors and resources, thereby offering a comprehensive profile of job characteristics [11]. While invaluable for organizational diagnosis, these measures do not usually differentiate between task types, even though workers encounter demands sequentially, moment to moment, as they carry out different activities. Likewise, task-level granularity is largely absent from the literature, and particularly with regard to strains as emotional responses to demands, sufficient data to support a solid empirical foundation for precise modelling are typically lacking.

3 Concept: A Manual Assembly Process

For the process modelling in this study, the exemplary assembly process is based on the framework proposed by Zeiner-Fink [5], illustrating how demands and strains are incorporated and how psychological factors related to mental health, task characteristics, and worker skills interact to influence task outcomes.

The Production Process is structured around four roles: Management, Pre-Assembly, Assembly, and Recycling. Across these roles, a set of recurring task types are defined: sending and receiving messages, producing components, checking availability, checking correctness, disassembling items and delivering/receiving products. Fig. 1 provides a summary: Management handles customer contact, PreAssembly generates intermediate materials, Assembly integrates all components into final products, and Recycling supports material distribution.

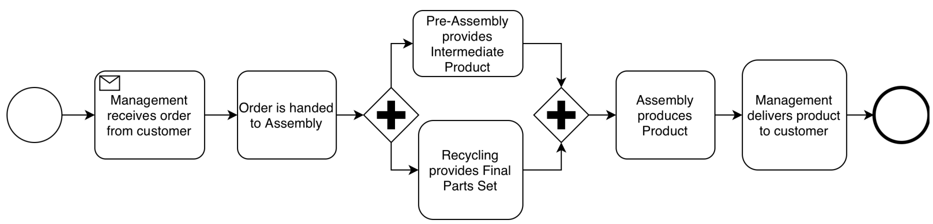

Fig. 1: Overview of production process

Management is the system's entry and exit point. Incoming customer requests are received, passed to assembly, then completed once the finished product has been provided. Assembly (shown in fig. 2) constitutes the central coordinating role of the workflow. If required parts are missing, Assembly dispatches appropriate requests to PreAssembly and Recycling depending on which components are needed. After confirming material availability, Assembly performs the final production step, transforming inputs into the completed product. The production step includes a correctness check to ensure that the output meets the required specificatons. Should discrepancies occur—e.g., missing components, incorrect sets, or failed quality checks—rework cycles are triggered. Due to its central function as integration hub, Assembly is the site where upstream fluctuations most visibly propagate: delays or errors in PreAssembly or Recycling manifest as waiting times, repeated checking, or additional coordination loads. Once Assembly successfully completes the product, it delivers the final item to Management.

PreAssembly creates intermediate components required for final assembly. Upon receiving an order from Assembly, PreAssembly first checks the availability of required raw parts. If necessary materials are missing, a message flow is triggered to request additional items from Recycling, temporarily halting production until the deficit is resolved. Once materials are confirmed, PreAssembly produces the relevant subcomponents. Analogously to the production step in

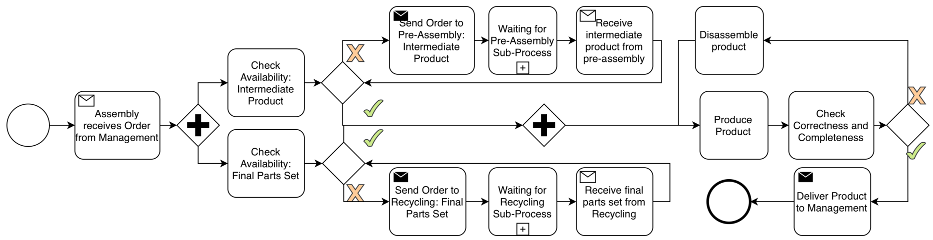

Fig. 2: Assembly process

Assembly, produced parts are checked and, if required, disassembled and reassembled. Successful components are delivered to Assembly for integration.

Recycling provides materials for other stations. Its principal tasks are to disassemble old items and prepare sets with required parts for the different products and intermediate components produced by PreAssembly and Assembly. The correctness and completeness check follows the same logic as other production tasks. Once sets are ready, they are delivered back to the requesting station.

Due to space constraints, detailed figures of recycling's and preAssembly's workflows were left out—they follow the same verification and communication loops as assembly, which serves as representative example of the other production processes. The process structure is characterised by numerous verification points, communication loops, and iterative correction steps—precisely the loci at which job demands and strains become operationally relevant. By examining the process through these roles and their associated task types, the model provides a foundation for embedding human factor dynamics into simulation.

Demands and Strains in Task Execution Success Rates To reduce the complexity and scope of the prototype and to put more emphasis on the aspects at task level, production tasks are put in a spotlight—the binary outcome of success or failure to fully meet requirements is an observable and measurable indicator. Based on Leva et al. [6]'s take on the Rasch-model, it is calculated whether a task (assembly or construction) is successfully executed or not, which is determined by the probability, $P_{success}$ as shown in 1, which builds upon Operator Capability OC and Task Complexity TC:

$$P_{success} = \frac{e^{OC-TC}}{1+e^{OC-TC}} \tag{1}$$

The task complexity, TC, is expressed through the characteristics of a given task, such as production for example, in terms of required skills or challenging circumstances, such as lack of available time. Empirical research rates the extent of the different difficulty dimensions on a Likert scale (in this case, 1 to 5). With product variance v, ergonomic workstation design ew, and the requirement for strictly adhering to procedure ap, TC is normalised to a [0,1] range as shown in equation 2.

$$TC = \frac{(v + ew + ap) - 3}{15 - 3} \tag{2}$$

The operator capability, OC, is composed of two parts: the 'raw' capabilities and skills of a person, as well as their mental health state, which moderates the extent to which their available skills can be leveraged. Based on Dettmers & Stempel [7], the probability of having psychological health impairment (PHI) is formed as a combination of perceived stressors and resources of one's working conditions. These subjective impressions are sourced from the FGBU [12] and can vary from one person to another, even when performing the same role in an organization or process. As such, the perceived stressors and resources are not entirely tied to the task itself, but to the executing worker as well.

In this study, three stressors are chosen to be taken into consideration: socio-emotional stress s_{em}, work intensity wi and a perceived lack of (or insufficient) communication c_l. On a positive note, a feeling of autonomy au and a sense of social support su can balance out the perceived stressors. Accordingly, PHI can be expressed as in eq. 3 with Z as an intercept denoting a base probability of psychological distress even without stressing factors and a, b, c, d, e as coefficients for weighting the constructs. The exact values we used based on Blackman et al. [19] are included in the model configuration section.

$$PHI = Z + (a * s_{em}) + (b * wi) + (c * c_l) - (d * su) - (e * au) \tag{3}$$

As an important change to account for empirical findings, some components of PHI interact and influence each other: low au intensifies the perception of wi, or, in the opposite case, high au alleviates perceived intensity. Likewise, low su acerbates s_{em} or reduces it in case of high su. In such cases, the values used for su and s_{em} in 3 should be adjusted accordingly to account for the empirically observed interactions between these variables.

For the assembly task, the following skills are selected as specifically relevant: coping skills related to pace or stress co_s, task experience t_e, manual skills ma, and the ability to accurately adhere to procedures ad_P. Combined with the moderating influence of PHI, eq. 4 shows OC normalized to [0,1]:

$$OC = \frac{(co_s + t_e + ma + ad_P) - 4}{20 - 4} * (1 - PHI) \tag{4}$$

The distinction between TC and OC as two separate factors facilitates a clearer view on work (or task) related aspects separate from influencing factors stemming from human heterogeneity. As shown in the results discussion, the separation of OC, TC and PHI opens up the possibility to examine possible corrective actions in a more nuanced and precise way.

4 Simulation Study and Outcome Analysis

As human performance outcomes depend on varying individual skills and mental health states, they differ from the output of idealised machines. This study thus examines how simulation results reflect individual-level influences on the process.

Model Configuration, Assumptions and Experiment Setup The model was implemented in the python-based simulation framework SimPy. The experiment used 100.000 replications, simulating 300 time units, with an order arrival interval of 6 time units. A single production action requires between 3 and 5 units of time. The process was initialised with one person in Management, 4 Workers in Pre-Assembly, 4 workers in Assembly and 3 workers in Recycling. Based on the serious game by Zeiner-Fink [5], the assembly task is characterised by the following dimensions of complexity on a 4-point Likert scale:

- **Variance**: while different components have slight variations in composition, the overall variety of tasks is rather low with a subjective estimate of 2.
- **Ergonomics**: the ergonomic requirements of the assembly task were rated as 2, requiring some manual dexterity during a seated activity with no heavy lifting or other physical labour involved.
- **Procedure**: for successful order completion, strict adherence to the procedure (order of assembly of individual parts) must be observed, which is why the maximum value of 4 is assigned to this trait, making it the main source of complexity in this example.

Perceived Demands (FGBU) [7]	**Mean**	**STD**
Socio-emotional stressors	2.15	0.84
Work Intensity	2.4	0.91
Lack of Communication	1.67	0.76
Autonomy	3.02	0.74
Social Support	2.95	0.81

Table 1: Parameters of job demands

With the production/assembly part being the primary activity in which outcomes (success or failure) can be observed immediately, those outcomes are employed as central indicator for employee performance instead of continuous variables like efficiency or quality. The characteristics of this task are the same for each station. The traits and subjective perceptions of workers are expressed on a 5-point Likert scale. Skills like coping with pace, experience, manual dexterity and the ability to adhere to procedures are initialised with a random integer in the permitted range. Since data is available for the FGBU items, the perceptions of demands follow a normal distribution function parametrised to empirically observed properties as shown in table 1 [7]. Lacking raw data, independent variables without explicit correlations had to be assumed.

For the computation of PHI, a linear function is used with coefficients taken from Blackman et al. [19], updating eq. 3 to eq. 5. The intercept of 11.15 is a base score for the probability of having PHI, without considering job related demands, derived from the sum of their intercepts. Likewise, the actual formula for success probability (eq. 1) is enriched with the empirical findings of Leva et al. [6] which incorporates the coefficients of their regression analyses to predict errors, inverted to fit the success rate instead as shown in eq. 6.

$$PHI = 11.15 + (1.08 * s_{em}) + (1.07 * wi) + (0.58 * c_l) - (0.85 * su) - (0.51 * au) \quad (5)$$

$$P_{success} = -(1.57751 * TC) + (0.4711 * (OC * (1 - PHI))) + 2.41163 \quad (6)$$

Mental Health, Skills and Task Outcomes Fig. 3 summarises the joint interaction of PHI, OC and the observed success rates for assembly tasks. As shown in the figure, capabilities and mental health both influence the outcome of tasks, with both conditions needing to be met for a high success rate. The transition from higher to lower success rates is not symmetric. The gradient is particularly pronounced for low-capability operators: in the upper rows of the heatmap, the decrease in success from low to high PHI probability is steeper than it is at high OC. This suggests that workers with lower skill levels are disproportionately sensitive to PHI.

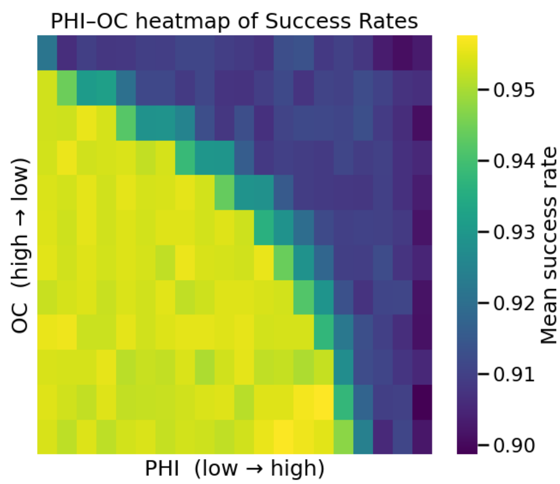

Fig. 3: Heatmap between mean success rate, OC and PHI

The heatmap demonstrates a monotonic, additive interaction: Excellent working conditions, expressed through a very low PHI, cannot compensate for a lack of skill and, likewise, high skill cannot be utilised effectively under mental duress. A similar relationship is made more explicit in Fig. 4, depicting the average success rate depending on OC-stratified by the probability of having PHI in quantiles. Success rate is also depicted in relation to OC, while the dots grouped based on their PHI probability range. Again, it is observed that excellent capabilities cannot compensate for very poor mental health in executing the task effectively and vice versa. At the highest values of PHI (between 0.75 and 1.0), large capability increases produce only modest gains. At the same time, those with lower PHI (between 0 and 0.75) converge at high capability, implying a diminishing return effect of stronger capabilities. The main difference is the slope of the curves, with good mental health accelerating the rising success rate of increasing skills.

Practical Implications of Prototype Results These observations have practical implications: as PHI scales OC by $(1 - PHI)$, its effect is immediate at the task-level, turning mental health into a potential dynamic moderator and access

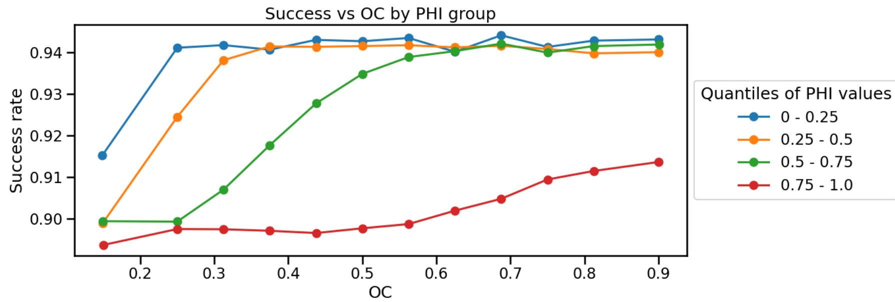

Fig. 4: Plots of success rates depending on OC, stratified by PHI quantiles

point for corrective measures. While the objective characteristics and requirements of a task often do not change over a short period of time and a worker's skills and characteristics are relatively stable over the long term, the improvement of perceived working conditions supports higher performance which can leverage existing resources and worker's skills.

The findings of Dettmers et al. [7] demonstrate that workers' subjective assessments of autonomy, communication quality, or emotional demands systematically shape their moment-to-moment experience of tasks. Thus, beyond reducing stressors, organizations can focus on strengthening their job resources—such as feeling of autonomy, clarity through enough communication, social support, and structured handovers of task. The results of our simulation illustrate precisely why such psychosocial interventions matter. The heatmap shows a distinct pattern: when operator capability is held constant, higher PHI (i.e., poorer perceived working conditions and thus experience of job strain) reliably reduces success rates. Conversely, improvements in PHI (or mental health) yield immediate performance benefits across task types. Notably, the gradient is steepest in the area representing low capability (OC) and high PHI, meaning that workers already at the boundary of their skills are disproportionately affected by deteriorating mental health, while standing to gain the most from improvements in working conditions. This makes psychosocial interventions not merely a matter of wellbeing, but also a targeted lever for reducing error likelihood precisely where the system is most vulnerable.

Poor mental health also dampens the return on capability investments. This implies that, if organizations focus solely on training or hiring skilled workers without addressing psychosocial resource deficits, they may risk leaving a large portion of their performance potential untapped. Taken together, these findings show how incorporating mental health variables into process simulation can inform tailored, systems-aware interventions. Because the model isolates the effects of PHI, OC, and TC at the micro-level, it becomes possible to identify which leverage points are likely to yield the greatest resilience gains:

- Modification of task complexity (TC) through ergonomic improvements, simplification of procedures (or clear-cut instruction of procedures), or reduction of variance in products—especially where TC pushes tasks into the OC $\approx$ TC region that is highly sensitive to PHI.

- Targeted qualification measures (OC) such as improving coping skills, procedural knowledge, or experience distribution across teams—implemented where the slope of the OC–success curve is steepest in the simulation.
- Reorganization of workflows or teams to distribute demanding tasks among workers with higher capability or lower PHI, thereby reducing bottlenecks that magnify PHI-sensitivity in the system.
- Interventions aimed at improving perceived working conditions, which directly shifts PHI and thereby unlock the full effect of existing capabilities.

A simulation can provide a foundation for preemptive resilience building in workplaces. Instead of reacting to bottlenecks, errors, or rework after they appear, organizations can use such a model to foresee where psychological strain will have the largest operational impact and which interventions will offer the highest benefits. This moves resilience planning from abstract, high-level guidelines toward data-grounded, task-specific strategies that incorporate the dynamic role of human psychological states in sociotechnical processes.

5 From Toy Models to Precise Micromechanisms

The present study demonstrates the potential to simulate task-specific actions within work processes by integrating psychological parameters such as demands, strain, and capabilities. Although the current prototype yields actionable insights, the identified open questions and challenges indicate that several issues must be addressed before such approaches can be applied reliably in practice, such as building an operational digital twin, a process replica that can be used to predict cascading effects of multiple factors.

Defining Optimal Task Granularity for Simulation From a psychological perspective, actions within a task are considered the smallest conscious unit of analysis [20]. However, it is impractical to represent demands, strain, and capabilities at the level of single actions. From a technical standpoint, it is unclear at which level of micro-processes simulations can adequately capture not only outputs but also psychological experiences and behaviours. For example, within a task sequence A, B, and C, stress experienced during task B would need to differ meaningfully from A or C to justify its representation as an independent action. Determining the appropriate level of granularity is therefore a key future research area, particularly regarding valid measurement and explanatory power.

Task-Specific Measurement of Demands, Strain, and Capabilities In addition to defining task granularity, the psychometric assessment of task characteristics and psychological experiences must be both valid and reliable. Psychological research, as well as regulatory requirements such as risk assessments according to DIN EN ISO 10075 [8], impose high standards on measurement quality. At very fine-grained levels of analysis, current subjective questionnaire measures are problematic, as they either interrupt workflow when applied in situ or are prone to retrospective bias. Future research should therefore focus on the development of short scales or objective alternative measurement approaches.

Multi-Level and Sequential Relationships Beyond measurement issues, future research must address the assumptions regarding relationships and interactions within task sequences (sequential causality) as well as cross-level influences from job, individual, or team characteristics. For instance, demands associated with task A may influence experiences and behaviours in subsequent tasks B and C, with effects potentially being additive, exponential, or multiplicative. Additionally, cross-level factors such as task resources and demands or individual and team capabilities may amplify or buffer observed task effects [21]. These complex relationships are currently not sufficiently represented in psychological research and offer significant potential for interdisciplinary collaboration.

Team-Level Concepts Beyond the individual level, psychological theories of work highlight the importance of team-level factors, even in workflows that appear to be primarily individual in nature [22]. Concepts such as cohesion, shared understanding of tasks, communication norms, and perceived interdependence shape how workers jointly coordinate their contributions to a process. Even in seemingly solitary tasks, team processes such as a sense of belonging influence resilience and shared coping responses. Team-level psychological mechanisms form an important background against which human behaviour unfolds [23]. These team-level factors strengthen team resilience by enhancing the group's capacity to perceive and effectively manage complex situations or unexpected change during task fulfilment, enabling the team to withstand or regain stability if needed [24, 25]. Further, these factors may be challenged by different forms of adversities and should therefore be sufficiently developed or trained to maintain stable team outcomes [26]. Team-level constructs have so far been insufficiently integrated into process-oriented analyses of psychological risk assessment and simulation. Simulation offers opportunities to incorporate not only human actors but also interactions with digital agents [4, 27]. This opens up novel perspectives for understanding team dynamics and collective processes within complex work systems.

Transfer Potential to Practice Beyond scientific contributions, the interdisciplinary integration of simulation approaches and psychological models offers important practical implications. First, in the design of resilient work processes, awareness of potential risks or resource losses represents a crucial initial coping step [26]. Simulation models could enable teams to build prospective resilience by identifying and discussing risks early [28]. Second, such models can support strategic planning and decision-making by allowing intended changes in tasks, personnel allocation, or process design to be simulated and critically reflected upon before implementation, thereby anticipating potential side effects [29]. Third, practical implementation must address issues of acceptance regarding comprehensive measurement and continuous monitoring at the task level. To operationalise these models, employees must trust in the fair and human-centred use of data, while being able to recognise both benefits and risks. Consequently, questions of user acceptance, procedural fairness, and distributive justice must be carefully addressed during the transfer process.

6 Conclusion

Modellers in social simulation often expect direct feedback loops and micromechanisms which explain the genesis of observable behaviour. At the same time, there is an expectation of rigorous validation and backing through empirical data. When it comes to process modelling, we observe a conflict of these two requirements: the atomic interactions and causal links between task characteristics, individual traits and subjective experience lack the necessary empirical support to model processes with such micromechanisms. Based on the example of a manual assembly process, we demonstrated how different psychological concepts can be integrated into an empirically founded process simulation and what insights can be derived from such models even without the inclusion of micromechanisms and internal feedback loops. Based on the simulation findings, the trifecta of mental health, operator capability and task complexity allows identifying optimal pathways towards the improvement of the overall quality of results based on existing resources and constraints. Based on the obstacles and missing evidence encountered during the modelling phase, we propose an interdisciplinary research agenda between organizational psychology and simulation sciences to close these knowledge gaps in future work. These five main open challenges and questions that were identified as pathways towards precise process models with empirically grounded mechanisms:

1. What is the optimal granularity of tasks in terms of measurement validity and explanatory power?
2. How can existing measure instruments be adapted to measure task-specific demands, strain and capabilities?
3. What are the sequential, causal, mutually dependent and multi-level relationships between tasks and different dimensions of characteristics?
4. How do team-level constructs influence individual performance and wellbeing in an individual-based process simulation?
5. What are ethical considerations regarding user acceptance and fairness required for practical applications in designing workplace resilience?

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