Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 118 (2023) 324–329

www.elsevier.com/locate/procedia

16th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME '22, Italy

Towards A Human-Centered Digital Twin

Kai Preuss[a,]*, Svenja Nicole Schulte[b], Lukas Rzazonka[b], Lilian Befort[a], Carina Fresemann[b], Rainer Stark[b], Nele Russwinkel[a]

[a]*Technische Universität Berlin, Cognitive Modeling in dynamic Human-Machine Systems, Marchstraße 23, 10587 Berlin, Germany*
[b]*Technische Universität Berlin, Industrial Information Technology, Pascalstraße 8-9, 10587 Berlin, Germany*

* Corresponding author. Tel.: +49-(0)30-314-27821; *E-mail address:* preuss@tu-berlin.de

Abstract

The Digital Twin paradigm incorporates the application of virtual prototypes established during product development as well as sensor data collected during the production and use phase. Another aspect concerns digital representation of the product's end users. A stronger connection between a digital product and its digital user would complement the Digital Twin. This paper investigates the concept of coupling a geometrical model of an adjustable operating table including position sensors with a cognitive digital user. Users interacted with both real and virtual instances of the table. Resulting data allow for evaluation of the usability of different interface variants and virtual product representations to develop a cognitive model of end users, showing the potential of a combined Digital Twin in human-centered design.

Keywords: Digital twin; Cognitive modeling; Human-centered design; User study

1. Introduction

Systems evolve from technical systems to socio-technical systems, which requires consideration of the human being and its behavior in combination with the technical system. [1] therefore propose to consider the customer (end user), the technical system and its purpose as interdependent objects.

In this regard, Advanced Systems Engineering emphasizes the role of the user and postulates the protection of human factors especially in early phases of product development [2]. Still, human factors such as usability and cognitive workload are tested on real prototypes in late stages of product development, when changes to the product and interaction design are usually too expensive to include. Including human factors and cognitive requirements in early stages of product development is a central challenge, proving high relevance for a holistic model mapping of the product and the human interacting with it.

Digital Twins are often considered in the context of products, production systems or product service systems. However, a consistent concept of a Cognitive Digital Twin able to plan and make decisions on interaction with an interface and manipulation of a physically reacting system – which in turn changes the perceived environment of the user – is still missing.

Digital Twins in industry aim at creating a digital representation of a physical product. [3, p. 1] define Digital Twins as "a digital representation of an active unique product [...] or unique product-service system [...] that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases". More specifically, Digital Twins contain a combination of a Digital Master and a Digital Shadow. A Digital Master is composed of product description models such as geometry and kinematics models; a Digital Shadow is composed of data such as operation and usage data [4,3]. Potential applications include improved data availability and interpretation and thereby supporting decision-making, monitoring of products or processes or enabling predictive maintenance as well as higher efficiency [5].

This concept of product-centered Digital Twins can analogously be applied to humans in order to create a Digital Twin of an (end) user. Here, we consider a Cognitive Digital Twin, which according to [6] describes a digital reflection of the user, intended to make decisions and carry out tasks on the

10.1016/j.procir.2023.06.056

user's behalf. The intention of the Cognitive Digital Twin is to model the cognitive processes underlying the user's decision. This includes perceptual dependencies (e.g. visual search) as well as reacting to physical changes in a given environment, including those caused by the user. A Cognitive Digital Twin can simulate a human interacting with a product and facilitate human-centered product development. Cognitive Digital Twins are based on cognitive models of a task, a formalization of presumed human behavior during task-solving. Ideally, such a cognitive model would make use of existing behavioral data collected during user interaction.

First examples of cognitive models interacting with or anticipating humans interacting with complex systems and reacting to changes caused in the environment by its actions have been developed before (e.g. [7,8,9]). But these approaches are focused on simulating realistic cognition and behavior, and do not interact with a virtual product that shows specific realistic behavior.

A Cognitive Digital Twin able of physical, real-world interactions requires the cognitive architecture to offer mechanisms that implement recognition of objects in three-dimensional space, as well as a way to plan interactions with these objects. A custom extension to the ACT-R architecture introduces support for spatial cognition, namely mental planning of spatial transformative efforts in the form of object interaction [10].

In this paper we aim to develop a methodology to realize a holistic modeling approach for early phases in product development. Evaluating this approach necessitates comparing interactions of real participants with a physical product with interactions of a digital human and digital product, and by extension of a digital human with a physical product and a real human with a digital product. One relevant question here is how closely such Digital Twins capture reality and where the boundaries in such an approach lie.

A complete Digital and Cognitive Digital Twin setup thereby requires the following steps:

1. creation of a Digital Master,
2. user data collection to create a Digital Shadow,
3. creating a Digital Twin able to mimic the product in real-time,
4. creating a Cognitive Digital Twin able to mimic a user in real-time,
5. connecting both representations into a combined, predictive system that is then able to guide and improve product development.

A cognitive model representing a Cognitive Digital Twin needs to meet the following requirements: (1) reasonable and sufficient formalization of user behavior – the cognitive processes of a user guiding his interaction with the product need to be reasonably replicated by a formalization of goal-oriented device interactions and to be able to fulfill the given task sufficiently; (2) close fit of predicted model data to behavioral data – the cognitive model should closely replicate behavioral markers, such as task-solving time, success rate, strategy use etc.; (3) ability to predict or give insight on regular and specific use cases – the cognitive model needs to offer reasonable explanations and mechanisms for factors influencing product usage, e.g. task difficulty, cognitive workload, memory limitations, or device usability.

This paper discusses cognitive modeling as part of a Digital Twin. We describe the behavioral data collection necessary for a Cognitive Digital Twin and report two experiments with a modular and remote-controlled operating table, in the form of both physical system and Digital Master, as an exemplary product. This system was chosen because of its physical size, inherent transformability and beginner-friendly user interface. The first experiment aims at gaining valuable insight of user behavior for the development of a cognitive user model developed with the cognitive architecture ACT-R. We analyze human interaction with two different kinds of interfaces as the basis for a comprehensive cognitive model. The second experiment focuses on establishing a better understanding in regard to human interaction with a physical product compared to a digital model of a product, while serving as a proof-of-concept for extending the product with sensor data for a Digital Shadow. Thus, the first steps towards a complete, integrated system of Digital and Cognitive Digital Twin are taken.

2. Methods

Ongoing research intends to reveal the behavior of end users when interacting with a transformable technical system. The first experiment examines interaction with virtual table and remote variants, while a follow-up experiment gauges the use of sensor data for use with a physical version of the table on one hand and compares user interaction quality between the virtual and physical operating tables on the other. The first study aims at understanding factors of user behavior and product usability to inform the development of a cognitive model. For this, human measures like difficulty, cues on cognitive (spatial) processing and their influence on task planning and precision are considered. The second study seeks to build a Digital Shadow using sensor data and test the validity of a Digital Twin compared to its physical counterpart in user interaction by analyzing planning time, correctly adjusted parts and the influence of product virtualization.

2.1. Experiment 1

Participants were asked to use a virtual version of the default remote interface provided with the physical table to interact with a 3D model of the table displayed in a neutral CAD environment, with the goal of configuring a series of positions. A desktop monitor showing the CAD model, a tablet computer running the virtual interface, as well as the current target position were visible at all times during the experiment. The software remote control was intended to be used as a touchscreen interface running on a Microsoft Surface tablet.

Two variants of the software interface were developed to serve as input mechanisms for the virtual table. Remote control interfaces were switched halfway through the experiment for each participant, with interface order alternating between participants. The default version of the software remote control is designed to mimic the default physical, vertically aligned remote in both form and function. A revised interface was developed that was displayed horizontally and incorporated color-coded buttons and was used in conjunction with a CAD model colored accordingly (see Fig. 1). Both remotes feature horizontal and vertical tilt buttons (2 each), back rotation buttons (*upwards/downwards*), leg rotation buttons (*upwards/downwards*), a button controlling leg rotation mode (*left leg/right leg/both*) as well as a confirmation button to signal planning or trial completion, respectively. An LED signaled the current leg rotation mode, while another LED signaled the current trial state to the participant (*planning phase / action phase*). Additional buttons for lifting or lowering the table, moving the table along its length axis, changing movement speed or resetting the table to its default position were not used in the experiments.

Pre-experiment, a questionnaire on technical affinity [11] as well as a mental rotation pretest based on [12] were administered. The task required participants to set the operating table to a sequence of different positions. For each trial, the difficulty of reaching a position was determined by the number of table parts necessary to be manipulated. Three curated blocks of ten trials each were presented to the participants in semi-randomized order for each interface variant. After each remote control set, NASA-TLX and SUS [13,14] were administered to gauge workload and usability of the presented remote control. At the start of each trial, the experimenter presented the target position while participants were asked to press the confirmation button once to synchronize time measurement. They were then asked to mentally plan their movements before actively using the remote control, after which their first button press initiated the action phase. After participants were content with their configuration, they were asked to press the confirmation button again to end time measurement of the trial. The next trial then started with the target position of the last. The final offset to the target position was calculated as the sum of the absolute angular disparity of each table part.

Variables of interest are remote control variant, trial difficulty, overall trial time, length of planning time and offset compared to the target position.

2.2. Experiment 2

As mentioned initially, the second experiment gauges the use of sensor data with a physical product, to analyze how precisely participants accomplished the tasks. Focus lies on mentally configuring a physically changing technical system, compared between virtual and physical setups. The study was divided into two main parts, the virtual and physical block. The first block design is an adaptation from experiment 1. A virtual CAD-Model of the operating chair was displayed on a desktop monitor while the software remote control ran on a tablet computer for touchscreen interaction. The second block focuses on physical device interaction, therefore the physical table and the default physical remote control unit from Getinge were included in this setup. During both blocks the target positions were viewable at any time.

Order of physical and virtual block was pseudorandomized, i.e. alternated between participants to control whether block order influences overall performance. After each block the same questionnaires as in experiment 1 had to be completed. Trial difficulty was determined by the number of parts necessary to be manipulated. Due to technical limitations, a new block consisting of three new trials with increasing levels of difficulty was developed to ensure that all tasks could be executed properly in both virtual and physical task environments. 12 part positions in total had to be configured by the participants: three within the first (easy difficulty), four during the second (medium) and five within the third trial (hard). In total six target positions had to be completed by the participants.

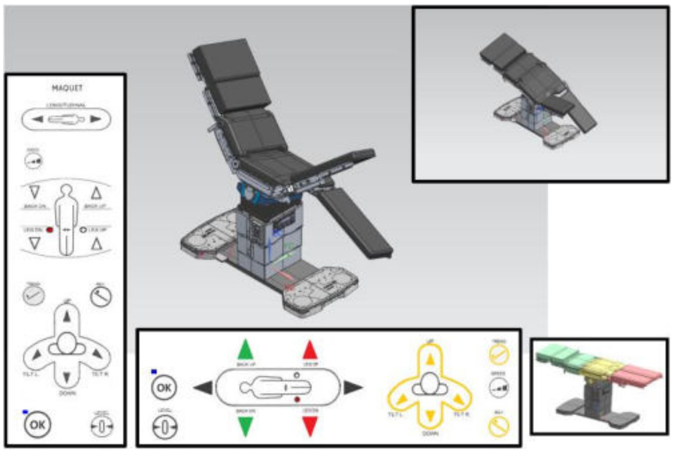

Fig. 1. Depiction of the presented CAD model (*center*), the target position (*top right*) as well as default (*left*) and revised remote control interface (*bottom*), as well as the alternate, colored CAD model (*bottom right*).

To reliably compare virtual and physical human-machine interactions, it was necessary to implement angular rate sensors. All manipulable parts of the operating chair had to be rigged with sensors independently. Sensors measured positions of the left and right leg, back, as well as tilt and roll of the entire chair. Thus it was necessary to implement a total of four sensors onto the physical device for angular position tracking. The kinematics of a part being moved are first recognized by the hardware and subsequently processed by a custom software script. Finally, accurate positions are collected and logged at 2Hz.

2.3. Cognitive Model

The cognitive model concept is designed to be a reasonable representation of a typical user tasked with Experiment 1. It is assumed that the user follows the experiment instruction and has already completed a short training, i.e. is familiar with the functions of device and interface. For the cognitive model, this knowledge is implemented as world knowledge in the form of declarative and procedural memory. The model roughly follows the cognitive processes presumed to be necessary for human solvers to competently fulfill the task while adhering to the given instructions. Following those, it is assumed that the user plans the necessary table transformations before using the remote control to enact them.

The processes can be formalized as follows:

- **visual encoding**: the current position of the table and its parts, as well as the configuration of the target position, are perceived
- **spatial comparison**: the user focuses on either the complete table or single table parts and considers necessary changes
- **spatial transformation**: the changes are mentally simulated, after which another area of the table is put in focus

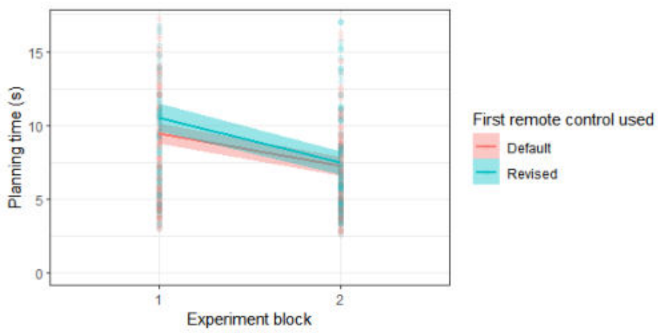

Fig. 2. Interaction between experiment block and remote control variant on planning time.

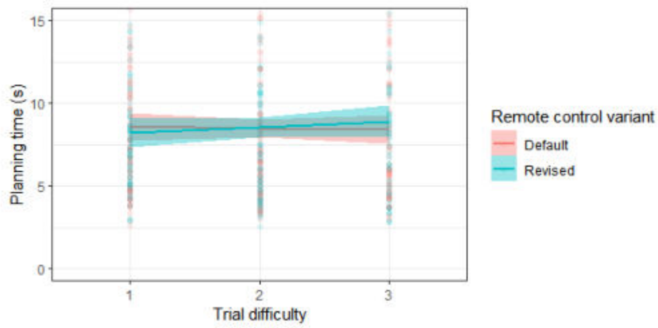

Fig. 3. Interaction between difficulty and remote control variant on planning time.

- **action phase**: after all necessary changes have been planned, they are enacted via remote control. If planned changes are forgotten or incorrect, new changes need to be considered ad-hoc

These steps are then implemented as a software simulation of an end user of the operating table. Based on data collected during experiment 1, the model should closely fit behavioral data like completion times and success rate over experiment variables like difficulty or learning experience to prove validity as a Cognitive Digital Twin. On this basis, the model will then be able to offer insight into cognitive bottlenecks, strain on cognitive resources, or strategy choices and their development over the course of the experiment. The concept above explicitly allows for different strategies (e.g. first bringing the table into position, then adjusting singular parts, or vice versa) and memory constraints (e.g. pre-planning of necessary changes may strain working memory capacity).

3. Results

3.1. Experiment 1

As of yet, 15 participants (6 female, 9 male) took part in the experiment, with an average age of 29 years (SD=5.73). Participants on average needed 59.15s per trial, of which 8.51s were used for planning. On average, participants solved trials with a total angular offset to the target of 23.75 degrees. Outlier correction was applied by setting data beyond a 95% confidence interval to that limit for trial time, planning time and offset each.

To understand the effects of user and task environment on planning time and precision, linear models were fitted to each. For planning time, the linear model measured the effects of remote control variant, first variant used and their interactions on log-transformed planning time. Random effects in the form of random intercepts for participant, block and trial were included. The models fixed effects explained 6.21% of variance ($R^2_m = 0.062$), while the complete model explained 54.43% of variance ($R^2_c = 0.544$), implying most variance stems from the random effects: differences between participants accounted for 45.29% of prediction error, with experiment block and trial accounting for 0.97% and 5.15%. Nonetheless, predictors remote control variant and the interaction of remote control variant first variant used are highly significant (both $p << 0.001$).

The linear model explaining precision again included remote control variant, first variant used and their interactions as predictors, trial and block as random intercepts and difficulty for participants as a random slope to gauge their effect on log-transformed offset. Fixed effects account for 0.61% of variance ($R^2_m = 0.006$), with the complete model explaining 43.8% of variance ($R^2_c = 0.438$), again showing a high influence of random effects on experiment results. Influence of difficulty per participant explains 30.76%, experiment block 2.41% and trial 4.52% of prediction error. Although the variance explained by the fixed effects is negligible, they show a significant effect for the interaction of remote control variant and first variant used ($p < 0.05$) and show a trend for remote control variant ($p = 0.052$). Overall, results imply a high variance between participants. See Fig. 2 and 3 for an overview.

3.2. Experiment 2

Data from 11 participants (3 female, 8 male) was collected, with an average age of 26 years. For this experiment, we define the threshold for correctly manipulated parts to be ±6° offset for both physical and virtual setup.

The number of correctly positioned parts differs significantly between the virtual and physical block ($p<0,05$). The average of correctly positioned parts during the virtual block is 9.54 total (n=11) compared to 7.09 parts during the physical block. Also, for each level of difficulty (i.e. trials 1 - 3), the average of correctly positioned parts was higher during the virtual block. The differences between the virtual and physical block are statistically significant only for trial 1 ($p<0.05$) and trial 2 ($p<0.01$), however not for trial 3 ($p=0.26$).

Participants who started with the virtual block (n=6) scored an average of 9.83 correctly positioned table parts during the virtual block and an average of 8.67 during the second, physical block; whereas participants starting with the physical block (n=5) scored an average of 5.20 correctly positioned table parts during the physical block and 9.20 during the second, virtual block. Hence, task performance was better for both groups during the virtual block compared to the physical block.

Planning time does not differ significantly between virtual and physical block ($p=0.45$). The average planning time during the virtual and physical block are 98.4s and 86.6s, respectively. During both blocks planning time increased continuously from the first to the last trial, corresponding to task difficulty (Fig. 5).

Participants who started with the physical block had an average of 83.77s planning time during the physical block and

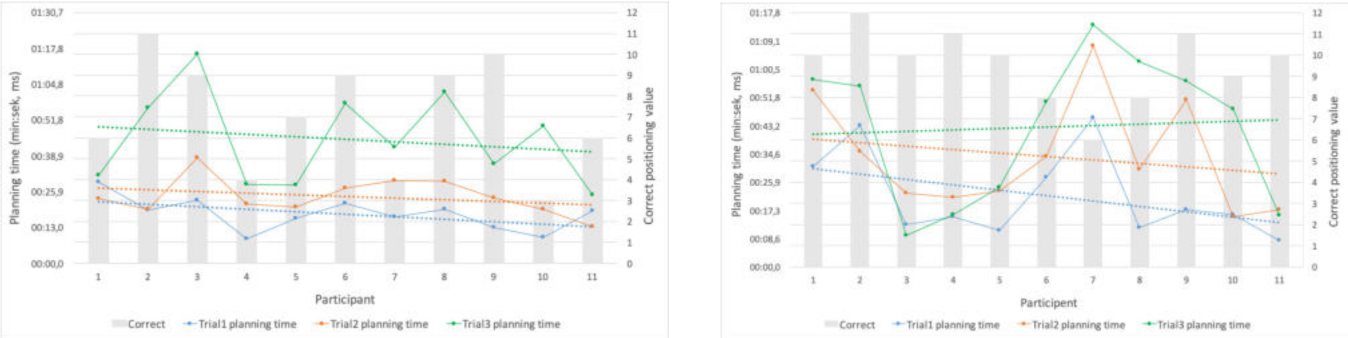

Fig. 2. Presenting physical (left) and virtual (right) user data. In both figures, the left y-axis shows planning time, the right y-axis indicates the number of correctly positioned parts during the experiment. The coloured lines represent planning time during all three trials; the linear coloured, dotted graph represents the planning time trendline. Gray bars (background) indicates the total amount of correctly manipulated parts per participant and for the particular experiment part.

an average of 81.2s during the second, virtual block. Participants who started with the virtual block had an average of 112.7s planning time during the virtual block and an average of 88.99s during the second, physical block. Hence, independent of the setup, both groups used less planning time during the second block.

4. Discussion

4.1. Experiment 1

Preliminary results show that a learning effect is apparent: on average, participants improve over time in trial time, planning time and precision measures. Additional planning time seems to improve precision, implying that a more carefully planned trial was executed with less offset to the target position. A higher difficulty led to an increase in overall trial time, which is no surprise as additional necessary movements take longer to execute. Interestingly however, task difficulty has no effect on planning time – although more parts need to be transformed, the data show no planning time increase. This suggests that planning time is subject to limited cognitive resources, e.g. memory capacity or individual time constraints.

A significant effect and a trend for remote control variant were found for planning time and precision, respectively. Preliminary trends also show an interaction between remote control and remote control order for planning time and precision. This also has implications for creating Digital Twins: certain patterns of interaction could be learned by using a specific remote first that either facilitate or hinder improvement of task proficiency when forced to change interfaces halfway through the experiment.

4.2. Experiment 2

Planning time increases with trial difficulty during both experiment blocks as expected and visualized in Fig. 5. Also, an overall trend can be identified in Fig. 4, the amount of correctly positioned parts increases with an increase in planning time. Therefore, planning time seems to be successfully used for the planning of mental spatial transformations.

As mentioned above, the virtual experiment setup leads to better results than the physical setup. It can be assumed that the visualization of the virtual model of the operation table during the virtual condition facilitates this, making it easier for participants to apply their strategy developed during planning time. Also, our results show that interacting with a digital model of a product improves performance using a physical product/machine afterwards. Overall, the results lend evidence to the validity of virtual models in product development.

4.3. General Discussion

The two conducted experiments both deal with virtual and real table representations, but differ in their extent of virtualization (two interface types with a virtual table in experiment 1, virtual and real table in experiment 2). Slight differences in task presentation, table movement speed or time measurement are thus inevitable. Nevertheless, both experiments show comparable results.

A general improvement in overall trial time, planning time and precision over the course of the experiment could be found in both studies. Specifically, although longer planning time effected better precision overall, planning time decreased over the course of both experiments while precision increased. Proficiency with the device was thus not only improved on the level of interaction, but on the level of task preparation, implying a growing understanding of the device's functionality.

The interactions of remote control variant in experiment 1 and virtual or real setup in experiment 2, respectively, imply an effect of the order of the experiment on task proficiency. Interaction patterns seem to be adapted over the respective first block of each experiment that can lead to either beneficial or detrimental performance in the respective second block.

As experiment 1 is still ongoing, additional participants could further explain some of the trends found for the effect of remote control variant on those factors.

4.4. Outlook

The concepts outlined in this paper serve as the first steps towards establishing a holistic Digital Twin. To reach that goal, the cognitive model will be completed (based on behavioral data from experiment 1) and connected to the Digital Twin (further refined by data gathered during experiment 2). In the future, we aim to establish a custom data connection to the modular operating table, enabling us to fully connect both

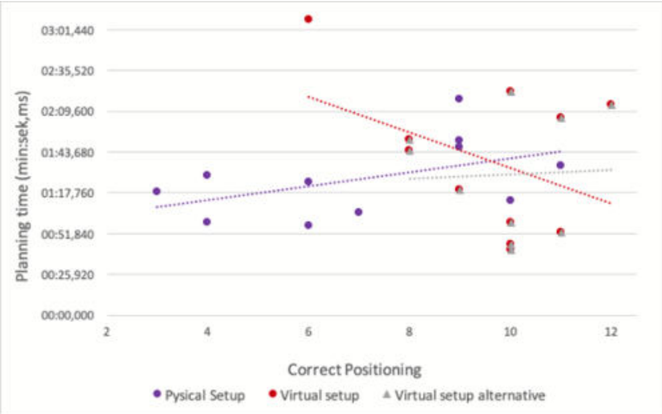

Fig. 3. During the physical block, an increase in planning time with higher correctly positioned parts becomes apparent (purple dotted line). Throughout the virtual experiment block the slight increase of correctly positioned parts in tandem with increasing planning time is notable after outlier correction (gray dotted line), excluding an outlier with over three minutes total planning time along with only six correctly positioned parts in total. Inclusion of the outlier led to conflicting results (red dotted line).

virtual & real product to both virtual & real user, thereby fully realizing the Digital Twin concept.

The upcoming cognitive model seeks to imitate the effects found in the experimental data: apart from providing a close fit of model predictions to experimental data in regards to trial completion time and precision, a more interesting application will be offering explanations for results on e.g. planning time or interactions of experiment conditions. A decrease in planning time with a simultaneous improvement in precision implies a sophisticated learning effect that a cognitive model could replicate and substantiate. Furthermore, similar planning times over all difficulties in experiment 1 could result from cognitive limitations regarding memory or mental image complexity. Differences in planning time by first shown experiment setup could likewise originate in cognitive processes like reinforcement learning or motor memory. The cognitive model should help pinpoint the exact mechanisms behind these effects and in consequence provide pointers on improved product ergonomics.

Extensive additional data was collected during experiment 1, but has not been evaluated at the time of writing. Pretests on spatial ability, as well as questionnaires assessing individual workload, technical affinity and perceived device usability might shed some light on personal factors influencing the experiment results.

By default, the operating table only features input and output by its default remote control and does not allow custom external connections. An IR interface is currently in development to enable additional input connections, i.e. the revised remote control variant running as tablet software or commands selected by the cognitive model. This would enable interaction of both Digital Twin and Cognitive Digital Twin with the physical product, thus taking another step towards a complete and closely integrated representation of digital product and digital user.

By gathering user data on both human- and product-centered aspects of the operating table, we effectively finalized its Digital Master and Shadow. This serves as foundation for creating real-time representations of the user and the product: a Digital Twin to closely reflect product behavior in regards to user interaction, and a Cognitive Digital Twin incorporating a human-centered view on the product's ergonomics. Finally, this approach works as a proof-of-concept and can be applied to product development in general: these closely intertwined simulations can be integrated into a single closed-loop system able to offer direct feedback on proposed product changes early in development, bypassing the need for resource-intensive and expensive physical prototyping with additional user feedback studies.

Acknowledgements

The authors would like to thank Getinge AB (formerly Maquet GmbH) for providing both the operating table and its CAD model. We thank Moritz Sontheimer for early CAD work and system connection efforts, Severin Reuter for cognitive model consultation and technical support for the operating table, and Christopher Hilton for technical support. This research is financed through the German Research Foundation (DFG) as part of project #*396560184*.

References

[1] Albers A, Lohmeyer Q. Advanced Systems Engineering – Towards a model-based and human-centered methodology. International symposium series on tools and methods of competitive engineering, TMCE; 2012.
[2] Geiger A, Brandenburg E & Stark R. Natural virtual reality user interface to define assembly sequences for digital human models. Applied System Innovation 3.1; 2020; 15.
[3] Stark R, Damerau T. Digital twin. In: Chatti S, Tolio T, editors. CIRP Encyclopedia of Production Engineering. The International Academy for Production Engineering. Springer; 2019; 8.
[4] Stark R, Kind S, Neumeyer S. Innovations in digital modelling for next generation manufacturing system design. CIRP Annals - Manufacturing Technology; 2017; 66, 169-172.
[5] Rasheed A, San O, Kvamsdal T. Digital twin: values, challenges and enablers from a modeling perspective. IEEE Access; 2020; 8, 21980-22012.
[6] Somers, S, Oltramari A, Lebiere C. Cognitive twin: a cognitive approach to personalized assistants. In AAAI Spring Symposium: Combining Machine Learning with Knowledge Engineering; 2020; 1.
[7] Klaproth OW, Halbruegge M, Krol LR, Vernaleken C, Zander TO, Russwinkel N. A neuroadaptive cognitive model for dealing with uncertainty in tracing pilots' cognitive state. Topics in Cognitive Science; 2020; 12(3), p. 1012-1029.
[8] Scharfe M, Russwinkel N. towards a cognitive model of the takeover in highly automated driving for the improvement of human machine interaction. In Proceedings of the 17th International Conference on Cognitive Modelling; 2019.
[9] Prezenski S, Brechmann A, Wolff S, Russwinkel N. A cognitive modeling approach to strategy formation in dynamic decision making. Frontiers in psychology; 2017; 8, 1335.
[10] Preuss K, Russwinkel N. Cognitive modelling of a mental rotation task using a generalized spatial framework. In Proceedings of the 19th International Conference on Cognitive Modelling; 2021.
[11] Karrer K, Glaser C, Clemens C, Bruder C. Technikaffinität erfassen – der Fragebogen TA-EG. Der Mensch im Mittelpunkt technischer Systeme; 2009; 8, 196-201.
[12] Wright R, Thompson WL, Ganis G, Newcombe NS, Kosslyn SM. Training generalized spatial skills. Psychonomic bulletin & review; 2008; 15(4), 763-771.
[13] Hart SG, Staveland LE. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research; Elsevier: Amsterdam, The Netherlands, 1988; pp. 139–183. ISBN 9780444703880.
[14] Brooke J. SUS: A "quick and dirty" usability scale. Usability evaluation in industry; 1996; 189(3).