Computer Aided Ergonomics: Evaluation Study of a Interaction Model for Digital Human Models

A. Wolf ✉, K. Fackler, M. Reulbach, S. Wartzack and J. Miehling

Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany

✉ a.wolf@mfk.fau.de

Abstract

In user-centred design, digital human models hold the potential for proactive evaluations of ergonomics or discomfort in terms of a computer aided ergonomics tool. Therefore, models predicting human interaction behaviour, are necessary. In this contribution we present such a model as well as its initial evaluation. The evaluation is performed by applying the interaction model to a specific use case, conducting a comparison with an empirical subject study. The evaluation shows that similar and realistic human behaviour was predicted, which was consistent in terms of whole-body strain.

Keywords: user-centred design, interaction design, digital human models, evaluation, computer-aided ergonomics

1. Introduction

In the context of user-centred and simulation-based design, digital human models (DHM) hold the potential for proactive evaluations of usability, ergonomics or discomfort on digital product models in early development phases (Chaffin, 2005; Irshad *et al.*, 2019). DHM like Siemens Jack (Raschke and Cort, 2019), the AnyBody Modelling System (Rasmussen, 2019) or OpenSim (Seth *et al.*, 2018) are increasingly utilized as computer aided ergonomics tools (Wolf *et al.*, 2020). In order to analyse user-product interactions, the interaction between a digital product model and a DHM needs to be modelled in terms of a virtual mock-up (Ahmed *et al.*, 2019). Customarily, this interaction modelling is conducted either manually (creating postures and movements by hand) or with help of experimental data (motion data, external forces, etc.). Both approaches have distinguished disadvantages. Manual interaction modelling on the one hand, is time-consuming, fault-prone and requires specific knowledge and expertise in human behaviour modelling (Chaffin, 2005; Reed *et al.*, 2005; Perez and Neumann, 2015; Ranger *et al.*, 2018). Experimental data on the other hand, has to be gathered in motion capture laboratories with human subjects, which is time-consuming, expensive and requires specific knowledge and expertise in motion capturing, force measurement and kinematics / dynamics modelling (Wartzack *et al.*, 2019; Wolf and Wartzack, 2018). Furthermore, it requires a physical prototype or a mock-up of the product to be analysed. Hence, the experimental data used for interaction modelling is of limited use, as it can solely be used for reactive / retrospective analyses of certain product states.

In order to achieve an proactive analysis of the user-product interaction, predictive interaction models are necessary alongside the DHM and the digital product model (Wolf *et al.*, 2020). In former research we reviewed corresponding literature in order to identify existing interaction models (Wolf *et al.*, 2020). We found, that existing interaction models either address specific use cases in engineering and industrial design, like vehicle interior design (Jung *et al.*, 2009; Wirsching, 2019) or sports equipment (Miehling *et al.*, 2015), or are utilized for occupational design tasks, like assembly line or workplace

design (Bauer *et al.*, 2019; Hanson *et al.*, 2019). This is due to the fact, that all methods of interaction modelling (no matter if using statistical, machine learning or optimization based approaches) rely on some sort of experimental data in order to predict human behaviour validly (Wolf *et al.*, 2020). In the case of occupational design tasks, working task catalogues, like the MTM-system (Kuo and Wang, 2009), exist, which enable the development of versatile applicable interaction models. In engineering design however, a versatile applicable, data-driven interaction model is non-existent. We understood this research gap as a call for action and developed a phenomenological predictive interaction model which shall enable an proactive, time-efficient, standardized, accessible and versatile applicable interaction modelling, in order to analyse digital product model states virtual and proactive in terms of a computer aided ergonomics tool. We conducted an initial evaluation study regarding this data-driven interaction model. In this contribution we present the predictive interaction model as well as the results of the initial evaluation study.

2. Predictive interaction models

The phenomenological predictive interaction model is composed of two components (see Figure 1). A task modelling component in a computer aided design (CAD) application (Siemens NX) and a interaction prediction and analysis component embedded in a musculoskeletal simulation environment (OpenSim). Both components make use of the assumption, that many interaction concepts between humans and products occurring in technology can be reduced to a relatively small catalogue of elementary affordances. Affordances (artificial term for 'to afford something') describe the possibilities of interaction directly linked to physical objects, resulting from the abilities of the actor and the characteristics of the object (Gibson, 1979; Norman, 2013). The idea of using affordances as a interaction modelling item, is to enable designers to manually choose affordances as intuitively as they do in their daily lives.
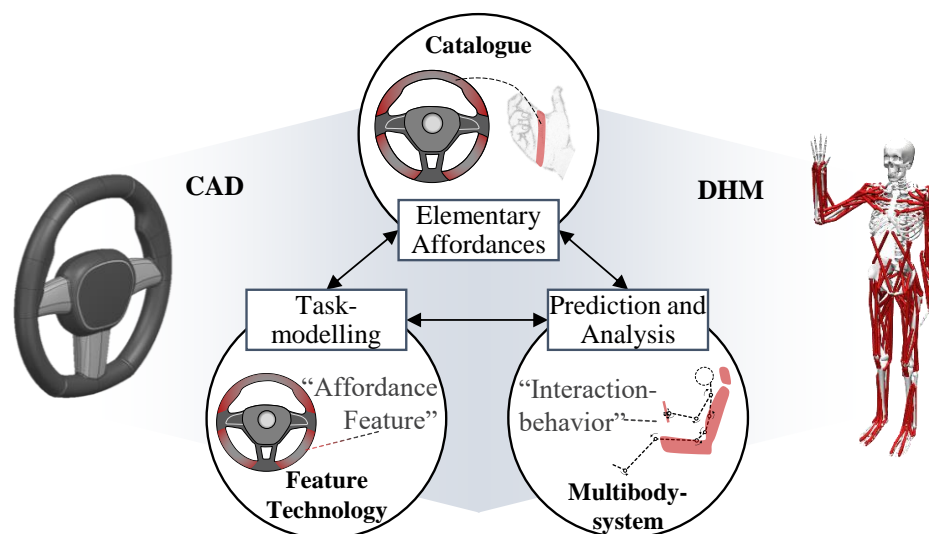

Figure 1. Approach of the predictive interaction model

We identified 31 elementary affordances using a database of interaction possibilities and a taxonomy development approach (see Wolf *et al.*, 2021). These elementary affordances contain information about the mechanical interaction possibilities (mechanical coupling) between certain human body parts / end-effectors (e.g. hands, feet, back or buttock) and rudimental geometries (e.g. cylinder, surface or cuboid). The elementary affordance "hand grabs cylinder" for instance, contains information how a hand and a cylinder are coupled when contacted with a palm grip. The mechanical coupling is described as a kinematic-minimal dependency, which in this case consists of a joint with one rotational and translational degree of freedom, and a dynamic-minimal dependency, which in this case allows force and moment transmissions to a predefined limit. All identified elementary affordances were implemented as CAD-features (Weber, 1996) in a CAD-integrated task editor. Those enable designers to attach information of interaction possibilities to a digital product model in an intuitive way. The modelling is

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conducted manually, by applying an elementary affordance to a product geometry and by concretizing the predefined mechanical coupling. Accordingly, the default kinematic-minimal dependency can be supplemented with further kinematic restrictions or the default dynamic-minimal dependency can be supplemented with additional external forces (which have to be overcome by the DHM) and reaction forces (supporting the DHM against the environment). Thus, the product model becomes a carrier of specific interaction information. This information can subsequently be used to generate constraints for the prediction and analysis of human interaction behaviour, which is realized using a DHM. The task modelling environment in Siemens NX as well as the identification and elaboration of the catalogue of elementary affordances is described in detail in Wolf *et al.* (2021).

The interaction prediction and analysis component is realized using a musculoskeletal human model (Miehling, 2019) in the dynamic multibody simulation environment OpenSim (Seth *et al.*, 2018). The human interaction behaviour is predicted in terms of postures using an kinematic optimization approach which requires a set of affordance features and so-called behaviour cards as input (see Figure 2).
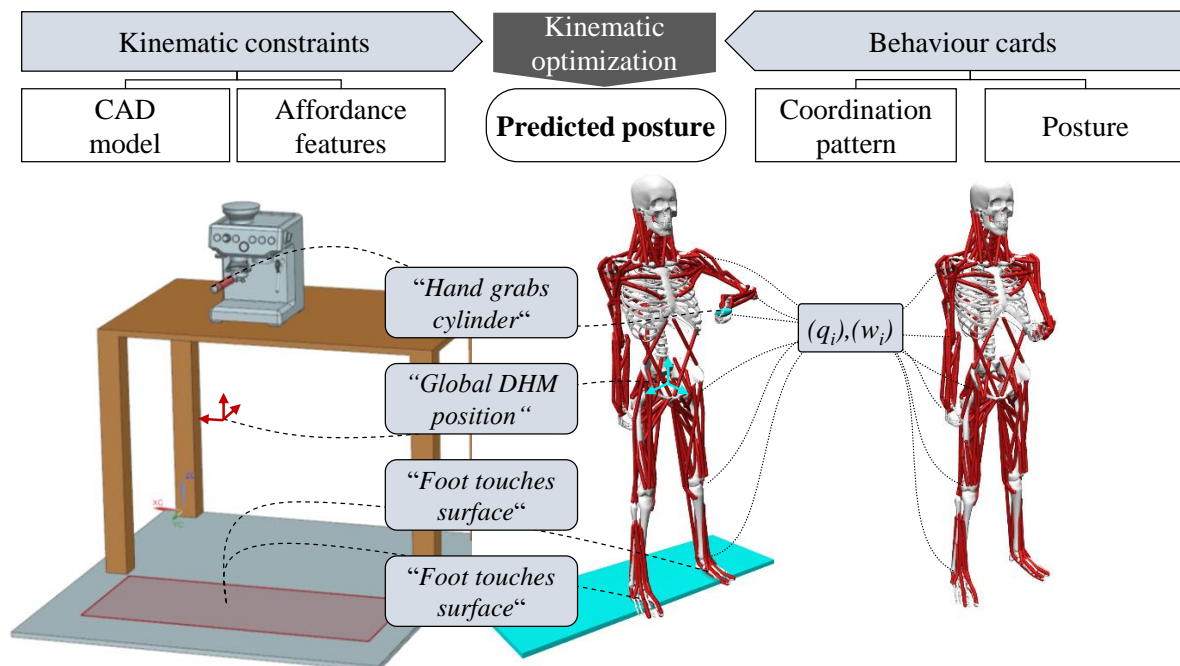

Figure 2. Principle of the interaction (posture) prediction approach

Using the Matlab-OpenSim interface, the affordance features of interest (defined on the CAD-model) can automatically be transferred into kinematic constraints, by introducing rudimental rigid-body representations of the respective product geometries (at the respective positions in the OpenSim environment and by introducing joint definitions between these rigid bodies and the respective DHM end-effectors / body parts. The behaviour cards provide experimental posture data as a start solution for a comprehensible, data-driven / phenomenological prediction of human behaviour. The idea behind the interaction cards is to gather posture data of specific interactions in a one-off expenditure and to reuse the data in order to predict similar or related human behaviour. A behaviour card contains a specific body posture (which can be understood as a start solution), described in generalized coordinates (joint angles and positional coordinates) q_j^{Strat}, and a coordination pattern, consisting of weight factors w_j for each generalized coordinate q_j. Using a modified version of the inverse kinematic optimisation algorithm (1) introduced by Delp *et al.* (2007), this information can be used to compute a body posture:

$$\min\left[\sum_{j=1}^{g.c.} w_j(q_j^{Strat} - q_j)^2\right] \tag{1}$$

$$G(q) - G_0 = 0 \tag{2}$$

Hereby, q_j correspond to the degrees of freedom of the DHM and thus to the body posture to be predicted (j corresponds to the number of generalized coordinates (*g.c.*) to be optimized). q_j^{Strat},

correspond to the pre-specified joint angles (posture) from the behaviour card (start solution). The squared differences of these values, are weighted using the factors w_j, which correspond to the coordination pattern. The solution of the optimization problem is subject to constraint equations (2). These require compliance with all kinematic constraints and (joint) definitions. Hence, the goal of this optimization algorithm is to minimize the kinematic error and thus to enable the best possible compliance with the body posture from the behaviour card, while fulfilling the kinematic constraints exactly. This is done by taking the coordination pattern and the movement possibilities of the musculoskeletal DHM into account (see Figure 2). Since, the computation of the posture is performed kinematically, posture adaptations due to support or external forces, have to be covered by the experimental posture data in the behaviour cards. The resulting (predicted) posture can subsequently be analysed using inverse dynamics under consideration of a static optimization (Delp *et al.*, 2007) and dynamic constraints. The dynamic constraints are defined in the task modelling environment (see Wolf *et al.* 2021). The results of the static optimization are biomechanical parameters like muscle and joint reaction forces. Those can be used as quantitative measures for ergonomics, discomfort or usability.

3. Methods

The evaluation of this predictive interaction model was conducted as a part of the so-called Initial Descriptive Study II of the Design Research Methodology presented by Blessing and Chakrabarti (2009). One major aim of this initial descriptive study is to find indications for the applicability and usefulness of the predictive interaction model.

3.1. Study design

For this purpose, interactions with different product characteristics of a fictitious use case (operation of a dual rudder system of a sailing yacht) are investigated both reactive / experimentally in a subject study and proactive / simulative with the predictive interaction model (see Figure 3). Subsequently, the results of the experimental and simulative study are compared. The comparison of the results is conducted using an dynamic (biomechanical) evaluation criterion. For this purpose, subject anthropometry and interaction movements are measured in the subject study (via motion capture technology), transferred to a appropriately scaled musculoskeletal DHM and dynamically analysed. The behavioural cards needed for the postural interaction prediction are derived from the empirically determined movements of the subject study. Besides the comparison of the dynamic results, an initial evaluation of the analysis capabilities regarding product ergonomics and usability was conducted. For this purpose the discomfort perceived by the subjects was surveyed. This experimental discomfort evaluation was compared with the dynamic results of the predictive interaction model.
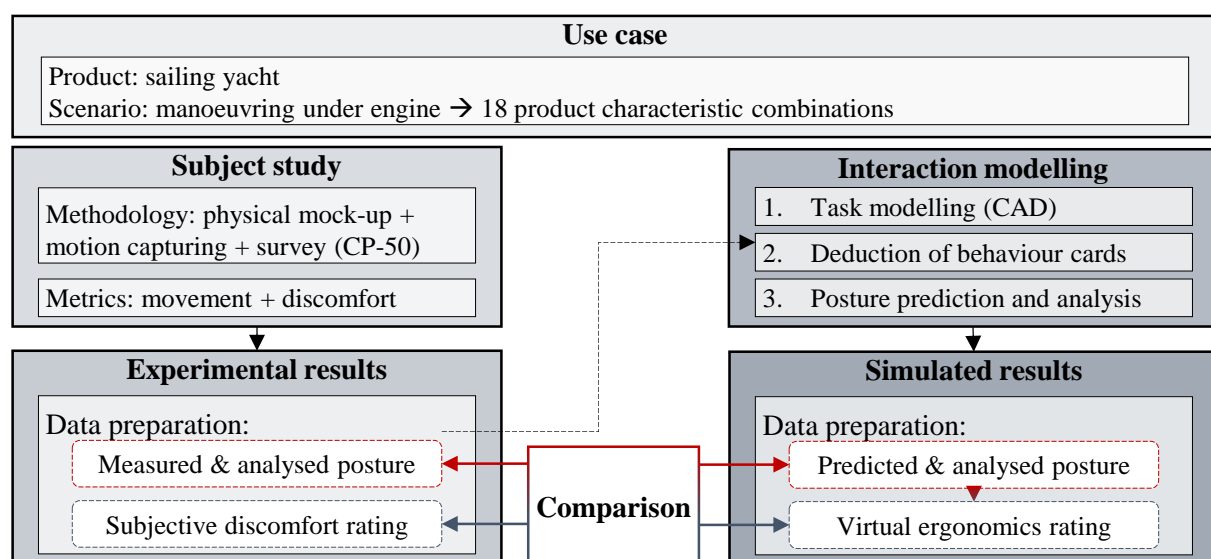

Figure 3. Study design for the evaluation of the interaction model

As a fictitious use case a human-product interaction was chosen, which describes a whole-body interaction with a certain complexity and a relation to a real problem. Specifically, the operation of a dual rudder system of a sailing yacht is to be investigated. In series-produced yachts, the throttle lever for operating the engine is often located just above the deck, which is why operating the rudder and throttle lever usually results in bent and uncomfortable postures with a limited view over the bow of the yacht. The use case includes 18 characteristic configurations of a fictitious rudder stand. These result from the combination of three rudder positions (RP), three lever heights (LH) and two lever depths (LD) (see Figure 4). The product configurations are named using the nomenclature LH-LD-RP.
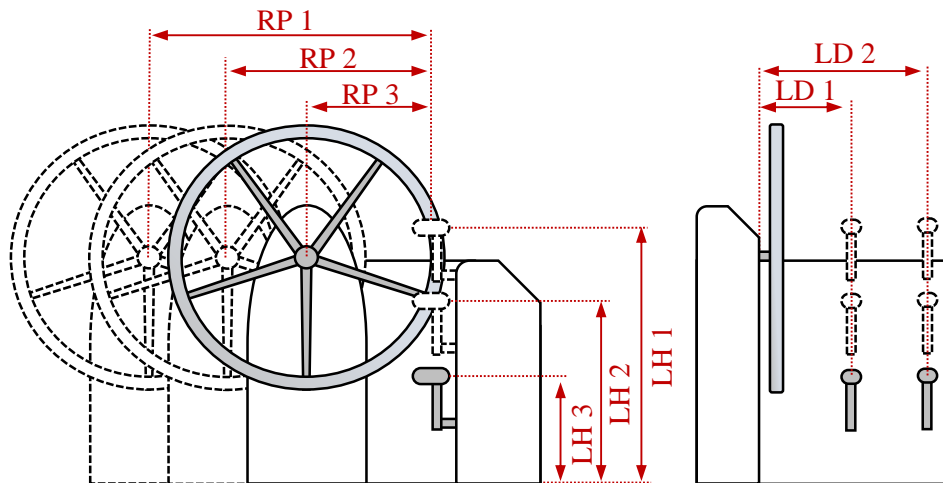

Figure 4. Characteristic configurations of the fictitious rudder system

3.2. Conduction of the subject study

A mock-up of the rudder system was designed and assembled to perform the subject study. The mock-up includes all relevant interaction actuators, providing the necessary functionalities (see Figure 5). The subject study was conducted with five male subjects. Due to the Covid-19 pandemic and the accompanying policy of social distancing, it was unfortunately not possible to survey a larger and more diverse subject group. The test persons were introduced to the scenario and given a steering task. They had to push the throttle forward and turn the rudder to a predefined position while looking forward. This steering task was performed by the subjects for each product configuration. The order in which the characteristics were changed was different for each subject. After each interaction, the subjects were asked about the discomfort felt during the interaction. The discomfort was determined using the categories of the CP-50 scale introduced by Shen and Parsons (1997). While performing the tasks, the subjects wore a motion capture system, based on inertial measurement units (Perception Neuron Studio; Noitom), which recorded the movement during the interaction (see Figure 5). The measurements were carried out twice for each product configuration. This improves the data basis for the derivation of the behaviour cards and allows for the analysis of the variability of human behaviour. Subsequently, the measured movements were transferred to musculoskeletal human models (same as used in the predictive interaction model), which were scaled to the respective test persons according to the anthropometric data collected. The transfer was conducted by applying a virtual marker tracking procedure, similar to the approach of Karatsidis et al. (2018). The scaling of the musculoskeletal human models was also carried out using virtual markers. From each of the transferred movements one representative posture was extracted. The representative posture chosen, was one in which the rudder is steered out to a predefined extent, whereas the test persons had to stretch. To ensure reproducibility, a quantitative selection criterion (hand position on the rudder) was defined. These representative body postures, expressed in the joint angles of the scaled musculoskeletal human models, were dynamically analysed using static optimisation. This allows a comparison of the dynamic state of the experimentally determined and predictively generated postures. To ensure comparability, the same dynamic constraints were used for these simulations as for the static optimisation of the predicted postures.

Figure 5. Subject in interaction with the physical mock-up, wearing the motion capture suit

3.3. Application of the predictive interaction model

In order to apply the predictive interaction model, the rudder stand was implemented as a CAD model and the affordance-features for the defined movement state (representative body posture) were generated with the developed CAD-integrated task editor (see Wolf *et al.*, 2021). With help of the affordance features, the left hand was coupled to the rudder, the right hand to the throttle as well as the feet on the deck. Within the affordance features, the reaction forces were modelled in such a way that most of the body weight is transferred to the deck over the feet. In addition, there is the possibility of supporting part of the body weight via the hand on the rudder or throttle. The affordance features were defined without using external forces, since both the operation of the rudder and the throttle require negligible forces. By adjusting the CAD model (product configurations) and deriving affordance features the described 18 tasks were generated.

The behavioural cards needed for postural interaction prediction were determined using the representative postures from the experimental data. For this purpose, the representative postures were reviewed and a qualitative manual search for different movement strategies was conducted. It turned out that four of the five subjects always choose a similar strategy. This strategy was used to characterise the interaction behaviour with help of one behaviour card per LH (a total of three behaviour cards were used). The specific generalized coordinates (joint angles and global DHM positional coordinates) of a behaviour card were determined by calculating the median for each generalized coordinate of all postures of a LH. In addition, the ranges of the individual joint angles of all postures of a LH were calculated. These were used to estimate how much the respective joints were used to adapt to the different product configurations. From this information, the coordination patterns of the behaviour cards were generated.

The 18 generated tasks were simulated using the predictive interaction model with the three determined behaviour cards. For comparability, the simulations were carried out for each of the five scaled DHM (according to subject anthropometry). Accordingly, 90 predictive simulations were carried out.

3.4. Evaluation and comparison measures

Due to the redundancy of human movement possibilities, a direct comparison of predicted and measured posture by means of joint angle values is only of limited significance. A predicted posture can have a different joint angle pattern than the measured posture and still represent a valid solution. Hence, the comparison of the joint angle patterns of predicted and measured postures are primarily used to gain a better understanding of results rather than to find indications for the applicability and usefulness of the approach. To assess these indications, dynamic results are of higher significance. One important dynamic measure is the magnitude of the so-called residual forces (Delp *et al.*, 2007). Residual forces act along each global degree of freedom on the pelvis and are activated as soon as the

DHM is no longer able to maintain dynamic equilibrium. As soon as one residual force exceeds 10 N the respective predicted posture is considered unrealizable. Additional to this measure, the results are compared in terms of the whole-body muscle activation (WBMA; equation 3):

$$WBMA = \sum_{i=1}^{n} \alpha_i \qquad (3)$$

The WBMA corresponds to the sum of all muscle activations α_i of the body. The parameter n corresponds to the number of muscle models considered. Following the load-strain concept of Rohmert (1986) this parameter can be interpreted as an ergonomic evaluation criterion.

4. Results

With the help of the predictive interaction model, postures in dynamic equilibrium could be generated and analysed for each of the 90 simulations. Accordingly, none of the generated postures has residual forces above the defined limits. Figure 6 representatively shows the predicted posture of product configuration 3-1-3 using the musculoskeletal human model scaled to subject 4 in frontal and lateral view (a) in comparison to the corresponding experimentally measured posture (b). Qualitatively, the postures show similarities, while a quantitative comparison of the joint angle pattern reveals, that the predicted postures defer slightly from the measured ones.
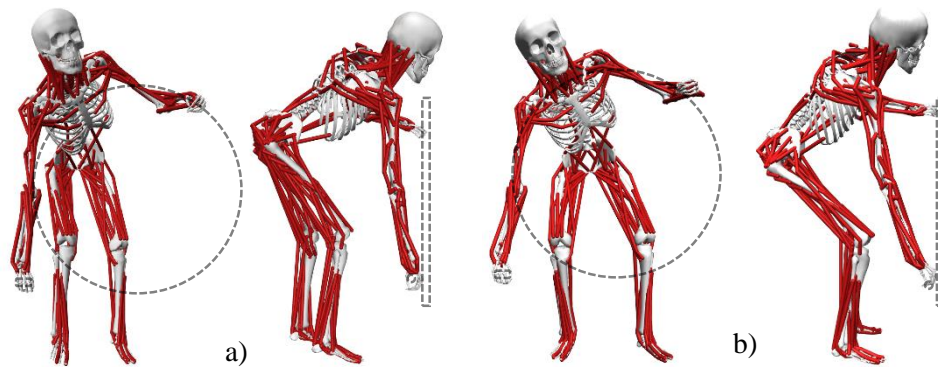

a)   b)

Figure 6. Comparison of the predicted and experimentally measured posture of product configuration 3-1-3

Figure 7 shows the distribution and mean values of the WBMA of the predicted postures and experimentally measured postures for each product configuration. The boxplot shows the median (black line in the box), the range from the 2nd quantile to the 3rd quantile (grey or orange box) as well as the total range from the 1st quantile to the 4th quantile in the form of the whiskers. On the secondary axis, the mean values of the surveyed subjective discomfort (CP-50 score) are plotted for each product configuration. When comparing the distributions directly, it is noticeable that the WBMA of the predicted postures are mostly within the range of the WBMA of the experimentally measured postures and in most cases are less distributed. Accordingly, the experimentally measured and predicted body postures show a similar WBMA magnitude for each product configuration, both in their mean values and in the distributions. For the most configurations, the distributions of the predicted and experimentally determined WBMA coincide from the 2nd quantile to the 3rd quantile.

On the secondary axis of the diagram (Figure 7), the subjective discomfort rating is plotted as mean values of the recorded CP-50 ratings. The test persons used the entire scale to evaluate the product configurations. It is noticeable that the basic correlations between the product configurations and the subjective perception of discomfort are also found in the correlations between the product configurations and the simulated WBMA values. The influence of the LH is most clearly discernible in all assessment approaches. The lower the LH, the higher the subjectively perceived discomfort and the simulated WBMA. Furthermore, it can be seen that the RP 1 (outermost rudder position) within a LH and LD has the highest discomfort rating and WBMA values, while the RP 3 within a LH and LD produces the lowest discomfort and WBMA values. However, the significant drop in subjective discomfort ratings from RP 1 to RP 2 is not observable in the WBMA. In addition, the subjective evaluations of the configurations 1-1-1 and 1-2-1 stand out. These correlations are also not discernible

within the WBMA values. The differences in the subjective discomfort rating in relation to the LD are comparatively small for LH 2 and 3. The subjective evaluation of LH 1 stands out here too, as the differences between LD 1 & 2 are more elaborated. When looking at the WBMA with regard to the LD, again hardly any differences are discernible for all LH and RP.
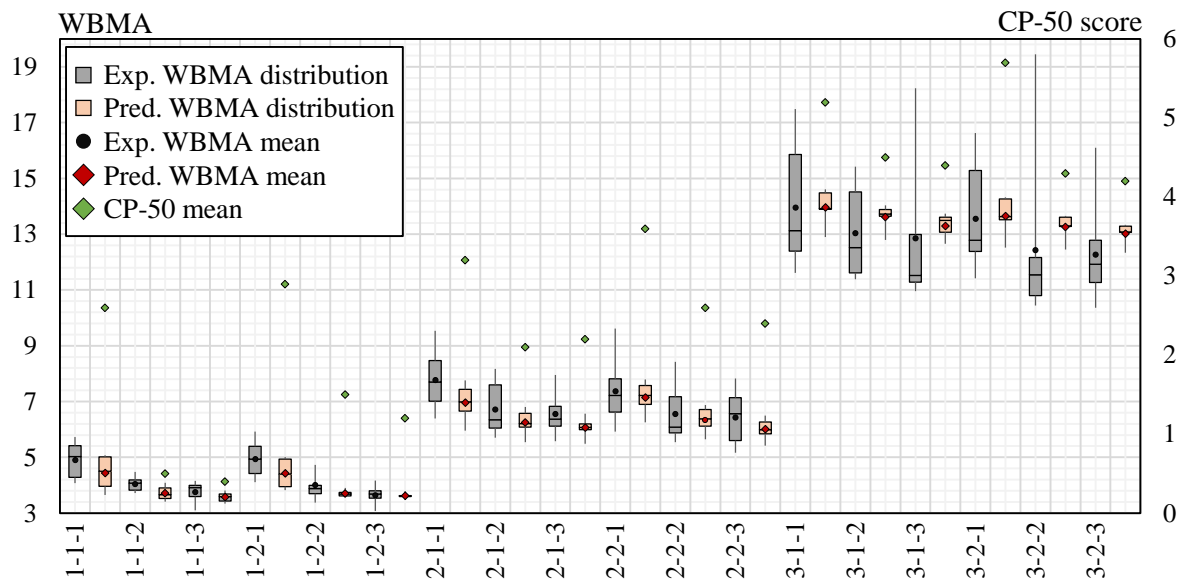

Figure 7. Distribution (boxplot) and mean values of the WBMA of both the predicted postures and the experimentally measured postures per product configuration (LH-LD-RP).

5. Discussion

The experimental methodology is subject to certain limitations that must be taken into account when interpreting the results. Sers *et al.* (2020) investigated the validity of the motion capture system Perception Neuron 2.0 (same measurement technology as in the Perception Neuron Studio used) for measuring upper body movements and came to the conclusion that the system can record upper body movements with an accuracy of 5° per joint angle. The transfer of the measured movements to the respective musculoskeletal human model is also subject to errors. Karatsidis *et al.* (2018) transferred gait movements, measured with inertial sensors to musculoskeletal human models using a similar procedure. They observed root-mean-square differences of 4.1 ± 1.3°, 4.4 ± 2.0° and 5.7 ± 2.1° for the joint angles of the ankle, knee and hip in the sagittal plane. In total, these sources of error can lead to the case that the experimentally measured postures (expressed in the joint angles of the DHM) do not correspond exactly to the postures actually performed by the subjects. This particularly is evident in the foot positions of the measured postures, which are often not parallel to the ground (see Figure 6). This is not the case with the predicted postures and, along with other deviations, can be seen as a reason for the slightly higher or lower WBMA values of the measured postures compared to the predicted postures. Furthermore, it must be taken into account that the predicted postures were generated for the same tasks that were used to characterise human behaviour. In future evaluation studies, cross-validation could allow a deeper analysis. With the help of the developed predictive interaction model, body postures in dynamic equilibrium could be predicted for all five human models and 18 product configurations. The qualitative and quantitative comparisons of predicted and measured postures (joint angle values) show, that the predicted postures differ from the measured postures quantitatively, but show great similarities qualitatively. The WBMA of the predicted postures are mostly within the distribution of the WBMA of the experimentally captured postures and thus describe the same correlations in respect to the product configurations in a whole-body dynamic point of view. Thus, indications for the applicability and usefulness of the predictive interaction model are clearly recognisable. The evaluations show that although the measured postures were not exactly reproduced by the predictive interaction model, similar and realistic postures were predicted that were consistent in terms of whole-body strain.

The comparison of the subjective discomfort evaluation with the calculated WBMA shows that the predictive interaction model using the WBMA as an ergonomic evaluation criteria can reveal basic correlations between the product configurations and the subjective discomfort perception. The predictive ergonomics evaluation shows that the discomfort increases with decreasing LH and that a small distance between throttle and rudder (RP) leads to less discomfort. However, some correlations could not be resolved with the predictive method. Since these correlations are not shown in the WBMA of the experimentally captured body postures either, it is not the predictive interaction model but the ergonomic evaluation criterion (WBMA) or the subjective discomfort evaluation that has to be questioned. The assessment of discomfort using the CP-50 scale is exposed to subjective biases. In future studies, the subjective discomfort assessment should therefore be supplemented with objective measurements (such as EMG measurements). The WBMA as ergonomic evaluation criterion also seems not to be sufficient for an assessment of discomfort perception. In order to further develop the predictive interaction model into a computer-aided ergonomics tool, it is therefore necessary to research additional assessment criteria or schemes in order to validly interpret ergonomics, discomfort and usability.

6. Summary and Outlook

Engineering design lacks data-driven methods and tools for predictive and versatile applicable interaction modelling, in order to analyse digital product model states virtually and proactively using DHM, in terms of a computer aided ergonomics tool (Wolf *et al.*, 2020). In order to address this research gap we developed and initially evaluated a phenomenological predictive interaction model. The initial evaluation shows indications for the applicability and usefulness of the developed method. Nevertheless, some open points remain. The need to characterize human behavior (behaviour cards) is a limitation to the applicability and usefulness of the presented interaction model. Hence, a behavior card library of elementary or recurring human-product interactions (e.g. pulling, lifting, pressing, etc.) should be established, alongside a standardized approach to deduce behaviour cards from empirical data.

Acknowledgement

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DESIGN SUPPORT TOOLS AND METHODS