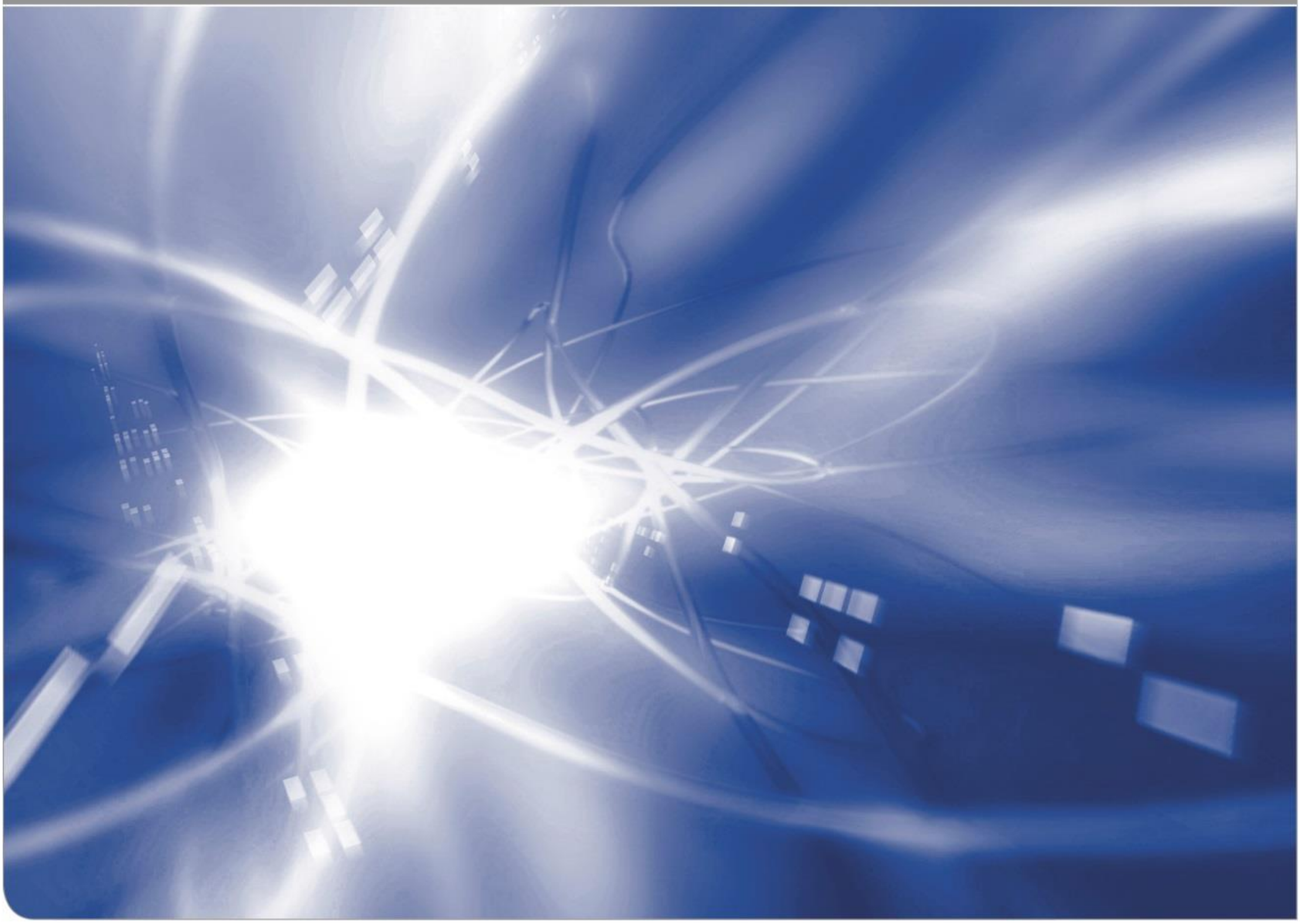
JEMSyS: Jerk Experience Model for Human-Machine Symbiosis – Exploring the Influence of Translational Jerks on Sense of Agency and Embodiment

Robens, Jan Heinrich[1*]; Saurbier, Simon[1*]; Voormann, Anne[2]; Döllken, Markus[1]; Kiesel, Andrea[2]; Matthiesen, Sven[1]

KIT SCIENTIFIC WORKING PAPERS 256



[1] IPEK Institute of Product Engineering
[2] Albert-Ludwigs-Universität Freiburg
* *These authors contributed equally to this work and share first authorship.*

IPEK – Institute of Product Engineering

Kaiserstraße 10
76131 Karlsruhe
www.ipek.kit.edu

Impressum

Karlsruher Institut für Technologie (KIT)
www.kit.edu

2025

ISSN: 2194-1629

JEMSyS: Jerk Experience Model for Human-Machine Symbiosis – Exploring the Influence of Translational Jerks on Sense of Agency and Embodiment

Robens, Jan Heinrich[1*]; Saurbier, Simon[1*]; Voormann, Anne[2]; Döllken, Markus[1]; Kiesel, Andrea[2]; Matthiesen, Sven[1]

[1]IPEK Institute of Product Engineering; [2]Albert-Ludwigs-Universität Freiburg

**These authors contributed equally to this work and share first authorship.*

Abstract:

Facing a shortage of skilled labor, Human-Machine Symbiosis aims to combine human adaptability with machine precision to enable productive, user-centered work. In physical interaction, sudden and unpredictable dynamic events - characterized by jerk - can disrupt the user's sense of control and integration. This study addresses a gap in understanding the impact of dynamic loads on human experience during machine operation. Specifically, we examine the influence of jerk intensity on Sense of Agency (SoA) and Embodiment. These experiential constructs reflect perceived control and bodily integration - critical for symbiotic human-machine interaction. In a controlled experiment, 43 participants performed milling tasks using a hand-guided router under systematically varied jerk conditions. SoA and Embodiment were assessed using validated questionnaires. Linear mixed-effects models identified maximum jerk as the most robust predictor, showing significant negative effects on both constructs. Segmented regression analysis revealed increased sensitivity to jerk at lower intensities, particularly for Embodiment. While movement direction influenced baseline SoA, it did not moderate the jerk-SoA relationship. Based on these findings, we propose an initial *Jerk Experience Model* that quantitatively links jerk intensity to experiential degradation. This model provides a foundation for deriving application-specific design requirements, thereby supporting the development of perception-aligned human-machine systems. We formulate hypotheses on influencing factors to guide future research aimed at broadening the model's applicability across use cases.

Keywords: *human centered design, ergonomics, haptic feedback, human-machine interaction, perception thresholds*

1. Introduction

The labor market is facing major challenges, with an ongoing shortage of skilled workers already affecting productivity across numerous sectors. According to the Association of German Chambers of Industry and Commerce [1], over 50 percent of skilled positions in Germany remain unfilled. According to forecasts by the Institute for Employment Research (IAB), this shortage will worsen in the coming years, with the potential labor force declining by 11.7 percent from 45.7 to 40.4 million by 2060 [2]. This situation poses specific challenges for occupational fields that depend on human manual activities and cannot be fully automated. This is the case, for example, when human work takes place in complex environments or requires a high degree of flexibility. In such settings, full automation to replace the human worker is neither technically feasible nor realizable under reasonable financial conditions, so the automation of the corresponding processes is associated with considerable difficulties.

Simultaneously, the ethical demand for a humane working environment requires close cooperation between humans and machines that not only take efficiency into account but also the health and well-being of employees. Fields such as healthcare, construction industry and skilled trades often involve high physically demanding tasks that can lead to long-term health issues and resulting absences [3]. These circumstances make such occupations less attractive to young people, who are increasingly prioritizing a healthy work-life balance. Consequently, sectors like construction and skilled crafts face rising demand coupled with a lack of incoming talent, resulting in quality decline and economic losses.

In this context, human-machine symbiosis [4] is becoming increasingly important. The concepts of Industry 5.0 [5] and human-centric manufacturing [6] address these challenges by placing humans at the center while striving for symbiotic interaction with machines. The research results of Inga et al. [4] suggest that a multivariate approach can enable a new form of human-machine interaction that optimally combines the strengths of both partners. In this context, humans are a central component of a dynamic working environment.

A critical question for human-machine symbiosis concerns the experiential state of the human while conjointly working with the machine. Specifically, does the human sense control over the joint work output and simultaneously experience a sense of unity with the machine during the joint work? Scientific research has already gained important insights into experiential processes such as Sense of Agency (SoA) and Embodiment, which are crucial for successful human-machine interaction. SoA refers to the feeling of causing and being responsible for an action and its consequences [7]. Longo et al. [8] describe Embodiment as the subjective experience of the body becoming one with the environment. Both experiential constructs depend on the ability of humans to predict future states of an action. SoA is reduced for unexpected action consequences [9], and Embodiment is related to predictive processes [10, 11]. Embodiment, for example, can be elicited even in artificial limbs when visual and motor feedback are congruent with the users expectations [12, 13]. Similarly, studies in virtual interaction environments have shown that Embodiment and perceived control do not strictly depend on realistic haptic feedback but can be modulated through the congruence between expected and actual system behavior [14].

In physically coupled human-machine systems, such as hand-held power tools, users are directly exposed to dynamic interaction forces. These forces and their dynamic characteristics can result in continuous periodic oscillations (e.g. hand-arm vibrations) or irregular mechanical impulses. While vibrations are typically characterized by acceleration, sudden, transient events are better described by jerk, the time derivative of acceleration [15]. Jerks often occur unexpectedly and are perceived as abrupt mechanical disturbances. A recent review by Hayati et al. [16] highlights the broad relevance of jerk in fields such as robotics, vehicle dynamics, and human factors, while noting its underrepresentation in design practice.

Jerk, especially when experienced as sudden and unexpected changes in machine behavior, has been associated with discomfort, perceived loss of control, and stress-like reactions in various contexts [17, 18]. A study by Priester et al. [19] identified perceptual thresholds for translational jerk in vehicle collisions, ranging from 8 to 14 m/s^3. Furthermore, the subjective perception of physical stimuli, such as jerk, follows the Weber-Fechner law [20], which states that perceived intensity increases logarithmically with physical stimulus intensity. As a result, the same physical change in jerk may be perceived more strongly at lower baseline levels than at higher ones. This suggests that perceptual thresholds for jerks and their experiential impact may vary across application scenarios with different physical user load levels.

Despite these findings, the role of jerk in shaping subjective experience during human-machine interaction - specifically its influence on constructs such as SoA and Embodiment - has not yet been investigated. Given that both constructs are highly dependent on the predictability of action outcomes [9–11], and that jerks often occur unexpectedly, it is reasonable to assume that jerk has an impact on SoA and Embodiment in physically interactive systems.

To address this research gap, the present study investigates how translational jerks of varying intensities impact SoA and Embodiment in physically coupled human-machine interaction. Specifically, we aim to answer the following research questions:

1. ***What influence do translational jerks have on human experience of Sense of Agency and Embodiment in human-machine interaction?***
2. ***Are there threshold values for the translational jerk at which the influence on Sense of Agency and Embodiment changes significantly?***
3. ***How does the direction of movement (concentric vs. eccentric) affect the relationship between translational jerk and Sense of Agency?***

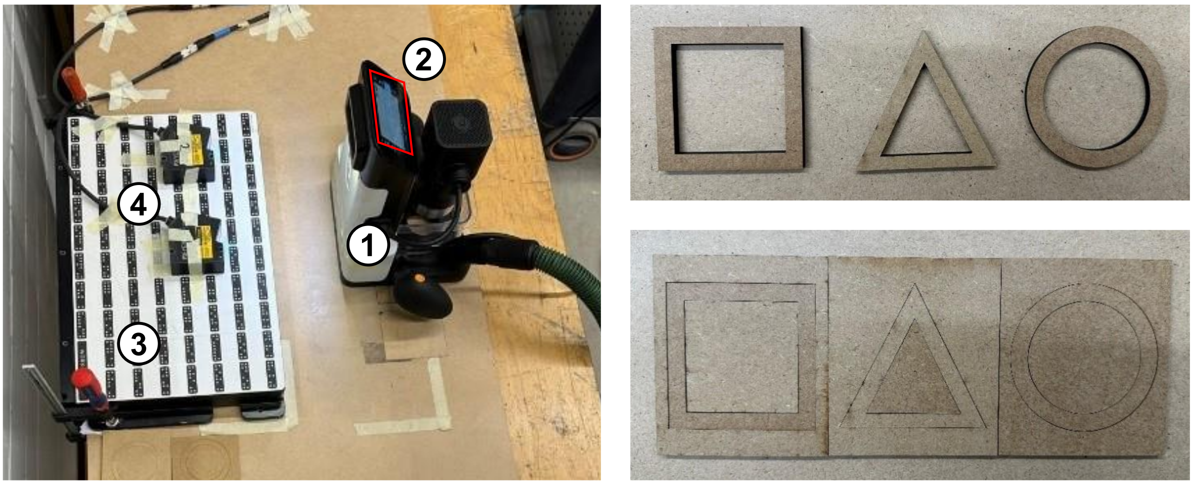
The objective of this study is to develop a quantitative description modelling the experiential dimensions of SoA and Embodiment using translational jerk as a predictor. This knowledge enables the derivation of application-specific design requirements for developing intuitive, perception-aligned, and user-friendly human-machine systems. To this end, we conducted a controlled experiment using a hand-guided CNC router. Participants performed a series of precision milling operations during which translational jerk intensity was systematically varied. The subjective experiences were assessed using questionnaires on SoA and Embodiment. The results are used to derive a first version of a Jerk Experience Model that can serve as a basis for perception-aligned system design in the context of human-machine symbiosis.

2. Materials & Methods

2.1 Experimental Design

To answer the research questions, a laboratory study was conducted with 43 participants (35 males, 8 females; 39 right-handed, 4 left-handed). Most participants were aged 21-30 years (n = 33), with smaller groups aged ≤20 (n = 3), 31-40 (n = 6), and 41-50 (n = 1). The experimental setup is designed to generate and measure translational jerks occurring during the use of a power tool. The resulting human experience was assessed via questionnaire.

The study was carried out using a hand-guided CNC router (Shaper Origin, model SK) from Shaper Tools GmbH (Leinfelden-Echterdingen, Germany) (see Figure 1a, 1). The Shaper Origin enables precise milling along CAD-based contours, displayed on an integrated screen (2). For the experiment, the automatic milling correction was deactivated to preserve direct control. The router was used on the manufacturer’s reference workstation (3). The router was equipped with a suction device and a 3 mm diameter cutter (model SF1-8-3U, Shaper Tools GmbH, Leinfelden-Echterdingen, Germany). Milling tasks were performed on 5 mm high-density fiberboard (HDF) at a working height of 97 cm. Hearing protection and safety goggles were provided to minimize disturbances caused by noise and to ensure their safety.



a) b)

Figure 1: a) Study environment consisting of a hand-guided CNC router (Shaper Origin, 1) including display (2) for a supporting target path indication and workstation (3) for orientation of the router. The position of the machine is recorded by two laser sensors (4); b) Illustration of the milled objects rectangle, triangle and circle (top) and template for verification of the work result (bottom).

Participants milled three predefined shapes with generic motion profiles: a rectangle, triangle, and circle (see Figure 1b). To address the specific research questions of this study, only the datasets generated during the milling of the rectangle were analyzed. Milling the rectangle covered translational movements, including movements perpendicular to the body (away from and towards it). Precision was emphasized by requiring participants to match the milled objects to a test template, encouraging participants to concentrate on achieving high precision in their milling tasks. The rectangle was milled in two steps: first the inner, then the outer contour. An example of a milled rectangle and the corresponding test template are shown in Figure 1b.

Translational jerks were induced using a "Wizard of Oz" approach [21], in which hidden notches were pre-milled on the underside of the workpieces to locally reduce material thickness (Figure 2). When the cutting tool crossed a hidden notch, the sudden decrease in cutting resistance led to an increase in processing speed, resulting in a translational jerk. Jerk intensity was indirectly manipulated by varying the depth of these notches. While notch depth served as the directly controlled independent variable, the resulting translational jerk – assessed by triple differentiation of the router's position data (see Section 2.3) – was used as the predictor for SoA and Embodiment. Four notch depths were implemented to systematically vary jerk intensity: 0 mm, 1 mm, 3 mm and 4.5 mm (see Figure 3).

For each milling segment (towards and away from the body), two jerks were generated, resulting in four jerks per rectangular contour. Jerks occurred only in the push and pull direction, not laterally (left and right). To maintain consistency, each object – consisting of an inner and outer milling contours – was assigned a single notch depth per trial. The order of the notch depths was randomized across participants. The notch positions along the segments were randomized to prevent the participants from anticipating the occurrence of jerk events.

To determine the translational jerk, the machine position was measured using two laser distance sensors (model LK-G157, KEYENCE DEUTSCHLAND GmbH, Neu-Isenburg, Germany) operating at a sampling frequency of 10 kHz and a repeatability of 0.5 µm (see Figure 1, 4).

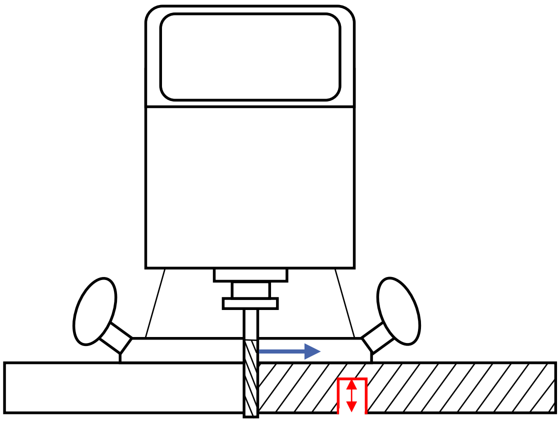


Figure 2: *Side view of the Shaper Origin and the workpiece as a schematic sketch. A pre-notch on the underside of the workpiece reduces milling resistance and allows translational jerks to be adjusted by varying the notch depth (0 mm, 1 mm, 3 mm, 4.5 mm).*

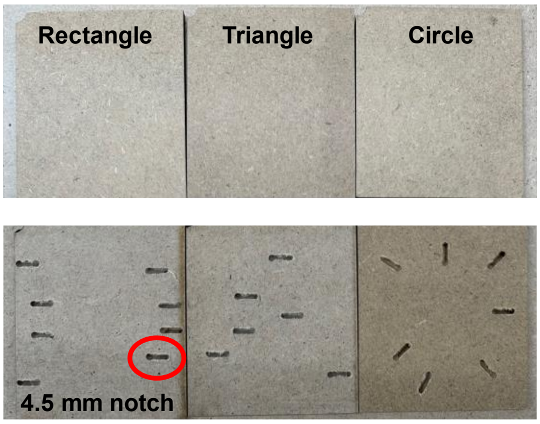


Figure 3: Notches on the back of the workpieces for random adjustment of the translational jerks using the Wizard of Oz method. The depths of the notches are 0 mm (top), 1 mm, 3 mm and 4.5 mm (bottom). Rectangles (left), triangles (center) and circles (right).

The experience of the participants was assessed using an experimental questionnaire with a 7-point Likert scale (see Appendix). The questionnaire included four items on SoA [7] and six items on Embodiment. The Embodiment questionnaire was developed based on the framework by Longo et al. [8]. According to Longo et al., the psychological construct of Embodiment consists of three sub-aspects: Ownership, Location and Agency. The questionnaire used in this study, adapted from Caspar et al. [22], specifically addressed the dimensions of Ownership (2 items) and Agency (4 items). To capture segment-specific experience a single item focusing on the SoA was included, namely: "*I have the feeling that I control the movement of the machine.*"*.* For practical reasons, no additional single items addressing other aspects of Embodiment were included. Questionnaire responses were collected via the online platform LimeSurvey (LimeSurvey GmbH, Hamburg; Germany).

2.2 Experimental Procedure

The experimental setup was implemented at two locations[1]. 10 participants took part in Freiburg and 33 participants in Karlsruhe. Among the 43 participants, 21 reported no prior experience in operating a CNC milling machine.

At the beginning of the study, the demographic data of the subjects were recorded. These include age, gender, dexterity and the expertise of the subjects. After that, participants were shown an explanatory video explaining the test procedure and how to use the router to minimize the influence of the investigator and ensure that all participants received identical information. The participants were then allowed to familiarize themselves with the router and how it works in a dedicated training phase in which the subjects milled along straight lines (concentrically) towards the body supported by a target path indication on the display. The training phase could be repeated as often as the participants considered it to be necessary.

The actual work phase was divided into four test runs, each corresponding to one of the factor levels of the pre-notch depths (see Section 2.1). At the beginning of each test run, a reference track, similar to the one used in the training phase, was milled without any external influences,

[1] The main results were similar for both subsamples (Freiburg and Karlsruhe); therefore, the data were analyzed together.

such as induced jerks. This reference track served as a reference for the participants to evaluate SoA and Embodiment in the subsequent test run. The inner contours of the objects were always milled first. After completing each contour, participants rated their SoA based on a single item. At the end of each run, participants completed an online questionnaire assessing SoA and Embodiment before proceeding to the next test run.

2.3 Data Analysis

The analysis was based on data from 40 out of the 43 participants. Three participants were excluded due to either prior negative experiences with router or technical issues during data recording. The evaluation of the translational jerk was based on position data obtained from laser distance sensors during the test runs. The analysis was conducted using MATLAB (R2024a, The MathWorks, Natick, Massachusetts).

To calculate the physical jerk, the position data were filtered (Butterworth filter, 10 Hz cutoff) and segmented into the different milling segments. Only those segments were evaluated in which jerks had been induced using the Wizard-of-Oz method. The position data were then differentiated three times to obtain the translational jerk signal. The two largest jerk peaks were extracted per segment, corresponding to the number of induced jerks. Based on these values, several jerk-related characteristics (maximum value, mean, variance, and standard deviation) were calculated. Figure 4 illustrates the processing steps for determining the translational jerk, including a) the position signal and b) the resulting absolute jerk signal.

Statistical Evaluation

The initial step was to assess the reliability of the questionnaires utilizing Cronbach's alpha, with the objective of evaluating the internal consistency of the subscales. In accordance with the recommendations of Tapal et al. [7], the item "The consequences of my actions do not seem to follow logically from my actions" was inverted, as it is assigned to the "Sense of Negative Agency" (SoNA). The single item on the SoA was validated using a Pearson correlation analysis with the aggregated values of the SoA questionnaire. Additionally, the

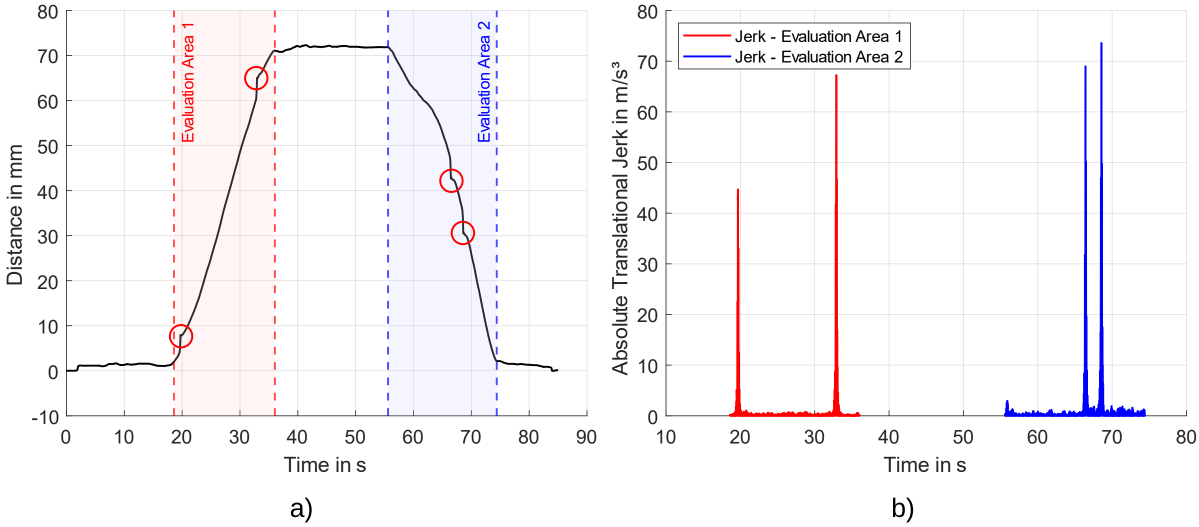


Figure 4: Processing steps for the determination of the translational jerk: a) Filtered position data (Butterworth low-pass filter, 10 Hz cutoff) with highlighted evaluation areas; b) Absolute translational jerk obtained by triple differentiation of the filtered position data, with peaks corresponding to the induced jerk events.

internal consistency between the single item and the main questionnaire was examined using Cronbach's alpha to assess the agreement and reliability of the two measurement instruments.

To conduct a statistical analysis, linear mixed-effects regression (LMER) models were employed to model the influence of different predictors on the translational jerk and its subsequent effect on the assessment variables SoA and Embodiment. Mixed-effects models enable the consideration of both fixed effects, such as the translational jerk as a derived predictor, and random effects, such as inter-individual differences between subjects. The maximum likelihood (ML) method was employed to evaluate the model quality.

Research Question 1 – Empirical Modeling of Sense of Agency & Embodiment

To predict the SoA and Embodiment, several jerk-related characteristics (maximum value, mean, variance, and standard deviation) were evaluated as fixed effects within LMER models. Among these, the maximum jerk value (JerkMax) exhibited the strongest explanatory power and robustness across both experiential constructs. To investigate potential nonlinear relationships, additional models were evaluated that included combinations of multiple predictors and polynomial terms (quadratic and cubic). Model comparisons were based on the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), log-likelihood values, and both marginal and conditional R^2 statistics. For SoA, a linear model using JerkMax provided the best balance between model simplicity and predictive quality. The Embodiment was best described by a model including linear and quadratic terms of JerkMax. Overall, JerkMax was selected as the central predictor for SoA and Embodiment due to its statistical performance, interpretability and practical relevance. The final model specifications and their performance are detailed in the results section.

Research Question 2 – Analysis of Potential Threshold Effects of Translational Jerk

Segmented regression analyses were conducted to investigate a possible threshold effect of the translational jerk on SoA and Embodiment. Three different model approaches were evaluated, each employing JerkMax as the predictor. To identify potential thresholds, the breakpoints were iteratively shifted in steps of 0.1 m/s^3 between 2.2 and 55 m/s^3 ensuring that at least 10 % of the data points were included on both sides. The model quality was assessed using the AIC and BIC, both determined based on maximum likelihood estimates. The following three segmented model approaches were considered for both SoA and Embodiment:

1. **Constant - linear model:** This model assumes no effect of JerkMax below the breakpoint, with a linear mixed-effects model with JerkMax as predictor applied above.
2. **Constant - quadratic model:** This model assumes no effect of JerkMax below the breakpoint, with a quadratic mixed-effect of JerkMax as predictor above.
3. **Two-part linear model:** Applies separate linear mixed-effects models on both sides of the breakpoint, assuming a change in effect strength at the threshold.

Research Question 3 – Effect of Movement Direction on Sense of Agency

To investigate the influence of the direction of movement ("towards the body" versus "away from the body") on the relationship between translational jerk and SoA, the segment-specific single item on SoA was used. In the first step, the existing LMER model with JerkMax as a predictor was extended to include direction of movement as a nominal factor, and their interaction was considered for model comparison. Model quality was assessed using marginal and conditional R^2. Statistical analyses were performed in the R programming language [23] using the lme4 package [24].

3. Results

Figure 5b illustrates the distribution of the measured translational jerk values across all factor levels of the notch depth. The distribution demonstrates a distinct accumulation of low intensities, with 83 of the 160 data points positioned below 8 m/s^3, corresponding to the first quartile (3.0 m/s^3) and median (7.3 m/s^3). The mean jerk intensity is markedly higher at 21.4 m/s^3, reflecting the impact of a prolonged rightward extension in the distribution. The third quartile is 41.3 m/s^3, and the maximum observed value is 72.3 m/s^3, indicating a broad range of jerk intensities. Above 8 m/s^3, the distribution of jerk intensities is relatively uniform. The basic dynamic user load measured during the experiment resulted in a mean root mean square (RMS) acceleration of 11.4 m/s^2 (standard deviation (SD) = 6.5 m/s^2) and a mean jerk of 0.356 m/s^3 (SD = 0.317 m/s^3).

Descriptive statistics for the SoA and Embodiment questionnaires and the single item on SoA (all assessed on a 7-point Likert scale with 7 as maximum experience of both constructs) are presented in Table 1. The mean SoA score ($M = 4.952$, $SD = 1.336$) is very close to the mean of the single items on SoA ($M = 4.945$, $SD = 1.578$), but the single items have a larger standard deviation, indicating greater variability in responses. The mean Embodiment score ($M = 4.080$, $SD = 1.203$) is below SoA measures.

Table 1: Descriptive statistics of the calculated Sense of Agency (SoA) and Embodiment scores.

	Mean	SD	N
Embodiment - Score	4.080	1.203	160
SoA - Score	4.952	1.336	160
SoA - Single Item	4.945	1.578	160

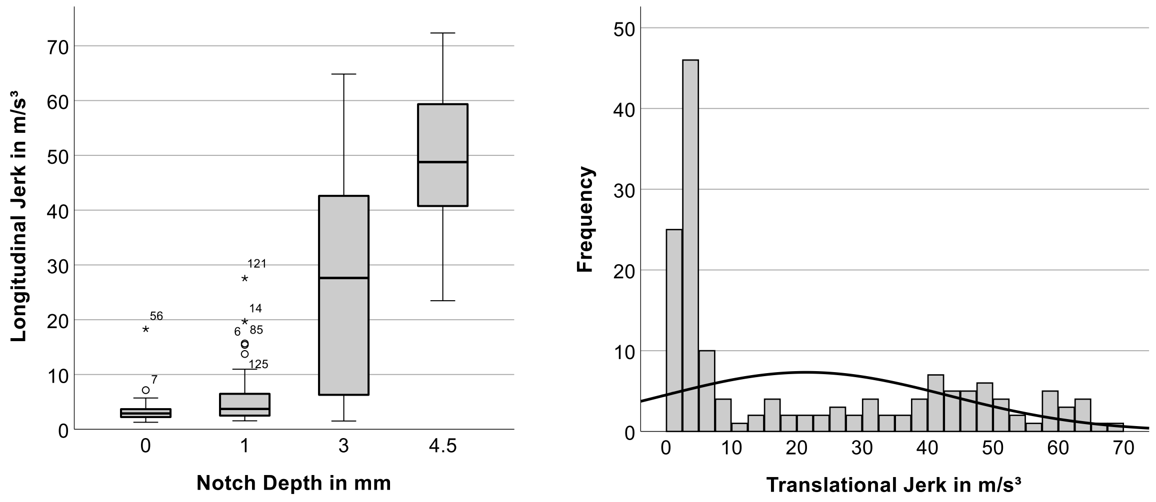
Reliability Evaluation of the Questionnaires & Single Item on Sense of Agency

The results of the reliability analysis of the questionnaires indicate a high level of internal consistency for both subscales. The SoA questionnaire exhibits a Cronbach's alpha of 0.843, while the Embodiment questionnaire demonstrates a Cronbach's alpha of 0.866. These values indicate a high internal consistency of the respective constructs.

The validity analysis of the single item on SoA revealed a significant positive correlation with the SoA Score of the main questionnaire ($r = .728$, $p < .001$, $n = 160$). According to Cohen [25], this corresponds to a strong effect. Furthermore, the reliability analysis demonstrates a high internal consistency between the single item and the main questionnaire, with a Cronbach's alpha of 0.836. This suggests that the single item and the main questionnaire are measuring the same theoretical construct and that the single item is a reliable means of capturing the SoA.

Correlation between Sense of Agency & Embodiment

The Pearson correlation was calculated to examine the relationship between the scores of the two questionnaires (SoA and Embodiment). The results showed a significant correlation between the subject’s SoA and Embodiment ($r = .736$, $p < .001$, $n = 160$), which is classified as a strong effect according to the criteria established by Cohen [25].



a) b)

Figure 5: Distribution and frequency of translational jerk: a) The box plot shows the distribution of translational jerk intensities across different notch depths; b) The histogram depicts the frequency distribution of translational jerk intensities across all notch depths.

3.1 Empirical Modeling of Sense of Agency & Embodiment

Research Question 1

"What influence do translational jerks have on human experience with regard to the Sense of Agency and Embodiment in human-machine interaction?"

Based on the systematic model evaluation outlined in Section 2.3, the maximum translational jerk (JerkMax) was identified as the most suitable predictor for both SoA and Embodiment. Alternative characteristics, including mean, standard deviation and variance, as well as models combining multiple predictors, were tested but did not yield improvements in model fit. Likewise, models incorporating higher order polynomial terms (e.g. cubic components) failed to enhance explanatory power. The final LMER models are presented below. Table 2 summarizes the statistical parameters of the selected models.

Due to the sample size of 160, normality of the residuals was assessed using the Kolmogorov-Smirnov test. The results indicated that normality could not be rejected for SoA ($D = 0.074$, $p = .341$) and Embodiment ($D = 0.050$, $p = .814$). These results suggest that the residuals did not deviate significantly from a normal distribution, supporting the requirements for further parametric analyses.

Regarding SoA, the linear mixed-effects model in which JerkMax represents the single predictor exhibits the best model quality (Marginal $R^2 = 0.390$; Conditional $R^2 = 0.549$; AIC = 464.14). The negative effect of JerkMax on SoA is significant ($\beta = -0.04$; CI: -0.05 to -0.03; $p < .001$), indicating that higher jerk intensity is associated with a reduction in SoA.

Regarding Embodiment, the model with a linear and an additional quadratic component of JerkMax exhibits the highest model Quality (Marginal $R^2 = 0.265$; Conditional $R^2 = 0.610$; AIC = 440.14). The linear ($\beta = -0.06$; CI: -0.08 to -0.03; $p < .001$) and the quadratic effect ($\beta = 0.50 \times 10^{-3}$; CI: 0.10×10^{-3} to 0.90×10^{-3}; $p = .015$) of JerkMax are both statistically significant. The quadratic effect indicates a reduction in the strength of the linear relationship at higher values of JerkMax.

Table 2: Statistical parameters of the mixed-effects models for Sense of Agency and Embodiment using the maximum value of the translational jerk (JerkMax) as predictor.

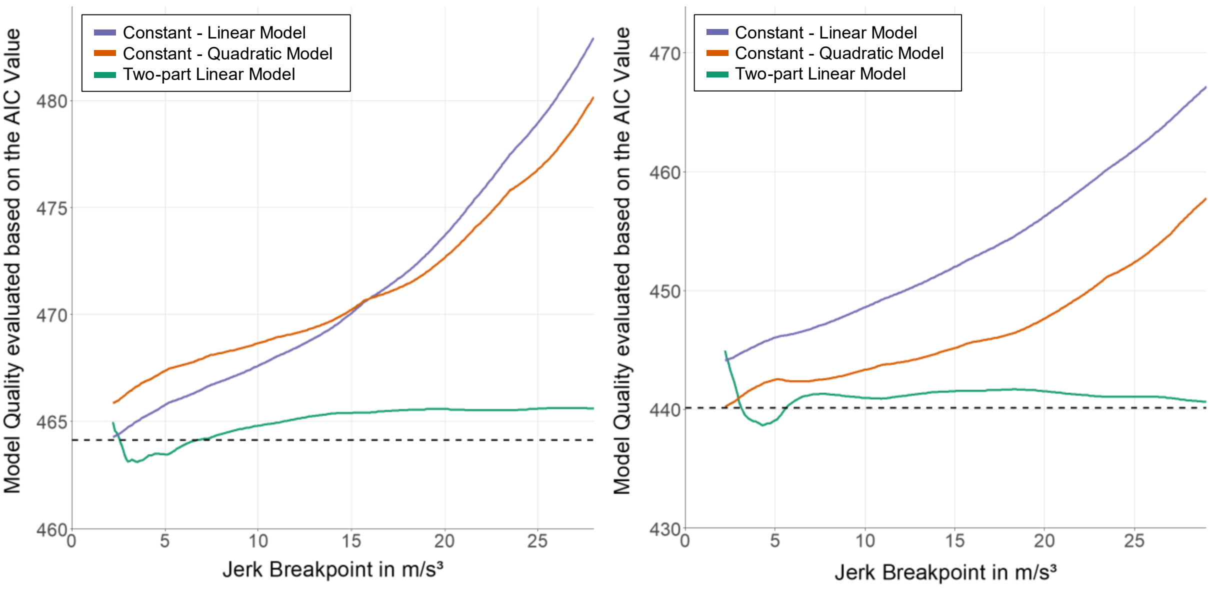
	Sense of Agency			**Embodiment**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	5.78	5.52 – 6.04	**<0.001**	4.84	4.53 – 5.16	**<0.001**
JerkMax	-0.04	-0.05 – -0.03	**<0.001**	-0.06	-0.08 – -0.03	**<0.001**
JerkMax²				0.00	0.00 – 0.00	**0.015**
Random Effects						
σ^2	0.82			0.60		
τ_{00}	0.29 Subject ID			0.53 Subject ID		
ICC	0.26			0.47		
N	40 Subject ID			40 Subject ID		
Observations	160			160		
Marginal R^2 / Conditional R^2	0.390 / 0.549			0.265 / 0.610		

3.2 Analysis of Potential Threshold Effects of Translational Jerk

Research Question 2

"Are there threshold values for the translational jerks at which the influence on Sense of Agency and Embodiment changes significantly?"

Figure 6 illustrates the quality of the segmented models predicting the a) SoA and b) Embodiment as a function of the breakpoint. The dashed horizontal line represents the model performance of the respective reference model, which was determined in Section 3.1. Thus, the reference model for SoA is a linear mixed-effects model with JerkMax as a predictor (AIC = 464.15, BIC = 476.45), while the reference model for Embodiment is a mixed-effects model with linear and quadratic terms of JerkMax (AIC = 440.14, BIC = 455.52).



a) b)

Figure 6: Threshold effect analysis for predicting a) Sense of Agency and b) Embodiment. Comparing the model quality of three segmented mixed effects approaches using the AIC for different breakpoints: Left-sided constant and right-sided linear model approach (purple), left-sided constant and right-sided quadratic model approach (orange) and two-sided linear model approach (green).

The results of the first two segmented model approaches show similar trends for SoA and Embodiment. The first model approach (purple curve), which assumes no effect of the jerk below the breakpoint and a linear effect above it, shows an almost exponential increase in AIC values with increasing breakpoints. The values remain consistently above the reference line (SoA: AIC_{min} = 464.3, Embodiment: AIC_{min} = 440.3). The second model approach (orange curve), which models a constant effect below the breakpoint and a quadratic effect above it, also shows an increase in AIC values with increasing breakpoints. As with the previous model approach, the model quality values remain consistently above the reference line. The AIC curves of the two model approaches do not show any clear local minima that could indicate a kind of threshold effect.

The third model approach (green curve) is based on two linear segments. It shows in Figure 6a for SoA a flatter course of the AIC values compared to the curves of the first two model approaches. A local minimum is observed at a breakpoint of 3.5 m/s³, with an AIC of 463.12 and a BIC of 478.49. Regarding Embodiment, the third model illustrated in Figure 6b shows a clear local minimum at a breakpoint of 4.3 m/s³. At this breakpoint, the model achieves an AIC of 438.68 and a BIC of 454.06, slightly below the values of the quadratic reference model.

The segmented model resulting from the threshold effect analysis for SoA (see Table 3), with a breakpoint at 3.5 m/s³, describes the relationship between JerkMax and SoA through two linear segments. Below the breakpoint JerkMax shows a moderately negative effect (β = -0.32, CI: -0.63 to -0.00, p = .049), while above the breakpoint there is a weaker but consistent negative effect (β = -0.04, CI: -0.04 to -0.03, $p < .001$). The ANOVA comparison with the reference model from Section 3.1 shows no significant difference ($\chi^2(1) = 3.022$, p = .082). This is confirmed by the low difference in AIC values (463.12 vs. 464.15), which according to Burnham et al. [26] indicates little or no evidence of a model difference.

The segmented model resulting from the threshold effect analysis for Embodiment (see Table 3) uses two linear segments separated by the breakpoint at 4.3 m/s³. Below the breakpoint JerkMax shows a moderate negative effect (β = -0.29, CI: -0.48 to -0.10, p = .002), while above the breakpoint a weaker negative effect is observed (β = -0.02, CI: -0.03 to -0.02, $p < 0.001$). According to Burnham et al. [26] and Raftery [27], the comparison of the AIC (438.68 vs. 440.14) and BIC (454.06 vs. 455.52) with the reference model from Section 3.1 indicates no or only weak evidence of a model difference.

Table 3: Segmented models for the prediction of Sense of Agency and Embodiment with threshold values at 3.5 m/s³ for Sense of Agency and 4.3 m/s³ for Embodiment.

	Sense of Agency			**Embodiment**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	6.60	5.64 – 7.57	**<0.001**	5.55	4.88 – 6.22	**<0.001**
JerkMax ≤ Threshold	-0.32	-0.63 – -0.00	**0.049**	-0.29	-0.48 – -0.10	**0.002**
JerkMax > Threshold	-0.04	-0.04 – -0.03	**<0.001**	-0.02	-0.03 – -0.02	**<0.001**
Random Effects						
σ^2	0.80			0.59		
τ_{00}	0.31 Subject ID			0.55 Subject ID		
ICC	0.27			0.48		
N	40 Subject ID			40 Subject ID		
Observations	160			160		
Marginal R^2 / Conditional R^2	0.399 / 0.564			0.273 / 0.624		

3.3 Effect of Movement Direction on Sense of Agency

Research Question 3

"How does the direction of movement (concentric vs. eccentric) affect the relationship between translational jerk and Sense of Agency?"

Based on the single item on SoA, a model comparison was conducted to determine whether the direction of movement (i.e. towards the body versus away from the body) affects the SoA.

Levene's test confirmed homogeneity of variance for the single item on SoA ($F(1,638) = 0.228$, $p = .633$). Due to the sample size of 640, the normality of the residuals was assessed using the Kolmogorov-Smirnov test. The results indicated that normality could not be rejected ($D = 0.042$, $p = .206$), suggesting that the residuals did not significantly deviate from a normal distribution, supporting the requirements for further parametric analyses.

The results, as presented in Table 4, show that the direction of movement as a nominal factor has a significant effect on SoA ($\beta = -0.11$; CI: -0.21 to -0.02; $p = .017$). Participants reported significantly lower SoA when movements were directed away from the body ($M = 4.86$, $SD = 1.73$) compared to movements towards the body ($M = 5.03$, $SD = 1.79$). The interaction effect between JerkMax and the direction of movement was not significant ($\beta = -0.00$; CI: -0.01 to 0.00; $p = .977$), indicating that the direction of movement does not moderate the relationship between JerkMax and SoA. Adding the direction of movement as a nominal factor slightly increased the Marginal R^2 values from 0.310 to 0.314.

Table 4: Mixed linear model - comparison between the jerk characteristics maximum value (JerkMax) & direction of movement as predictors for the Sense of Agency (SoA) evaluated based on the single item per segment.

	Single Item on SoA Per Segment			**Single Item on SoA** Per Segment			**Single Item on SoA** Per Segment		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	5.79	5.51 – 6.08	**<0.001**	5.80	5.51 – 6.08	**<0.001**	5.80	5.51 – 6.08	**<0.001**
JerkMax	-0.05	-0.06 – -0.05	**<0.001**	-0.05	-0.06 – -0.05	**<0.001**	-0.05	-0.06 – -0.05	**<0.001**
Movement Direction				-0.11	-0.21 – -0.02	**0.017**	-0.11	-0.24 – 0.01	0.076
JerkMax × Movement Direction							-0.00	-0.01 – 0.00	0.977
Random Effects									
σ^2	1.47			1.46			1.46		
τ_{00}	0.68 $_{\text{Subject ID}}$			0.68 $_{\text{Subject ID}}$			0.68 $_{\text{Subject ID}}$		
ICC	0.32			0.32			0.32		
N	40 $_{\text{Subject ID}}$			40 $_{\text{Subject ID}}$			40 $_{\text{Subject ID}}$		
Observations	640			640			640		
Marginal R^2 / Conditional R^2	0.310 / 0.528			0.314 / 0.532			0.313 / 0.531		

3.4 Jerk Experience Models for Sense of Agency & Embodiment

Based on the analyses of different predictors, model complexity and thresholds, the final models for predicting Sense of Agency and Embodiment were derived. These models provide a robust basis for the quantitative description of the influence of translational jerk (JerkMax) on the two evaluation variables.

The final model for **Sense of Agency** (SoA) is characterized by a linear relationship with JerkMax, as illustrated by the following equation:

$$SoA\ (Jerk_{Max}) = 5.780 - 3.872 \times 10^{-2} \frac{s^3}{m} \times Jerk_{Max} + \epsilon$$

The intercept value of 5.780 represents the initial expression of the SoA at minimum jerk intensity. The negative coefficient (-3.872 × 10^{-2} s^3/m) indicates that the SoA decreases with increasing jerk intensity.

The final model for **Embodiment** is characterized by a two-part linear relationship, with a breakpoint observed at 4.3 m/s^3. This is illustrated by the following equation:

$$Embodiment\ (Jerk_{Max}) = \begin{cases} 5.550 - 0.290 \frac{s^3}{m} \times Jerk_{Max} + \epsilon, & Jerk_{Max} \leq 4.3 \frac{m}{s^3} \\ 4.399 - 2.230 \times 10^{-2} \frac{s^3}{m} \times Jerk_{Max} + \epsilon, & Jerk_{Max} > 4.3 \frac{m}{s^3} \end{cases}$$

The coefficient below the breakpoint (-0.290 s^3/m) shows a moderate negative effect, while a smaller negative effect on Embodiment is observed above the breakpoint (-2.230 × 10^{-2} s^3/m).

In both equations, ϵ represents the random error components, which represent individual deviations or unmodeled effects. The scale of SoA and Embodiment ranges from 1 (very low) to 7 (very high). Figure 7 illustrates the relationship between the translational jerk and the SoA and Embodiment.

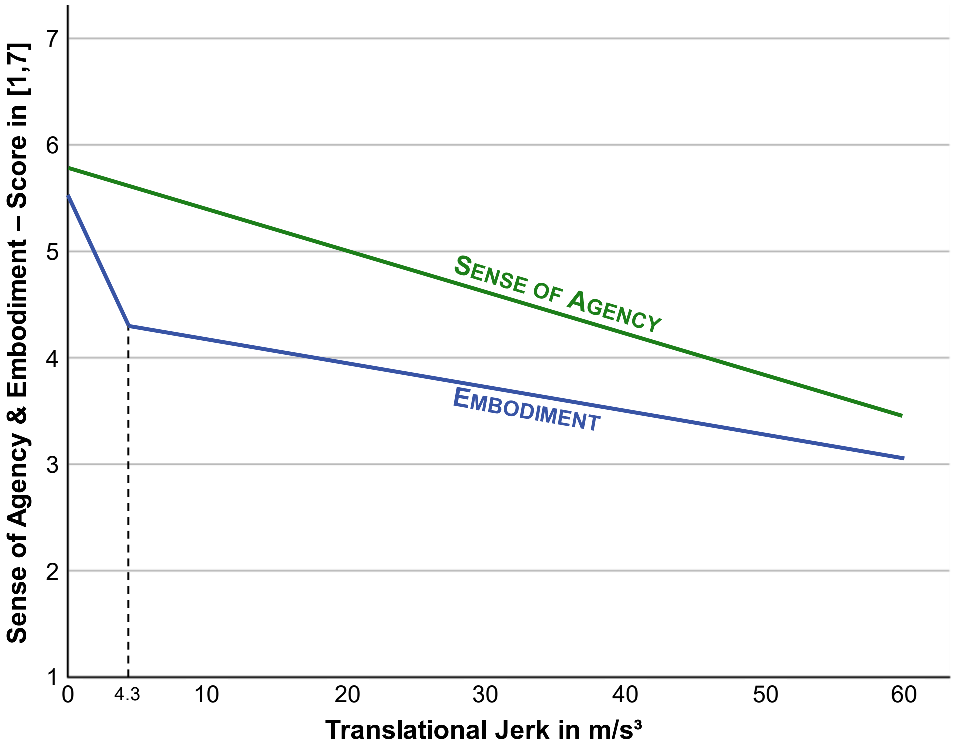


*Figure 7: **Jerk Experience Model for Sense of Agency & Embodiment** – As the intensity of the translational jerk increases, Sense of Agency & Embodiment decrease. A threshold at 4.3 m/s^3 marks increased sensitivity of Embodiment to low jerk levels.*

4. Discussion

4.1 Empirical Modeling of Sense of Agency & Embodiment

<u>**Research Question 1**</u>

"What influence do translational jerks have on human experience with regard to the SoA and Embodiment in human-machine interaction?"

Regarding the first research question, the results show that increasing jerk intensity (JerkMax) significantly reduces both the perceived Sense of Agency and Embodiment.

The significant decrease in the SoA with increasing jerk intensity can be explained by the limited human reaction time to sudden tactile stimuli (ca. 190 ms; 28). When abrupt changes in resistance occur within the workpiece, the participants are unable to adjust the applied feed force in time. This delay results in unintended accelerations that are not consciously initiated by the participant, thereby reducing the feeling of being in full control over the machine. Furthermore, as the resistance in the workpiece increases at a constant feed force, the discrepancy between the intended operating speed and the actual operating speed grows. This discrepancy not only increases the physically measured translational jerk but also accentuates the misalignment between the participant's intentions and the machine's actions. As a result, the SoA decreases as the jerk intensity increases.

A comparable effect is observed for Embodiment. The results of the quadratic mixed-effects model (see Table 2) indicate that translational jerks exert a significantly strong effect on Embodiment experience, with increasing jerk intensity leading to a decrease in Embodiment scores. According to Longo et al. [8], the psychological construct of Embodiment comprises three sub-aspects: Ownership, Location and Agency. The questionnaire used in this study, based on Caspar et al. [22], specifically addresses the dimensions of Ownership (2 items) and Agency (4 items). This overlap in measured dimensions explains the similar influence of the translational jerk on both SoA and Embodiment, as supported by the significant correlation between the two questionnaires.

The modeling results further highlight differences in the variability of responses. The proportion of random effects is significantly higher for Embodiment (ICC = 0.44) compared to SoA (ICC = 0.26) (see Table 2). This discrepancy arises from the inclusion of Ownership as a key component of Embodiment, alongside Agency. While the SoA reflects a subjective feeling of control that can be directly evaluated during operation, the Ownership aspect of Embodiment hypothetically is more strongly influenced by prior experiences and the development of trust in the machine. Participants with greater experience using the router are more likely to exhibit a stronger sense of ownership. These interindividual differences contribute to the higher proportion of random effects observed in the Embodiment model. This finding aligns with previous research suggesting that both SoA and Embodiment are influenced by predictive processes and expectation-based mechanisms [9–11].

Alternative model approaches for SoA and Embodiment, including the evaluation of different predictors, their combinations and different levels of complexity, were systematically evaluated. However, these alternative approaches did not yield improvements in model quality and are therefore not part of the results presented. The key findings are summarized and discussed below.

The comparison of different jerk characteristics shows that jerk intensity, represented by JerkMax and mean jerk, has the strongest influence on both SoA and Embodiment. JerkMax consistently emerges as the central predictor, providing the highest explanatory power and model quality for both constructs. Mean jerk shows a comparable effect but does not significantly improve model quality compared to JerkMax. In contrast, dynamic characteristics such as jerk standard deviation and variance, although statistically significant, contribute less to the variance explanation. This suggests that fluctuations in jerk intensity play a secondary role in the context under investigation. These results suggest that the participants primarily respond to the intensity of jerks, as these are directly associated with unconsciously initiated changes in operating speed and thus impair the SoA and Embodiment. The reduced relevance of the standard deviation and variance of jerk is likely since the jerks in the present study were applied randomly via the study design, which prevented participants from anticipating or adapting for fluctuations. In more predictable scenarios with regular jerk patterns, these dynamic characteristics may exert a stronger influence, potentially making targeted mitigation strategies more difficult. However, further investigation is necessary to confirm this hypothesis.

Differences emerge in the modeling approaches. For SoA, a linear mixed-effects model with JerkMax as the predictor is sufficient to capture the relationship. Additional quadratic or cubic terms do not significantly improve the model's explanatory power, supporting the assumption of a negative linear relationship between jerk intensity and SoA. For Embodiment, however, the inclusion of a quadratic term significantly enhances model quality. The quadratic term indicates that the relationship between JerkMax and Embodiment is not linear and weakens at higher jerk values. An additional cubic term, on the other hand, provides no additional explanatory value while adding unnecessary model complexity.

4.2 Analysis of Potential Threshold Effects of Translational Jerk

Research Question 2

"Are there threshold values for the translational jerks at which the influence on Sense of Agency and Embodiment changes significantly?"

The results of the segmented regression analyses **do not provide clear evidence of a threshold effect on the influence of translational jerks on Sense of Agency or Embodiment.** While some segmented models suggest minor improvements in model quality, **the findings do not support the presence of a distinct perception threshold.**

For SoA, the segmented model with two linear segments and a breakpoint at 3.5 m/s^3 shows slightly better AIC values (AIC = 463.12) than the continuous linear reference model (AIC = 464.15). However, the BIC values, which account for model complexity, favor the simpler reference model (BIC = 476.45 vs. 478.49). Additionally, the ANOVA comparison does not indicate a significant difference between the models. Consequently, the continuous linear model is preferred due to its better applicability and generalizability. The slightly better explanation of the segmented model variance (R^2 = 0.399 vs 0.390; see Table 2 & Table 3) does not justify the additional complexity.

For Embodiment, the segmented model with two linear segments and a breakpoint at 4.3 m/s^3 exhibits slightly lower AIC (438.68 vs. 440.14) and BIC (454.06 vs. 455.52) values in comparison to the quadratic reference model. Although Burnham et al. [26] indicate that such minor differences provide little to no evidence of a superior model, the segmented approach offers a more plausible representation of the relationship at high jerk intensities. In contrast to the quadratic model, which predicts an implausible increase in Embodiment at very high jerk values, the segmented model reflects a consistent weakening of the negative effect above the breakpoint. This aligns with the expectation that extreme jerk intensities impair the sense of ownership and agency, making the segmented model more appropriate for Embodiment.

Furthermore, the results highlight important contextual considerations. For SoA, the absence of a threshold effect is consistent with the observation that jerk perception thresholds are highly dependent on the specific task and sensory context. Studies conducted by Priester et al. [19] identified jerk perception thresholds between 8 and 14 m/s^3 in light truck collisions, which differ significantly from the context of router operation. In the present study, lower jerk intensities were sufficient to impact SoA, likely due to the less intense background stimuli and the frequent alternation between movement and rest phases. According to the Weber-Fechner law [20], these factors influence perception thresholds, making the human-machine interaction context more sensitive to subtle stimuli.

The stronger negative effect of jerk intensity below the breakpoint in the segmented model for Embodiment (see Figure 7) suggests an additional mechanism. It can be assumed that even minimal but perceptible jerks can disrupt the sense of immersion in the human-machine interaction, thereby reducing the feeling that the machine is following the participant's movements with precision. In contrast to SoA, Embodiment includes the aspect of Ownership, which is strongly associated with Immersion [29]. This dependency may explain the stronger decline in Embodiment with smaller jerks, as the initial interruption of immersion has a disproportionately large influence on the sense of ownership. Alternatively, the stronger impact of low jerk intensities may also be due to increased perceptual sensitivity in lower stimulus ranges, as described by the Weber-Fechner law [20]. In this view, small increases in jerk may be subjectively more salient than equivalent increases at higher levels, amplifying their disruptive effect on Embodiment.

In addition, the comparatively poorer model quality of the segmented models, which posit that the intensity of the jerk below the threshold has no effect, supports this interpretation. Such models test the hypothesis of a perceptual threshold. Their poor fit suggests that a threshold is likely to be below the breakpoints examined in this study.

4.3 Effect of Movement Direction on Sense of Agency

Research Question 3

"How does the direction of movement (concentric vs. eccentric) affect the relationship between translational jerk and Sense of Agency?"

The segment-specific evaluation of the single item on SoA (see Table 4) shows that **the direction of movement has a significant influence on the Sense of Agency. Movements 'towards the body' (concentric) are associated with higher perceived control than movements 'away from the body' (eccentric).** This difference could be due to better motor control during concentric movements. For example, a study by Christou and Carlton [30] shows lower knee extension force control during eccentric compared to concentric movements.

However, a comparison of the models shows that the direction of movement has no moderating effect on the relationship between translational jerk and SoA. The negative relationship between jerk intensity and SoA remains independent of the direction of movement. The non-significant interaction effect between the direction of movement and JerkMax confirms this. It indicates that the direction of movement only influences the underlying level of SoA without modifying the effect of the jerk.

Future studies could investigate the influence of the direction of movement in further spatial dimensions as well as in more complex, non-linear movement patterns (e.g. lateral or free-form movements) to identify more differentiated effects on the SoA.

The results are of practical relevance, as they suggest that the direction of movement should be considered in the design of tools and work processes, not only to reduce ergonomic strain, but also to improve perceived control.

4.4 Limitations & Outlook

Several limitations of the present study must be considered when interpreting the results.

Concerning **methodological limitations**, the translational jerk was generated indirectly using pre-milled notches on the underside of the workpieces. This approach enabled a realistic variation of jerk intensities during the milling process, although the magnitude of each jerk could not be set precisely. Moreover, the translational jerk was calculated by means of triple numerical differentiation of filtered position data. This method enabled a consistent and reproducible assessment of jerk characteristics. However, minor inaccuracies in absolute values cannot be entirely excluded due to the inherent properties of multiple differentiation.

Furthermore, the perceptual threshold for jerk could not be derived directly since the precepted jerk intensity was not assessed. Instead, the experiences of the participants were captured retrospectively using validated questionnaires that focused on the resulting SoA and Embodiment. Consequently, it remains unclear whether each induced jerk event was consciously perceived or how specific jerks contributed to the overall experiential evaluations. In addition, the retrospective questionnaire recorded integrated impressions after each milling segment, rather than real-time responses to individual jerk events. This limits the precision with which unexpected jerks can be causally linked to changes in subjective experience.

Regarding **application specific limitations**, it should be noted that the results of the study are currently valid only for the tested application of contour-precise milling with a hand-guided router under relatively low dynamic user load. The transferability of the findings and the resulting Jerk Experience Model to other power tool applications therefore remains to be investigated. In comparison with other power tool applications involving higher dynamic loads, such as demolition work, the baseline user load in this study was moderate. In accordance with principles established by Weber-Fechner's law [20], it can be hypothesized that lower baseline loads may increase sensitivity to changes in stimuli. This suggests that jerk perception and its effects on SoA and Embodiment could differ under higher user loads.

To enhance the transferability of the findings and to further develop the Jerk Experience Model, additional influencing factors should be systematically examined. The present study investigated the influence of translational jerks on SoA and Embodiment under conditions of relatively low user load. Future studies should examine whether similar effects occur under higher user load conditions. In particular, the interaction between translational jerks and superimposed dynamic loads, such as hand-arm vibrations (HAV), should be analyzed. In addition to the physical load, the influence of increased cognitive load on jerk perception and vice versa, the effect of jerks on human cognitive performance should be investigated. It remains unclear whether perception thresholds shift and effect sizes change due to reduced sensitivity under higher physical or cognitive user load.

Results from Section 3.3 indicate that the direction of movement influences the baseline SoA. It is recommended that subsequent research examine how different movement patterns, including lateral, diagonal and non-linear trajectories, impact the relationship between jerk events and SoA and Embodiment. Particular attention should be given to scenarios in which jerk events strongly affect the quality of the work result, as this may retroactively modulate the SoA through feedback from task performance. In addition, rotational jerks, as observed in sudden torque peaks of handheld screwdrivers, should be included as a further class of movement dynamics.

Moreover, the role of predictability requires further investigation. In the present study, the induced translational jerk events were unexpected. If SoA and Embodiment depend on user expectations, it can be assumed that predictability modulates the impact of jerks. Future studies should therefore systematically investigate how the predictability of jerk events influences perception and subjective experience.

The present findings thus offer a foundation for describing the relationship between translational jerk and human experience in physical human-machine interaction. By linking the intensity of translational jerk to experiential constructs such as SoA and Embodiment, the study provides a foundational step towards integrating perceptual sensitivity into system design. This knowledge can support the formulation of design requirements that treat jerk not only as an unwanted disturbance, but as a modifiable parameter in interface development. In this sense, the results contribute to the advancement of human-machine symbiosis, where the mechanical behavior of a system is adapted to human perception and control expectations. These insights can contribute to the development of intuitive, ergonomic and effective human-machine systems, thereby supporting the human-centric approach promoted by Industry 5.0.

5. Conclusion

This study investigated the influence of translational jerks on human experience in physical human-machine interaction, focusing on the Sense of Agency (SoA) and Embodiment. A controlled experiment with varying jerk intensities during a milling task showed that higher jerk intensities significantly reduced both SoA and Embodiment. The maximum jerk emerged as the most robust predictor.

No distinct perceptual thresholds were identified, but segmented models suggest increased sensitivity to jerk at lower intensities, particularly for Embodiment. Thus, for Embodiment, a segmented two-part linear model provided a more plausible representation of the experiential decrease than a continuous quadratic model. While eccentric compared to concentric movements affected the baseline level of SoA, they did not modulate the effect strength of translational jerk on perceived control.

Based on these findings, **Jerk Experience Models** were derived to quantitatively predict SoA and Embodiment as a function of translational jerk intensity in physically coupled human-machine systems. The models provide a basis for anticipating how unexpected, rapidly changing machine dynamics influence the user experience of control and integration. This enables the derivation of design requirements for physically coupled human-machine interfaces that support a meaningful and self-attributed role of the human within the interaction, a key aspect of human-machine symbiosis and a guiding principle of Industry 5.0.

While the Jerk Experience Models presented were developed based on observations from a single use case involving contour-precise milling with a hand-guided router, further research is required to evaluate their applicability in broader contexts of human-machine interaction. Interacting factors such as higher physical user loads, cognitive demands, non-linear movement trajectories and the predictability of jerk events are expected to alter how translational jerk influences SoA and Embodiment. In addition, the development of analogous Jerk Experience Models for rotational jerks is recommended. The systematic integration of these factors in future studies will be essential to extend the scope of Jerk Experience Models and ensure their applicability for the design of user-centered human-machine systems across diverse applications.

References

[1] S. Hardege, "Fachkräfteengpässe gefährden Transformation und Innovation: DIHK-Report Fachkräfte 2023/2024," Nov. 2023. Accessed: May 5 2025. [Online]. Available: https://www.dihk.de/de/themen-und-positionen/fachkraefte/beschaeftigung/fachkraefteengpaesse-gefaehrden-erfolg-in-wichtigen-schluesseltechnologien-107880

[2] T. Hellwagner, D. Söhnlein, and E. Weber, "Modeling Migration Dynamics in Stochastic Labor Supply Forecasting," in *IAB-Discussion Paper.* Accessed: May 5 2025. [Online]. Available: https://hdl.handle.net/10419/274564

[3] European Agency for Safety and Health at Work, "Work-related musculoskeletal disorders: prevalence, costs and demographics in the EU," 2019. Accessed: May 5 2025. [Online]. Available: https://osha.europa.eu/sites/default/files/Work_related_MSDs_prevalence_costs_and_demographics_in_EU_summary.pdf

[4] J. Inga *et al.,* "Human-machine symbiosis: A multivariate perspective for physically coupled human-machine systems," *International Journal of Human-Computer Studies*, vol. 170, 2023, doi: 10.1016/j.ijhcs.2022.102926.

[5] S. Nahavandi, "Industry 5.0—A Human-Centric Solution," *Sustainability*, vol. 11, no. 16, p. 4371, 2019, doi: 10.3390/su11164371.

[6] Y. Lu *et al.,* "Outlook on human-centric manufacturing towards Industry 5.0," *Journal of Manufacturing Systems*, vol. 62, pp. 612–627, 2022, doi: 10.1016/j.jmsy.2022.02.001.

[7] A. Tapal, E. Oren, R. Dar, and B. Eitam, "The Sense of Agency Scale: A Measure of Consciously Perceived Control over One's Mind, Body, and the Immediate Environment," *Frontiers in psychology*, vol. 8, p. 1552, 2017, doi: 10.3389/fpsyg.2017.01552.

[8] M. R. Longo, F. Schüür, M. P. M. Kammers, M. Tsakiris, and P. Haggard, "What is embodiment? A psychometric approach," *Cognition*, vol. 107, no. 3, pp. 978–998, 2008, doi: 10.1016/j.cognition.2007.12.004.

[9] N. Sidarus, V. Chambon, and P. Haggard, "Priming of actions increases sense of control over unexpected outcomes," *Consciousness and cognition*, vol. 22, no. 4, pp. 1403–1411, 2013, doi: 10.1016/j.concog.2013.09.008.

[10] M. Kirchhoff, "Predictive brains and embodied, enactive cognition: an introduction to the special issue," (in En;en), *Synthese*, vol. 195, no. 6, pp. 2355–2366, 2018, doi: 10.1007/s11229-017-1534-5.

[11] A. Clark, "Embodied Prediction," in *Open MIND: Philosophy and the mind sciences in the 21st century*, T. Metzinger and J. M. Windt, Eds., Cambridge, Massachusetts, London, England: The MIT Press, 2016.

[12] M. Hara, H. Nabae, A. Yamamoto, and T. Higuchi, "A Novel Rubber Hand Illusion Paradigm Allowing Active Self-Touch With Variable Force Feedback Controlled by a Haptic Device," *IEEE Trans. Human-Mach. Syst.*, vol. 46, no. 1, pp. 78–87, 2016, doi: 10.1109/THMS.2015.2487499.

[13] D. Penner, A. M. H. Abrams, P. Overath, J. Vogt, and P. Beckerle, "Robotic Leg Illusion: System Design and Human-in-the-Loop Evaluation," *IEEE Trans. Human-Mach. Syst.*, vol. 49, no. 4, pp. 372–380, 2019, doi: 10.1109/THMS.2019.2896447.

[14] S. Bustamante, J. Peters, B. Scholkopf, M. Grosse-Wentrup, and V. Jayaram, "ArmSym: A Virtual Human–Robot Interaction Laboratory for Assistive Robotics," *IEEE Trans. Human-Mach. Syst.*, vol. 51, no. 6, pp. 568–577, 2021, doi: 10.1109/THMS.2021.3106865.

[15] *Mechanical vibration, shock and condition monitoring - Vocabulary*, ISO 2041, International Standard, Oct. 2018.

[16] H. Hayati, D. Eager, A.-M. Pendrill, and H. Alberg, "Jerk within the Context of Science and Engineering—A Systematic Review," *Vibration*, vol. 3, no. 4, pp. 371–409, 2020, doi: 10.3390/vibration3040025.

[17] M. Schlüter, "Objektivierung des subjektiven Insassenempfindens bei längsdynamischen Beschleunigungsmanövern," Dissertation, Universität Stuttgart, 2022.

[18] M. Huber, M. Rickert, A. Knoll, T. Brandt, and S. Glasauer, "Human-robot interaction in handing-over tasks," in *RO-MAN 2008 - The 17th IEEE International Symposium on Robot and Human Interactive Communication*, Munich, Germany, 2008, pp. 107–112.

[19] J. Priester, M. Weyde, and C. Ploetz, "Wahrnehmbarkeit von leichten Lkw-Kollisionen. Teile I und II," *Verkehrsunfall und Fahrzeugtechnik*, 344–356 & 266-274, 1998 & 2001. [Online]. Available: https://trid.trb.org/View/947163

[20] G. T. Fechner, *Elemente der Psychophysik: Vol. 2*: Breitkopf u. Härtel, 1860.

[21] A. Weiss, R. Bernhaupt, D. Schwaiger, M. Altmaninger, R. Buchner, and M. Tscheligi, "User experience evaluation with a Wizard of Oz approach: Technical and methodological considerations," in *2009 9th IEEE-RAS International Conference on Humanoid Robots*, Paris, France, 2009, pp. 303–308.

[22] E. A. Caspar, A. Cleeremans, and P. Haggard, "The relationship between human agency and embodiment," *Consciousness and cognition*, vol. 33, pp. 226–236, 2015, doi: 10.1016/j.concog.2015.01.007.

[23] R Core Team, *R: A language and environment for statistical computing.* Vienna, Austria, 2021.

[24] D. Bates, M. Mächler, B. Bolker, and S. Walker, "Fitting Linear Mixed-Effects Models Using lme4," *J. Stat. Soft.*, vol. 67, no. 1, 2015, doi: 10.18637/jss.v067.i01.

[25] J. Cohen, *Statistical power analysis for the behavioral sciences,* 2nd ed. Hillsdale, NJ: Erlbaum, 1988.

[26] K. P. Burnham and D. R. Anderson, *Model selection and multimodel inference: A Practical Information-Theoretic Approach,* 2nd ed. New York, NY: Springer, 2002.

[27] A. E. Raftery, "Bayesian Model Selection in Social Research," *Sociological Methodology*, vol. 25, p. 111, 1995, doi: 10.2307/271063.

[28] J. V. M. Hanson, D. Whitaker, and J. Heron, "Preferential processing of tactile events under conditions of divided attention," *Neuroreport*, vol. 20, no. 15, pp. 1392–1396, 2009, doi: 10.1097/WNR.0b013e3283319e25.

[29] T. Waltemate, D. Gall, D. Roth, M. Botsch, and M. E. Latoschik, "The Impact of Avatar Personalization and Immersion on Virtual Body Ownership, Presence, and Emotional Response," *IEEE transactions on visualization and computer graphics*, vol. 24, no. 4, pp. 1643–1652, 2018, doi: 10.1109/TVCG.2018.2794629.

[30] Christou, Evangelos A. and Carlton, Les G., "Motor output is more variable during eccentric compared with concentric contractions," *Medicine & Science in Sports & Exercise*, 2002, doi: 10.1249/01.MSS.0000035201.21310.CC.

Appendix

A.1 Questionnaire Items

Table 5: Questionnaire items assessing Sense of Agency and Embodiment, adapted to physically coupled human-machine-interaction. Items were originally presented in German. English translations are provided for reference.

		Item
Sense of Agency		1. Ich habe die volle Kontrolle über das, was ich tue. [I am in full control of what I do.]
		2. Ich bin der Urheber meiner Handlungen. [I am the author of my actions.]
		3. Die Konsequenzen meiner Handlungen scheinen nicht logisch auf meine Handlungen zu folgen. [The consequences of my actions feel like they don't logically follow my actions.]
		4. Ich trage die volle Verantwortung für alles, was aus meiner Handlung resultiert. [I am completely responsible for everything that results from my actions.]
Embodiment	Agency	5. Ich kann die Maschine genauso bewegen, wie ich es möchte, als würde die Maschine meinem Willen gehorchen. [I can move the machine exactly as I want, as if the machine were obeying my will.]
		6. Ich habe das Gefühl die Bewegungen der Maschine zu kontrollieren. [I have the feeling that I can control the movements of the machine.]
		7. Es fühlte sich so an, als würde ich die Bewegungen, die ich bei der Maschine gesehen habe, selbst verursachen. [It felt like I was causing the movements I saw on the machine myself.]
		8. Ich kann die Maschine so einfach bedienen, wie ich meine Arme und Beine benutzen kann. [I can operate the machine as easily as I can use my arms and legs.]
	Ownership	9. Es fühlt sich so an, als wäre die Maschine Teil meines Körpers. [I felt as if the machine was part of my body.]
		10. Es fühlte sich so an, als könnte ich die Bewegungen, die die Maschine ausführte, spüren. [It felt as if I could feel the movements that the machine was making.]

KIT Scientific Working Papers
ISSN 2194-1629