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Development and validation of a behavioural video coding scheme for detecting mental workload in manual assembly

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ABSTRACT

Manual assembly in the future *Industry 4.0* workplace will put high demands on operators' cognitive processing. The development of mental workload (MWL) measures therefore looms large. Physiological gauges such as electroencephalography (EEG) show promising possibilities, but still lack sufficient reliability when applied in the field. This study presents an alternative measure with a substantial ecological validity. First, we developed a behavioural video coding scheme identifying 11 assembly behaviours potentially revealing MWL being too high. Subsequently, we explored its validity by analysing videos of 24 participants performing a high and a low complexity assembly. Results showed that five of the behaviours identified, such as freezing and the amount of part rotations, significantly differed in occurrence and/or duration between the two conditions. The study hereby proposes a novel and naturalistic method that could help practitioners to map and redesign critical assembly phases, and researchers to enrich validation of MWL-measures through measurement triangulation.

Practitioner summary: Current physiological mental workload (MWL) measures still lack sufficient reliability when applied in the field. Therefore, we identified several observable assembly behaviours that could reveal MWL being too high. The results propose a method to map MWL by observing specific assembly behaviours such as freezing and rotating parts.

Abbreviations: MWL: mental workload; EEG: electroencephalography; fNIRS: functional near infrared spectroscopy; AOI: area of interest; SMI: SensoMotoric Instruments, ETG: Eye-Tracking Glasses; FPS: frames per second; BORIS: Behavioral Observation Research Interactive Software; IRR: inter-rater reliability; SWAT: Subjective Workload Assessment Technique; NASA-TLX: National Aeronautics and Space Administration Task Load Index; EL: emotional load; DSSQ: Dundee Stress State Questionnaire; PHL: physical load; SBO: Strategisch Basis Onderzoek

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1. Introduction

The current growing demand for mass-customization yields a greater product variety (Um et al. 2017; Wan and Sanders 2017) and thereby a higher manufacturing complexity (ElMaraghy et al. 2012; Hu et al. 2008). Despite the extensive automation of production processes, manual assembly still remains highly valuable for the extreme flexibility it provides (Booker, Swift, and Brown 2005). Cognitive demands on operators in this context and for sure in the future Industry 4.0 setup however increase accordingly, reinforcing the long-standing need for mental workload (MWL) measurement in order to optimise cognitive ergonomics

(Van Acker et al. 2018; Young et al. 2015). With a thorough and objective understanding of non-optimal MWL (i.e. overload or underload) the presentation of information and materials can be redesigned (Brolin, Thorvald, and Case 2017), assemblies can be made more intuitive (Parmentier et al. 2020) or smart technologies can be introduced to assist the operator (Erol et al. 2016; Longo, Nicoletti, and Padovano 2017).

Subjective measures have long been the preferred method to indirectly infer MWL (cf., Young et al. 2015), but are intrusive when applied in the field and only provide a subjective estimation (for a discussion, see de Waard and Lewis-Evans 2014; de Winter 2014; Matthews, De Winter, and Hancock 2020) of

accumulated load instead of more sensitive fluctuations in MWL-levels (Antonenko et al. 2010). More recent methods offer a more direct and continuous way of measuring MWL through physiological reactions within the operator and this with a very limited latency (Charles and Nixon 2019). EEG, for instance, or functional Near Infra-red Spectroscopy (fNIRS) measuring frontal cerebral blood flow velocity have demonstrated exciting potential for future unobtrusive MWL measurement (cf., Foy and Chapman 2018; Guru et al. 2015; Hairston et al. 2014; McKendrick et al. 2016) and even mental overload measurement (Morton et al. 2019). Such measures are nevertheless still in full development and do not yet achieve adequate effect sizes (Vanneste et al. 2020) nor adequate reliability or external validity in applied mobile settings, this due to numerous confounds such as movement and breathing artefacts (see Arico et al. 2018; Brouwer et al. 2015). Additionally, differences in MWL are often estimated by comparing discrete conditions, instead of measurement being instantaneous. To arrive at the stage of measuring MWL fluctuations within a short time span - say, seconds - and in a real-world context, great strides need to be made yet.

Where the field of subjective and physiological MWL measurement validation assesses MWL changes to eventually detect or predict decrements in performance (see, e.g. Young et al. 2015), here, we reversed the logic, in line with primary task performance measures (cf., Cain 2007). We designed a coding scheme by narrowly defining observable types of inefficient and ineffective assembly behaviours that potentially reveal MWL being too high. The current study is hence, to our knowledge, the first to explore behavioural observation as a measure of MWL in an ecologically valid assembly context. Specifically, it builds on current knowledge on human cognition in assembly performance (but not providing a validated measure yet) and translates this knowledge and similar work on behaviour analysis in human-computer interaction and driving into a novel and validated mental workload measure for manual assembly. It hereby aims to help design a method already meeting some of the widely envisioned criteria for in-the-field MWL-measurement on the short term, i.e. non-obtrusiveness, sensitivity to rapidly changing MWL fluctuations and ease-of-use (see Matthews et al. 2015).

2. Background

Scrutiny on the concept of MWL upholds a long tradition and even thrives during recent years, driven by

the expectations for the upcoming Industry 4.0 (Young et al. 2015). Altogether, MWL exists as a function of task demands and moderating variables, and can be understood as a subjective experience and a physiological reaction, resulting in task-related behaviour (Van Acker et al. 2018). Research on the measurement of MWL in industrial contexts has mainly focussed on subjective estimations and physiological reactions (Charles and Nixon 2019). Gauging the third, behavioural component in these settings has however rarely made the step beyond measuring, e.g. execution times, reaction times or errors. The same theorisation explaining fluctuations in the subjective and physiological components of MWL can however also help explain fluctuations in observable behaviour.

2.1. MWL revealing limited resources

MWL can be defined as a subjectively experienced physiological processing state resulting from the interplay between the human cognitive architecture and the work demands being attended to (Van Acker et al. 2018). Seminal work learns that the cognitive physiological resources propelling this interplay are limited (e.g. because of competition between visual and auditory sensory modalities; Wickens 2002, 2008) and draw from a common and also limited underlying pool of physiological resources from which also competing emotional load (for a distinction between cognitive and emotional load, see Van Acker et al. 2018) and physical load draw (Egeth and Kahneman 1975; Mandler 1979; Norman and Bobrow 1975; for an overview, see Staal 2004).

2.2. Performance revealing MWL

In assembly specifically, cognitive resources are allocated for perception, response selection and action, propelled by, i.a., attention and memory (Stork and Schubö 2010). For commissioning, the perception stage include, i.a., identifying relevant parts. For joining, the operator's perception entails, for instance, processing the required part position and orientation. An appropriate response is then selected (e.g. 'take this part and join it on that position in that orientation') to finally go through the process of motor execution of the joining operation (including planning and adjusting). Since resources are limited, this concrete assembly performance can become less efficient and less effective when MWL increases. Commissioning, for example, can take longer, while response selection can entail taking two wrong parts first.

Previous research shows that the relationship between (assembly) performance and MWL exhibits an inverted U-shaped trend (de Waard 1996; Montani et al. 2020; Young et al. 2015). In Figure 2 (inspired on de Waard 1996; Hart and Wickens 2008; Young et al. 2015), it can be observed that, in this way, performance is optimal when MWL resides around moderate levels (cf., flow theory; Bruya 2010), while it is non-optimal (i.e. too low) in case of MWL being too low or too high. The MWL ‘redlines’ represent the performance break points here, so that at the right side of the right redline, *overload*, and at the left side of the left redline, *underload*, leads to strong reductions in performance. In the current study, we focus on the levels of MWL around the right redline, i.e. the part of the curve where performance goes down. We coin this area the MWL upper red zone since these redlines rather represent a fuzzy zone when applied over contexts and people (cf., Young et al. 2015). We do not focus on performance decrements due to underload, i.e. lower red zone MWL (for an elaboration on underload and its relation to MWL levels, see Brookhuis & de Waard, 2001).

Within upper red zone MWL, a differentiation can be made between *impending* mental overload and mental overload per se. The MWL-redline approximates the break point (or a ceiling effect in terms of a limited resource system; Young et al. 2015) between both (see also, Grier et al. 2008; Paras et al. 2015). We define impending mental overload as high MWL associated with minor decrements in performance and visualise this concept as our first Area Of Interest (‘AOI 1’) on the curve in Figure 2. Mental overload is defined as high MWL associated with major decrements in performance and is represented by the second Area Of Interest (‘AOI 2’) on the curve. As the curve shows an exponential trend, overload should thus be associated with the largest and most severe drops in performance.

In all, we thus focus on red zone MWL associated with minor and major performance decrements – i.e. stretching over AOI 1 and AOI 2 in Figure 2. Our assumption subsequently states that performance decrements here will be observable in concrete assembly behaviour and can hence indicate changes in MWL, in turn revealing changes in the cognitive resources spent. We illustrate this assumption in Figure 1. To facilitate theory building and comparability of the presented work (Van Acker et al. 2018), our operational definition of MWL states that *the MWL measured here will be reflected in the observed participants’ assembly behaviour indirectly revealing the interplay between*

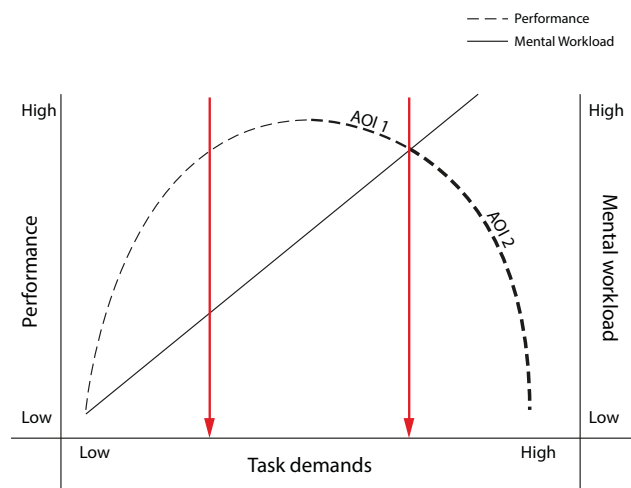


Figure 1. Graph of performance and MWL as a function of task demands, presenting the MWL-redlines and the areas of interest (AOI 1 = Area of Interest 1, AOI 2 = Area of Interest 2). Adapted from Young and colleagues (2014) and de Waard (1996).

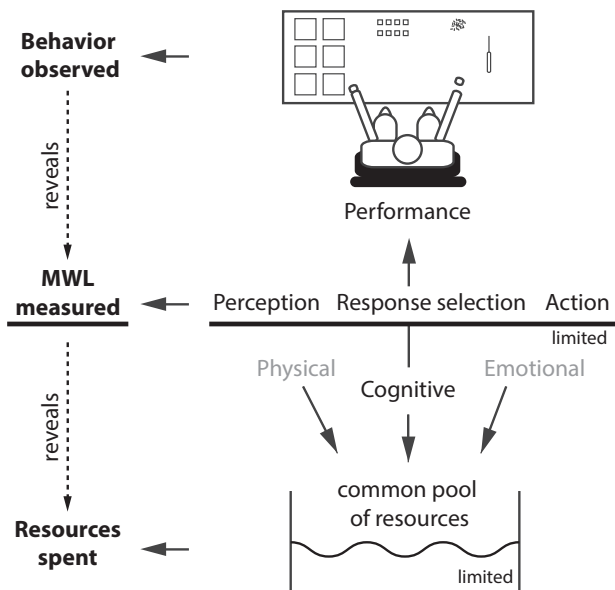


Figure 2. Schematic overview of rationale how observable behaviours indicate MWL levels and thereby reveal the latent, non-observable competition for, and expenditure of, physiological resources.

participants’ limited working memory modalities and the visual-spatial demands and working memory span demands being exposed to.

3. Study overview

After delineating our focus area, we formulated our central research question stating: ‘Which could be possible observable behavioural indications of upper red zone MWL?’. Based on Heyman and colleagues’ (2018) recommendations, we tackled this question in twofold.

We first developed a coding scheme identifying such behavioural indications based on literature (deductively) and by observing assembly behaviour in a subsample of videos from an assembly experiment validated to induce high and low MWL (inductively). After finalising the coding scheme, we, secondly, validated the scheme with a larger set of videos of the same experiment (excluding the subsample used in the first stage). Specifically, we analysed whether all behavioural codes would significantly differ per experimental condition (i.e. high and low complexity inducing high and low MWL) in their occurrence and, following Richardson and colleagues (2006), their duration.

3.1. Experimental procedures

For the experiment providing the video data for developing and validating the coding scheme, the same procedures as an earlier experiment exploring mobile pupillometry was followed (see Van Acker et al. 2020, for an extensive overview). In a within-subjects design experiment, participants performed both a high and low complexity assembly in a random and counterbalanced order and with a resting phase in-between. They assembled while being seated in a quiet room and wearing the SMI Eye-Tracking Glasses (ETG 2w) (SMI; Teltow, Germany), a lightweight glasses-type eye-tracking system (47 g; size: 173 × 58 × 56 mm) using small cameras implemented in the frame of the glasses (and compatible with contact lenses). Data were stored on a customised smartphone connected to the ETG with a cable. The smartphone was kept in the participants trouser pocket or waist bag. Participants were told that they would participate in a study 'exploring how people assemble and that their eye-movements would be tracked. They were explicitly instructed that they had all the time they needed to complete the assembly. In total the experiment would last for approximately one hour.

Both ecologically valid assemblies consisted of seven steps each, to be executed in a fixed order. Participants

saw instructions per step on a screen at the opposite side of the worktable. Our focus was not on this instruction phase. After seeing the instructions, participants turned around to select, position and mount two components per step (three for the first step) that they had to select out of a display of parts presented on the worktable. After completion of each assembly, participants filled out a questionnaire. Figure 3 shows a diagrammatic overview of the assembly process.

The assemblies were designed to induce low and high MWL based on 10 task variables defining assembly complexity as proposed and validated by Richardson, Jones, and Torrance (2004, Richardson et al. 2006), Pillay's (1997) use of non-familiar assembly objects (see also Norman's, 1983, Shalin et al.'s, 1996, insights on mental models in objects) and one material-related task variable introduced by the authors. Specifically, the following 10 task variables defined the, respectively, low and high complexity level of the assemblies: assembly model (cubicle box design vs. abstract unfamiliar design, respectively), amount of symmetrical planes (high vs. low, respectively), amount of components (low vs. high, respectively), component groups (low vs. high, respectively), selections of components (no redundant components and displayed in correct order vs. redundant components and displayed in randomised order, respectively), amount of fastenings (minimally required vs. high, respectively), amount of fastening points (low vs. high, respectively), amount of novel (sub-)assemblies (low vs. high, respectively), presenting orientation on work table (correct angle vs. randomly angled 90° to the left or right along the horizontal plane, respectively), material of sides (low transparency vs. high transparency, respectively). The original experiment (see Van Acker et al. 2020) showed that subjective MWL differed significantly between the low and high complexity condition, in that the high complexity condition induced higher MWL levels as compared to the low complexity assembly (see Van Acker et al. 2020). The same assemblies used in the current experiment were thus validated to induce low and high MWL.

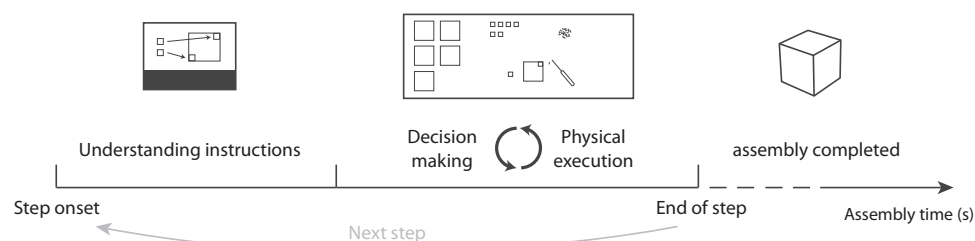


Figure 3. Diagrammatic overview of the assembly process. The low complexity assembly is used as an example. The high complexity assembly followed the exact same procedure.

3.2. Video capturing procedures

The frontal Scene Camera of the eye-tracking glasses (with a resolution of 1280×960 p; 24 FPS; H.264 video format, 60° horizontal and 46° vertical field of view; High Dynamic Range mode with high sensitivity for low light) was used to capture participants' assembly behaviour, i.e. their hands and upper arms manipulating the assembly. Videos (in .avi format) were then imported into the SMI BeGaze software (SMI; Teltow, Germany) in order to calculate the eye-gaze position (3-point calibration; binocular eye tracking at 60 Hz with automatic parallax compensation and dark pupil tracking; 80° horizontal and 60° vertical gaze tracking range; gaze position accuracy of 0.5° over all distances) to be used for the definitions of certain behavioural codes.

4. Development of the coding scheme

4.1. Method

Behavioural observation is a method in which a researcher sees and/or hears, and then systematically records specific behaviours of an individual or group within a certain context of interest (Heyman et al. 2018). These behaviours are then organised into categories by using clearly defined codes to be assigned based on certain rules. Together, these categorised codes form a coding scheme. After analysing these behaviours from, for example, video data, their occurrence or time duration can be analysed. No behavioural coding scheme for MWL measurement in assembly execution existed already. We - three of the current authors and a team of three trained graduate students - therefore developed a scheme through *deduction* and *induction*, inspired by the practical guide for developing behavioural coding schemes of Chorney and colleagues (2015).

4.1.1. Deductive path

From theory, we started with a profound understanding of MWL and how assembly behaviour is propelled by mental processing (cf., the Background section). Most central here is that cognitive processing competes with physical processing for the limited physiological resources. The MWL measurement literature learns that assembly-specific cognitive processing can subsequently be inferred from execution time (Richardson et al. 2006; Stork and Schubö 2010), reaction time and errors (Stork and Schubö 2010; Young et al. 2015), dwell time on assembly and amount of sub-steps needed (Stork and Schubö 2010), and even

hand movement parameters such as total movement time, speed-accuracy trade-off, peak velocity and latency of movement onset (Stork and Schubö 2010).

Other work outside assembly environments infers MWL levels based on behavioural parameters such as writing velocity and pen gesture (Badarna et al. 2018; see also Meulenbroek et al. 2005; for an overview, see Chen et al. 2016). Both strongly resonating with our work here, Qiu and Helbig (2012) used video-analysis to show how computer operators' task-unrelated body posture (coming closer or moving less) can indicate MWL, whereas Boer (2000) proposed a behavioural entropy index characterising MWL in driving (i.e. a quantification of corrective actions such as error corrections or startled responses reflecting the level of smoothness in driving control behaviour such as lane keeping and car following). Next, features of computer mouse behaviour such as contemplation-style pauses occur more and longer under high MWL (Arshad, Wang, and Chen 2013; see also target highlight time in Vitense, Jacko, and Emery 2003) - resembling the use of more and longer pauses when speaking under high MWL (Ruiz, Taib, and Chen 2006) or, oppositely but revealing the interplay of resources, resembling poorer performance on a difficult secondary cognitive task while walking (Srygley et al. 2009).

Based on these notions and in relation to the assembly stages for commissioning, joining and action execution, we first derived codes defined by execution time (e.g. the time to find the right position) and erroneous behaviour (e.g. the amount of wrong positioning attempts). Based on, i.a., behavioural entropy, body posture and pauses, we distilled generic behavioural codes, such as muscular freezing (reflecting thinking or startle responses) and changes in the relative position of the head. A first preliminary coding scheme was thereby crafted, importantly, before seeing any videos.

4.1.2. Inductive path

In a next phase, we used the first coding scheme to code three training samples, being three videos selected from the collected videos of the same experiment, but not used for the validation. By using the behavioural video analysis software BORIS (Friard and Gamba 2016), we now inductively refined, selected and pragmatized our first set of codes, and aimed at discovering new codes. For the latter, team members were instructed to identify additional exemplary behavioural indicators of MWL being too high, i.e. not yet captured in the first coding scheme. Specifically, they were instructed to gauge how decrements in

performance (quantified by duration and number of occurrences) manifested in observable behaviours other than those already identified in the deductive phase.

For this inductive method, team members alternated between working individually and discussing all adaptations in group. We discussed (also with team members not having been involved in the early stage iterations), tested and updated several coding schemes during multiple iteration rounds on completeness (i.e. do we agree that all possible behavioural indicators are included), accuracy and face validity (i.e. are the definitions adequate to grasp and delineate the behaviours aimed for), and feasibility (i.e. is the scheme usable for the raters, e.g. in terms of comprehensibility and vigilance).

4.1.3. Inter-rater reliability

The final coding scheme was fine-tuned during the last stages of the iteration process. Procedures for this were largely based on Lombard, Snyder-Duch, and Bracken (2002, 2010) and McAlister and colleagues (2017), and went as follows. First, three team members used BORIS to independently code parts of the three training videos (not used for the validation) and repeatedly assessed the inter-rater reliability (IRR) informally by reflecting on their coding disagreements in group. Specifically, they discussed where and why in the videos they seemed to disagree. Subsequently, they redefined the respective codes until adequate agreement on the coding scheme was reached.

In a next stage, as is common practice in behavioural coding research (see also Hallgren 2012; Neuendorf 2002), two raters (i.e. different team members) consolidated the coding scheme and now formally assessed IRR based on a subset of four videos of the full sample to be used for the validation (for a similar approach, see, e.g. Baranek et al. 2005). Specifically, they first coded the videos of the first participant of the subset independently from each other and afterwards calculated the Cohen's Kappa IRR coefficient in BORIS (a robust standardised statistic for agreement between raters ranging from -1 to $+1$, with 0 being agreement expected by from random chance, and correcting for random agreement due to guessing, Cohen 1960) with an interval time of 1.00 s (meaning that the behaviours coded by the two raters were checked for agreement/disagreement per second). Then, they discussed the minor unclarities remaining in the coding scheme as revealed by the IRR-calculation - for instance due to an atypical assembly strategy exhibited by the participant. When a

consensus was reached on refining these subtle ambiguities accordingly and when the codes were thoroughly understood by the raters, the same videos were coded again from the beginning, independently and without guidance. IRR was then calculated again. This process of training and consolidation continued for the first and, if necessary, for the following participant videos until an acceptable Cohen's Kappa IRR coefficient was reached of $K > .70$ for the complete subset (falling within the range for 'moderate agreement' of $0.60 - 0.79$, McHugh 2012; we opted for this threshold being appropriate for a first exploratory study on the topic, see Lombard, Snyder-Duch, and Bracken 2002, 2010).

4.1.4. Coding procedures

The following coding approach was used throughout the process of informal (i.e. the three training video's) and formal IRR assessment (i.e. the subset of four), and throughout the validation process (see below). Out of the, in total, seven steps both assemblies consisted of, only the first, third and fifth step of both assemblies were coded in order to make the labour-intensive video coding process feasible for the raters while selecting a representative sample of assembly behaviour (for a similar approach, see, e.g. Baranek et al. 2005). This provided in total approximately 10 min of data per participant¹ to be analysed with BORIS. Specifically, a combination of a topographical coding system measuring the occurrence of behaviours (i.e. the amount of times a code occurred) and a dimensional coding scheme gauging the time duration of behaviours was deployed (Heyman et al. 2018). For the detection of occurrence and duration, a timed-event sequential continuous coding approach was used (Chorney et al. 2015). That is, the raters continuously analysed behaviour during the complete assembly step by backwarding and forwarding throughout the videos.

Although preferred when possible, raters could not be blind for the manipulation, since the design of the assemblies were also visibly different in complexity for the raters. Since the codes are clearly delineated in time and define concrete physical behaviour (instead of, e.g. socially constructed behaviours, see Chorney et al. 2015), we do not foresee the coding having been prone to judgement subjectivity. Table 1 provides an overview of the steps and amount of participants coded per rater.

The final coding scheme differentiated codes between state events (for which both duration and occurrence was important) and point events (for which duration was not meaningful and only occurrence was hence coded). For the state events, onset

and stop times were coded. Point events were coded at the onset of the behaviour. For the onsets and stop times, both raters aimed to apply an accuracy of approximately 0.5 s. Not every behaviour was coded. Specifically, we did not account for ergonomic behaviour (i.e. repositioning one's hand, retaking a part for comfort or picking up a part the participant dropped), orderliness behaviours such as putting parts aside in a personally preferred way, screwing or picking screws. We did so, since we did not have deductive nor inductive grounds for linking such behaviours to upper red zone MWL. Figure 3 shows a screenshot of the behavioural video coding software deployed to apply (iterations of) the coding scheme.

4.2. Results

The final coding scheme, consisting of 4 categories and 11 codes, is displayed in Table 1 and was synthesised in a logic sequence of categories for assembly execution, being; I., Parts selection behaviour (3 codes), II., Positioning behaviour (4 codes), III., Transition behaviour (i.e. in-between completing an assembly step and starting the next) (1 code) and, IV., Generic behaviour (occurring throughout all assembly phases) (3 codes).

Only the code 'Freeze' involved modifiers to differentiate between three types of freezes. Importantly, we used the participant's eye-gaze point to distinguish between certain codes and to help define others. Table 1 also includes the available empirical referents that helped in the coding scheme development. Note that some codes were mainly driven by the inductive path, others deductively. In Appendices we included a table with rater instructions (Appendix A) and one with rater attention points (Appendix B), both especially to be used during rater training.

Finally, not all codes were mutually exclusive, meaning that some codes could be nested in another code, such as 'Gaze redirection' in 'Freeze', or 'Freeze' in 'Verification of fixed position'. Other codes were always nested in the main categorical code, such as 'Part touched' in 'Parts collection' (Table 2).

5. Validation of the coding scheme

To validate our central research question on possible observable behavioural indications of upper red zone MWL, we deployed our coding scheme on a set of 24 videos from the assembly experiment and hypothesised that:

H: The behaviours detected will last longer and/or occur more frequently in the high complexity condition as compared to the low complexity condition.

Table 1. Overview of assembly steps coded for both assemblies and the amount of subjects coded per rater.

	Assembly steps						
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7
Rater 1	x		x		x		
Rater 2	x		x		x		

'X' indicates that a step was coded by a rater.

We directly derived this hypothesis from previous work empirically addressing the limited resource theories (discussed in section 2. Background) by showing that, e.g. higher behavioural entropy in driving and more and longer contemplation-style pauses in computer mouse behaviour indicate high MWL (see section 4.1.1). The experiment leveraging a high and a low complexity assembly now served to validate, with a separate large-scaled sample of videos, whether the behavioural codes of the coding scheme are indicative of high MWL, as compared to low MWL. This way, we experimentally tested the coding scheme's discriminative validity, i.e. can the behavioural codes distinguish between groups that are hypothesised to differ (Heyman et al. 2018)?

5.1. Participants

Because no previous studies exist deploying behavioural video coding to gauge MWL, we looked for previous work using the most similar research methodology to help us determine the sample size. The work of Qiu and Helbig (2012) and Baranek and colleagues (2005) adhered most closely to our experimental setup. The former inferred MWL levels through automated video analysis of body posture based on 22 participants and a pair-wise comparison between cognitive tasks in a within-subjects experimental design. The latter study by Baranek and colleagues (2005) gauged autism in infants by deploying a retrospective video analysis method very similar to our method. In this study, 32 participants were distributed over three conditions in a between-subjects experimental design. In line with these most similar studies, and to keep the labour intensive video coding feasible, we aimed to also arrive at a minimum of 20 participants per condition in our within-subjects design experiment. A total of 25 university student volunteers of an engineering university faculty (20% female, $M_{age} = 21.48$, $SD_{age} = 1.19$), naïve to the manipulation participated after giving a written consent (no participant afterwards reported to have an idea about the experimental goal). Participants' inclusion criteria were the same as in Van Acker and colleagues (2020).

Table 2. Final behavioural video coding scheme.

Category, Code (Unit)	Definition	Empirical referents	Example
<i>I. Selecting Behaviour</i>			
1. Parts collection (state event)	Time needed to select all perceived correct parts.	Execution time (Richardson et al. 2006; Stork and Schubö 2010) and reaction time (Young et al. 2015)	The operator wants to select the required two parts, but under higher MWL levels touches five parts and rotates them several times before a decision is made on which the correct parts are. In total, the selection of both parts hence lasted longer.
2. Part touched (point event)	Number of new parts touched.	Making errors (Richardson et al. 2006; Stork and Schubö 2010), amount of sub-steps needed (Stork and Schubö 2010)	
3. Part rotation (point event)	Number of times operator is manipulating a part (here rotating, from velocity is 0 to velocity is 0).	Making errors (Richardson et al. 2006; Stork and Schubö 2010), amount of sub-steps needed (Stork and Schubö 2010)	
<i>II. Positioning Behaviour</i>			
4. Positioning (state event)	Time to select perceived right position. Includes rotation and alignment.	Execution time (Richardson et al. 2006; Stork and Schubö 2010) and reaction time (Young et al. 2015)	When then positioning the two parts, the operator, still under higher MWL levels, makes a few redundant positioning attempts, needs more time to verify whether a fixed position is then indeed correct and takes a while to correct a wrong perceived fixed position. Altogether, positioning the two parts lasted longer as would be expected.
5. Positioning attempt (point event)	Number of positions tried (defined by velocity = 0, part touches assembly-in-progress or is being held above, below or aside from it) on assembly-in-progress.	Making errors (Richardson et al. 2006; Stork and Schubö 2010), amount of sub-steps needed (Stork and Schubö 2010)	
6. Verification of fixed position (state event)	Time needed for operator to verify if a position (i.e. orientation, alignment, position) is correct after a component has been fastened, for at least 2 seconds.	Dwell time on assembly (Stork and Schubö 2010)	
7. Correction of perceived wrong position (state event)	Time operator needs to correct a (set of) perceived wrong fastening(s) and perform a perceived correction, for at least 2 seconds.	Error corrections in behavioural entropy (Boer 2000)	
<i>III. Transition Behaviour</i>			
8. Inspection of assembly-in-progress (state event)	Time operator needs to familiarise with or verify the assembly-in-progress including touching and rotating assembly-in-progress, for at least 2 seconds, in between visual intake of instructions and onset 'Parts collection' or 'Correction of perceived wrong position'.	Dwell time on assembly (Stork and Schubö 2010)	When proceeding to the next step, the operator first inspects the assembly-in-progress. Under higher MWL levels, this lasts longer.
<i>IV. Generic Behaviour</i>			
9. Freeze (state event)	Number of times both operator's hands and arms stop moving or only move very minimally (the latter not as a function of selection or positioning), at a fixed place in the workspace for at least 2 seconds.	Hand movement parameters (Stork and Schubö 2010), writing velocity (Chen et al. 2016), startled response in behavioural entropy (Boer 2000), contemplation-style pauses in computer mouse behaviour (Arshad, Wang, and Chen 2013) and dwell time on assembly (Stork and Schubö 2010)	During the entire assembly process, apart from the assembly stages, the operator also freezes more often, has several occasions of needing to redirect the eye gaze and more often inspects the assembly (parts) from closer by – all when under higher MWL levels.
Modifier 1	Head freezes too, eyes move		
Modifier 2	Not accompanied by freeze of head and eyes		
Modifier 3	Both eyes and head freeze too		
10. Gaze redirection (point event)	Number of times operator gazes away from worktable for at least 2s.	Behavioural entropy (Boer 2000)	
11. Relative head position change (point event)	Number of times operator's head is repositioned closer to or further away from parts or assembly-in-progress, because of the operator moving the upper body or oppositely, the parts or assembly-in-progress.	Task-unrelated body posture (coming closer, moving less) (Qiu and Helbig 2012)	

5.2. Measures

As the experiment now serves for validation of the codes, we first checked whether the manipulation of the experiment was successful in inducing MWL and

excluding confounders by including subjective measures and a test. The same measures and their theoretical background were used as in earlier work (see Van Acker et al. 2020, for more information). All items deployed a 7-point Likert-scale.

5.2.1. Manipulation check

As a manipulation check, perceived task *Complexity* was measured with a single item ('I perceived this assembly to be difficult.') and subjective *Mental Workload* (MWL) was gauged by the average of the scores on three items derived from cognitive load theory (Paas 1992; Paas, van Merriënboer, and Adam 1994), the Subjective Workload Assessment Technique (SWAT; Reid and Nygren 1988) and the NASA-TLX (Hart and Staveland 1988) (e.g. 'I experienced this assembly as cognitively demanding'; $\alpha_{\text{low complexity}} = .90$, $\alpha_{\text{high complexity}} = .91$).

Since we aimed to induce (impending) mental overload, we also measured emotional load (EL), as it can provide an indirect measure (Van Acker et al. 2018). *Emotional Load* consisted of five items selected from the Dundee Stress State Questionnaire (DSSQ; Matthews et al. 2013; Matthews 2016) (e.g. 'I felt frustrated while performing this assembly.'; $\alpha_{\text{low complexity}} = .77$, $\alpha_{\text{high complexity}} = .83$) measuring the negative emotions frustration and irritation, whether participants felt tense during the assembly, and appraisals covering whether they felt they could cope with the situation and to what extent they felt uncertain.

5.2.2. Measures of confounding variables

As we only aimed to measure (impending) overload, we wanted to minimise effects of other possible confounding variables. Therefore, we first measured perceived *Physical Load* (PHL) with one item ('I perceived this assembly to be physically demanding') as it can interact with mental and emotional load, hence confounding the duration of our behavioural codes (i.e. higher PHL inducing longer code durations because of physical fatigue). Additionally, two variables *Mind Wandering* and *Fed Up* consisting of one item each (also derived from the DSSQ, Matthews et al. 2013; Matthews 2016) checked for task engagement by asking whether the participant's mind started wandering and to what extent the participant was fed up with the assembly. We included these questions to check whether the coded behaviour could be caused by a lack of engagement into the assembly task (e.g. freezing longer because of mind wandering or more parts touched because of being fed up with the task).

Finally, two idiosyncratic control variables were included for which we reasoned they could correlate with our codes. First, we measured the self-reported *Dexterity* with one item ('In general, how dextrous do you estimate yourself to be - apart from how you experienced these assembly tasks'), again on a 7-point Likert answer scale (from 1, very clumsy, to 7, very

dextrous). Second, participant's *visual-spatial intelligence* was gauged with a subset of the Revised Minnesota Paper Form Board test (Stinissen 1977) subsequent to both experimental conditions and a resting phase of five minutes. We did so, since this intelligence factor can largely affect interpersonal differences in assembly performance.

5.2.3. Video coding procedures

As proposed by Hallgren (2012; see also Neuendorf 2002), after calculation of the inter-rater reliability (see above), the primary rater continued to analyse the remainder of the dataset in BORIS using the final coding scheme and following the same coding procedures (for a similar approach, see Baranek et al. 2005). The secondary rater thus only served for reliability. In total, 24 videos were coded by this rater², i.e. the four videos already coded for the IRR assessment and 20 remaining videos. These 24 coded videos were used for the analysis. Note that the first, third and fifth step were selected to code. Below, we refer to these steps as Step 1, Step 2 and Step 3, respectively.

From BORIS, we subsequently extracted the occurrence and duration of the codes per step. As duration and occurrence was sometimes important per code, while for other codes only occurrence was relevant, we hence did not have 22 dependent variables in total, but 19. All codes measured through duration were quantified in seconds. All codes measured through occurrence were quantified as the number of times the coder had coded the behaviour (e.g. 'Parts collection' sometimes occurred multiple times within a step, because the participant returned to a 'Parts collection' phase after starting 'Positioning').

5.3. Results

All subjective measures lacked normality of data. We therefore ran non-parametric tests. The results are reported in Figure 4.

5.3.1. Manipulation check

A Wilcoxon Signed Rank Test on perceived assembly difficulty showed that the high complexity condition was indeed perceived as more difficult ($M_{\text{high complexity}} = 4.84$, $SD = 1.56$, range: 1-7; $M_{\text{low complexity}} = 1.56$, $SD = .92$, range: 1-5; $N = 25$), $z = -3.99$, $p < .001$ (two-tailed), with a large effect size of $r = .56$ (i.e. $r = z / \sqrt{(N_x + N_y)}$, Rosenthal 1994). A Wilcoxon Signed Rank Test showed that MWL was perceived as higher in the high complexity condition with a rather neutral score ($M_{\text{high complexity}} = 4.39$, $SD = 1.58$, range: 1-7; M_{low}

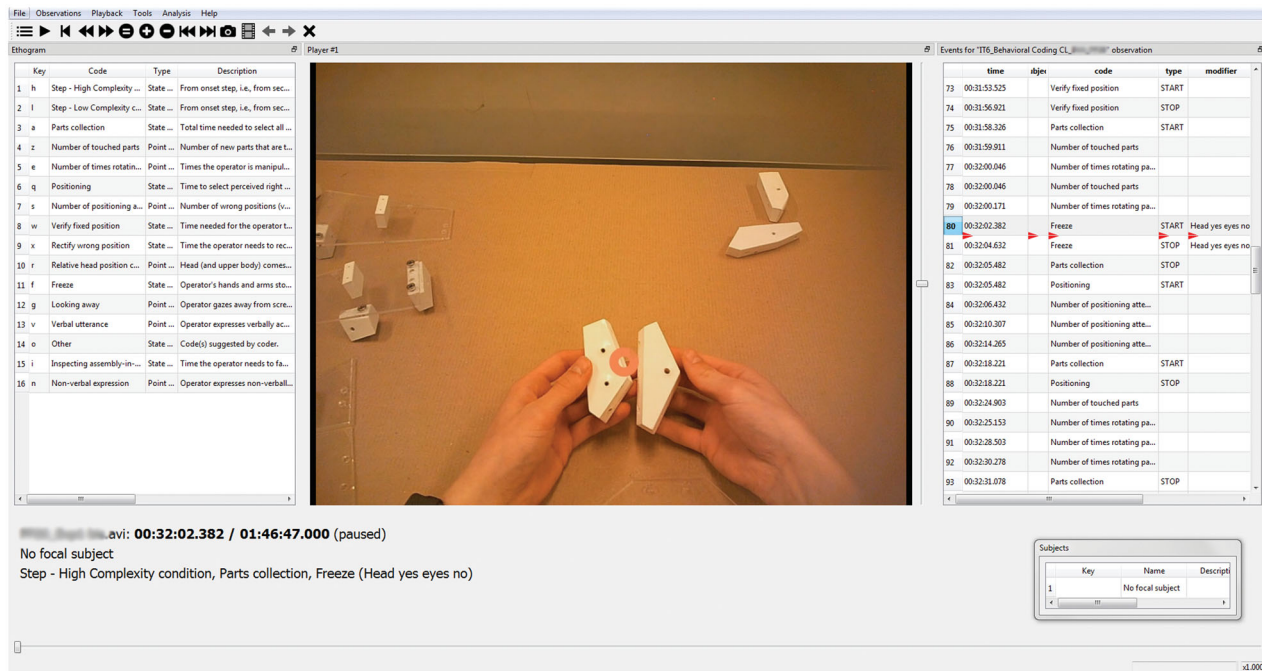


Figure 4. Screenshot of the coding scheme (left side of the screen, see 'Ethogram') deployed in BORIS, on a participant video (centre) (orange circle displays the eye gaze), resulting in a sequence of behaviours coded throughout the video (right side of the screen, see 'Events for ...').

complexity = 2.10, $SD = 1.12$, range: 1.00–5.33; $N = 25$), $z = -3.79$, $p < .001$ (two-tailed) and with a large effect size of $r = .54$. The complexity manipulation was hence effective.

For EL, a Wilcoxon Signed Rank Test revealed that EL was significantly higher in the high complexity condition ($M_{\text{high complexity}} = 3.72$, $SD = 1.21$, range: 1.60–6.00; $M_{\text{low complexity}} = 2.16$, $SD = 1.04$, range: 1.00–4.80; $N = 25$), $z = -3.71$, $p < .001$ (two-tailed), with a large effect size of $r = .53$.

5.3.2. Confounding variables

Physical Load (PHL) showed to be higher in the high complexity condition ($M_{\text{high complexity}} = 1.72$, $SD = 1.06$, range: 1–5; $M_{\text{low complexity}} = 1.16$, $SD = .55$, range: 1–3; $N = 25$), $z = -2.38$, $p = .018$ (two-tailed), with a medium effect size of $r = .34$, but was still low.

Being Fed Up with the assembly was higher for the low complexity condition, expressed in a neutral score as compared to a low score for the high complexity condition ($M_{\text{high complexity}} = 2.40$, $SD = 1.32$, range: 1–5; $M_{\text{low complexity}} = 4.00$, $SD = 1.89$, range: 1–6; $N = 25$), $z = -2.73$, $p = .006$ (two-tailed), with a medium effect size of $r = .39$. Mind Wandering was rated higher for the low complexity condition as well, expressed in a neutral score, as compared to a low score for the high complexity condition ($M_{\text{high complexity}} = 2.44$, $SD = 1.53$, range: 1–6, $N = 25$; $M_{\text{low complexity}} = 4.08$, $SD = 1.91$,

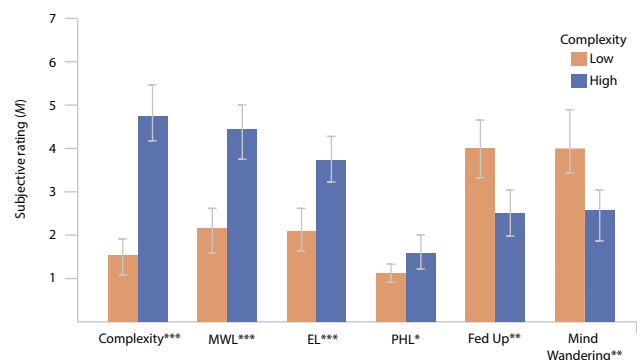


Figure 5. Overview of the means (with 95% CI) of all subjective ratings used for the manipulation check and possible confounding variables, $*p < .05$, $**p < .01$, $***p < .001$. Note. MWL: mental workload; EL: emotional load; PHL: physical load; 'Complexity' refers to the experimental conditions.

range: 1–7, $N = 24$), $z = -2.61$, $p = .009$ (two-tailed), with a medium effect size of $r = .37$ (Figure 5).

Summarised, our manipulation succeeded in inducing two different levels of MWL, though during the high MWL condition levels still remained rather neutral. EL also differed, but the high complexity condition neither yielded high EL, hence not potentially indicating mental overload. We hoped being fed up and mind wandering to be low, but they panned out closer to average. These negative indications of task engagement differed per condition too, potentially confounding our behavioural coding data towards not finding differences between conditions (i.e. possible

negative confounding because of slower and ineffective assembly behaviour in the low complexity condition). Finally, physical load unexpectedly differed per condition, although it remained low to non-existent for both conditions (i.e. very close to the lower extreme of the scale). For the latter reason, we do not expect physical load to confound the occurrence and duration of our codes.

5.3.3. Behavioural coding

Contrary to our subjective measures where the unit of analysis was our participants, in our behavioural coding analysis, we used a flattened, nested dataset consisting of $n=144$ coded observations across 24 participants³, that is, a dataset of all occurrences and durations per code (i.e. the 19 columns for the dependent variables) for; the coded steps (i.e. 3), per condition (i.e. 2), per participant (i.e. 24)—making 144 rows of observations (i.e. $3 \times 2 \times 24 = 144$).

As discussed by Snijders and Bosker (1999) approaches such as analysis of variance or general linear modelling assumes that no relationship exists between the individual observations in the sample. In our study, this is clearly not the case because multiple observations come from the same participant. As a result of this, there can be an assumption that the individual will impact our various outcome variables. We therefore used multilevel modelling (also called mixed effects or random-effects models) to test for the effects of the different codes, with the individual participant being the grouping variable. As discussed by Maas and Hox (2005), our sample size is sufficiently large to perform a multilevel model. We used the lme4 (1.0–5) R Package (Bates et al. 2019).

We first report a null model (I) including no variables, to show differences with the subsequent models, being a model (II) with only the control variables (i.e. spatial intelligence and dexterity), a model (III) with

only the independent variables, a model (IV) with the independent variables and their interactions and a final full model (V) including all these variables. Per model, we report the total explained variance with an R^2 estimate. Because of the large amount of dependent variables, we included all respective tables in Appendices. Note that Step 1, Step 2 and Step 3 referred to below are steps selected from the seven assembly steps and therefore represent, respectively, steps 1, 3 and 5 of both assemblies (see Table 1).

5.3.3.1. Selecting behaviour. For the full model (V), the code 'Parts collection' was found to indeed occur more ($p < .001$) and longer ($p < .001$) during the high complexity Condition, as compared to the low complexity Condition. This full model explained a total variance of 31% (of which 24% by the independent variables).

This behaviour also occurred more ($p < .01$) and longer ($p < .001$) during the first step, as compared to the second step. Step 2 (as compared to Step 1) interacted with Condition for the number of occurrences ($p < .01$) and duration ($p < .05$), so that during Step 1 this code was even more prevalent and took even longer during the high complexity Condition. Additionally, there was an interaction between Step 3 (as compared to Step 1) and Condition ($p < .01$) for the duration of this code in the same direction (see Figure 6). This full model explained a total variance of 48% (of which 43% by the independent variables).

'Part touched' did not differ per Condition. Again, the behaviour occurred more during the Step 1, as compared to Step 2 ($p < .001$), and Step 3 ($p < .001$) (see Figure 7). Dexterity interestingly, was positively related to this code too ($p < .05$), although its explained variance was low ($R^2_{\text{model II}} = .03$, $R^2_{\text{model III}} = .24$, $R^2_{\text{model V}} = .25$).

'Part rotation' occurred more under high complexity levels, $p < .05$, and again more during Step 1, as

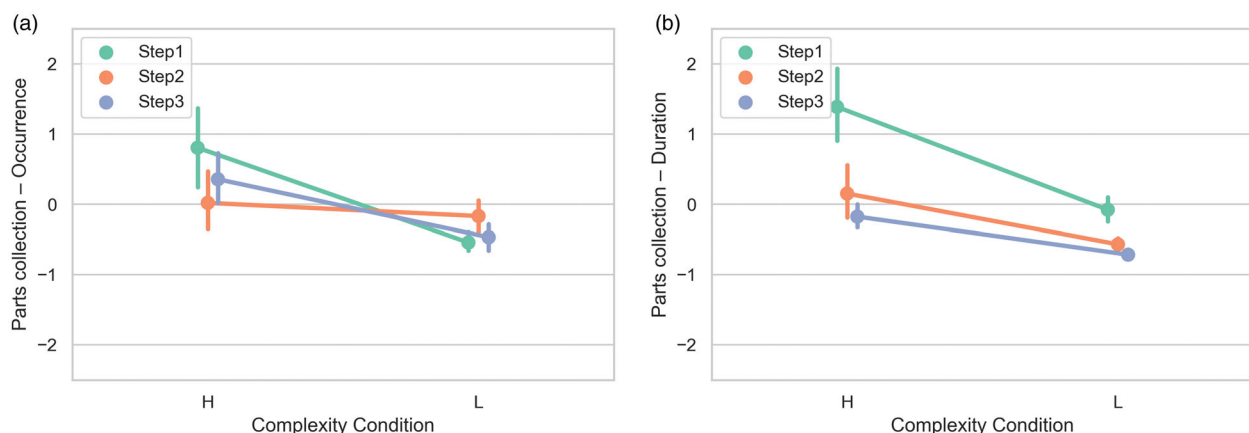


Figure 6. Occurrence and duration of 'Parts collection', expressed in z-scores.

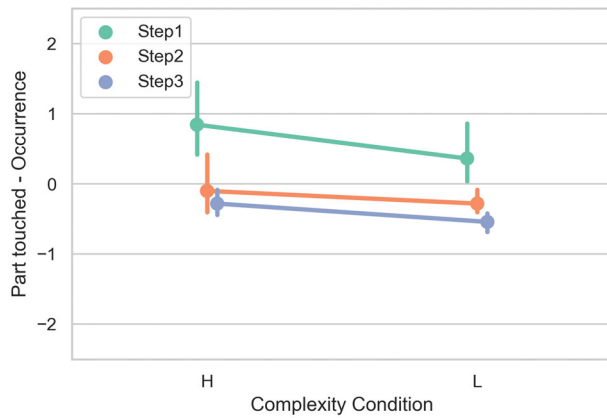


Figure 7. Occurrence of 'Part touched', expressed in z-scores.

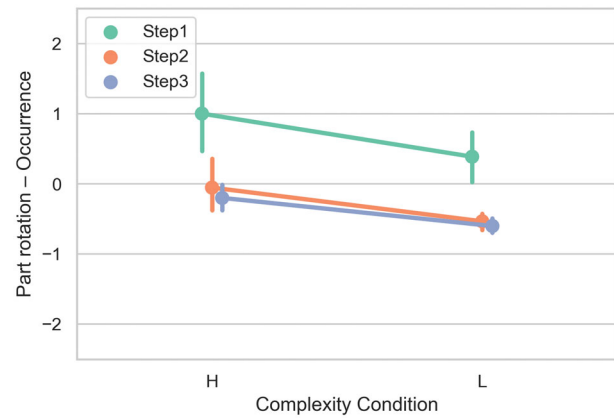


Figure 8. Occurrence of 'Part rotation', expressed in z-scores.

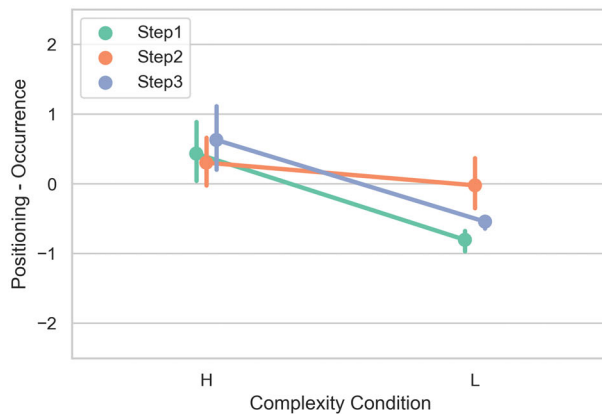


Figure 9. Occurrence and duration of 'Positioning', expressed in z-scores.

compared to Step 2, $p < .001$, and Step 3, $p < .001$ ($R^2_{\text{model III}} = .31$, $R^2_{\text{model V}} = .31$) (see Figure 8).

5.3.3.2. Positioning behaviour. 'Positioning' too, was more prevalent during the high complexity Condition, $p < .001$. An interaction effect between Condition and Step 2, $p < .05$, showed that the code occurred significantly more during Step 2 during the low complexity Condition as compared to Step 1 ($R^2_{\text{model III}} = .23$, $R^2_{\text{model V}} = .27$).

The duration of 'Positioning' also took longer during the high complexity Condition ($p < .001$) and, remarkably, during Step 3, as compared to Step 1 ($p < .001$). An interaction effect showed the behaviour took longer during Step 3 (compared to Step 1) under high complexity levels, $p < .01$ ($R^2_{\text{model III}} = .48$, $R^2_{\text{model V}} = .54$) (see Figure 9).

'Positioning Attempt' was observed more under high complexity levels, $p < .001$, and for Step 1 as compared to Step 2, $p < .05$ ($R^2_{\text{model III}} = .30$, $R^2_{\text{model V}} = .32$) (see Figure 10).

'Verification of fixed position' did not depend on Condition, but did occur more during the first step as compared to Step 3, $p < .01$ ($R^2_{\text{model III}} = .22$, $R^2_{\text{model V}} = .24$).

The duration of this code did not depend on Condition. Again, the code lasted longer during Step 1 when compared to Step 3, $p < .05$ ($R^2_{\text{model III}} = .27$, $R^2_{\text{model V}} = .30$) (see Figure 11).

The amount of occurrences of 'Correction of perceived wrong position' was not observed differently per Condition, but it did occur more during Step 2 as compared to Step 1, $p < .001$, and showed an interaction effect, $p < .001$, showing that the code occurred more often during Step 2 under high complexity levels when compared to Step 1 ($R^2_{\text{model III}} = .18$, $R^2_{\text{model V}} = .27$).

Nor did the duration of this behaviour show to depend on Condition. The duration was however longer during Step 2 ($p < .01$) and Step 3 ($p < .01$), both as compared to Step 1. An interaction effect additionally showed that the code lasted longer during Step 2 ($p < .05$) when compared to Step 1, during the high complexity Condition (see Figure 12). Finally, also Dexterity positively affected this code, $p < .05$ ($R^2_{\text{model III}} = .21$, $R^2_{\text{model V}} = .24$).

5.3.3.3. Transition behaviour. For 'Inspection of assembly-in-progress' we only compared Step 2 with Step 3, because during Step 1 no assembly-in-progress was yet present. This behaviour occurred more during

the onset of Step 3 as compared to Step 2, $p < .01$, but was independent of Condition. An interaction effect however revealed that this behaviour occurred more during Step 3 under high complexity levels as compared to Step 2 (see Figure 13). Dexterity was also positively related to this behaviour, $p < .05$, but only added little variance ($R^2_{\text{model III}} = .07$, $R^2_{\text{model IV}} = .17$,

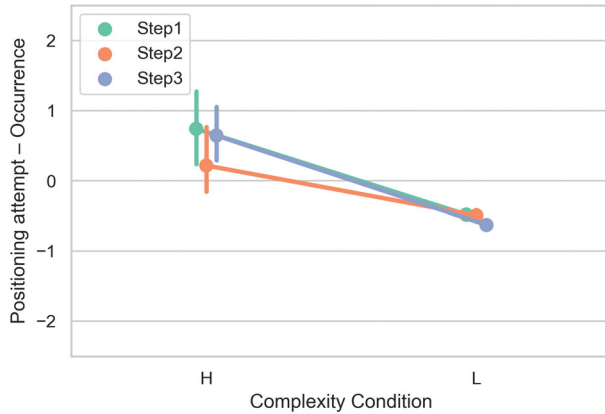


Figure 10. Occurrence of 'Positioning attempt', expressed in z-scores.

$R^2_{\text{model V}} = .20$). For the duration of this code, no effects were found ($R^2_{\text{model III}} = .6$, $R^2_{\text{model IV}} = .11$, $R^2_{\text{model V}} = .20$).

5.3.3.4. Generic behaviour. 'Freeze - Modifier 1' did not depend on Condition ($R^2_{\text{model III}} = .16$, $R^2_{\text{model V}} = .19$) after adding the interactions in model III. Its duration was independent of Condition, as well after adding the additional variables in model III. During Step 3 ($p < .05$) in general, this behaviour however lasted longer, as compared to Step 1 ($R^2_{\text{model III}} = .16$, $R^2_{\text{model V}} = .20$). Additionally, an interaction effect, $p < .05$, revealed that this behaviour lasted longer during Step 3 under high complexity levels, when compared to Step 1 (see Figure 14).

'Freeze - Modifier 2' occurred more during the high complexity Condition ($p < .05$) ($R^2_{\text{model III}} = .17$, $R^2_{\text{model V}} = .17$). The effect of Condition on its duration disappeared after adding the interactions in Model III ($R^2_{\text{model III}} = .10$, $R^2_{\text{model V}} = .10$) (see Figure 15). 'Freeze - Modifier 3' was only observed once, so that no analyses could be run.

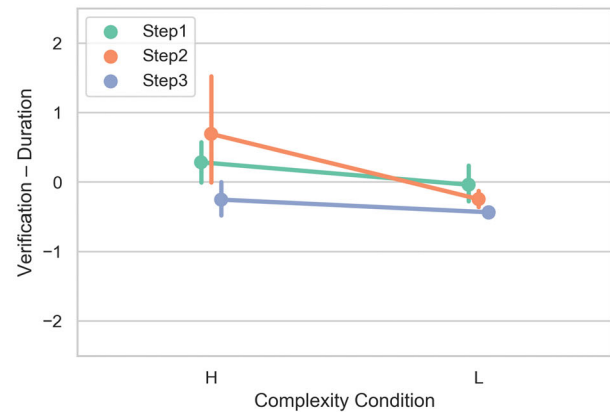
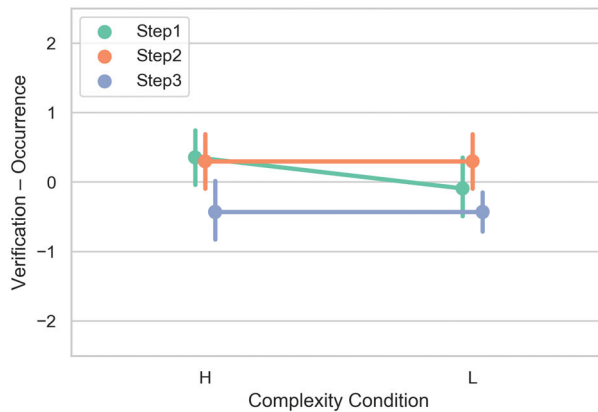


Figure 11. Occurrence and duration of 'Verification of a position', expressed in z-scores.

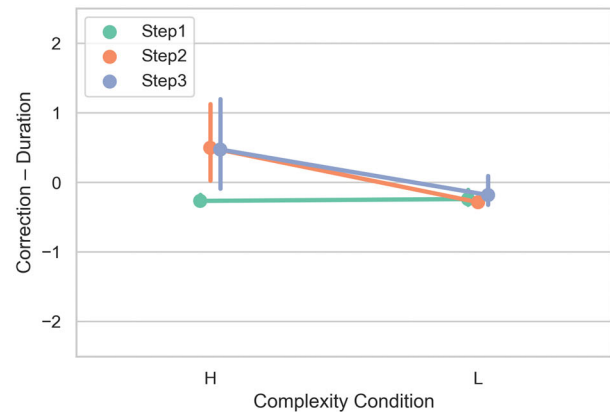
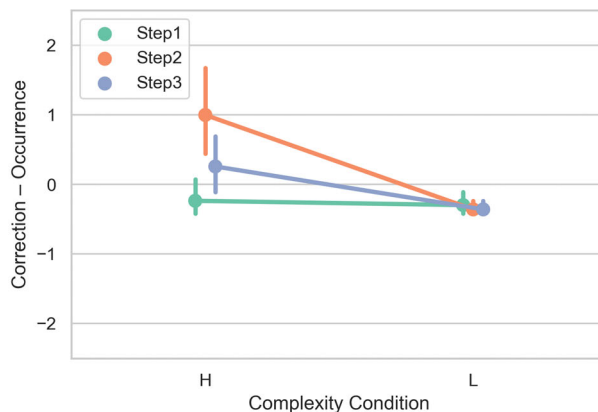


Figure 12. Occurrence and duration of 'Correction of a wrong position', expressed in z-scores.

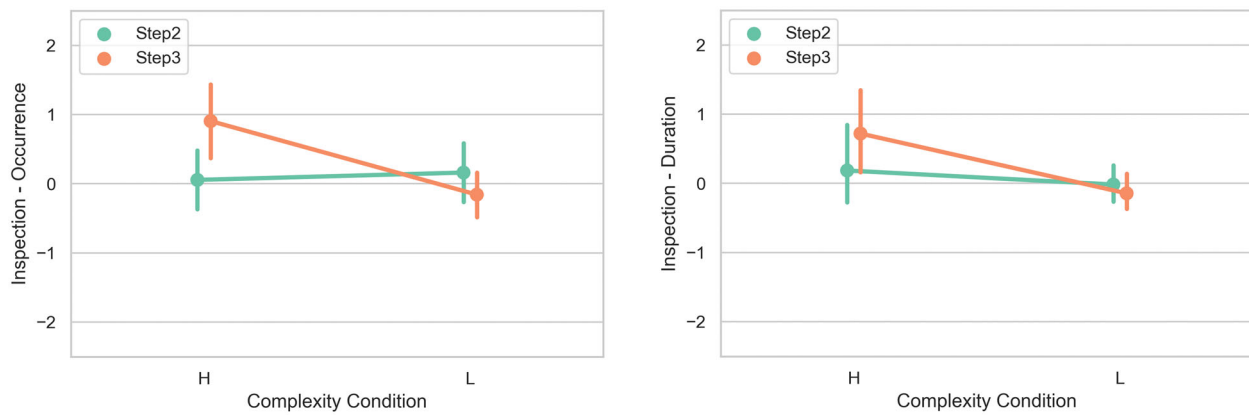


Figure 13. Occurrence and duration of 'Inspection of the assembly-in-progress', expressed in z-scores.

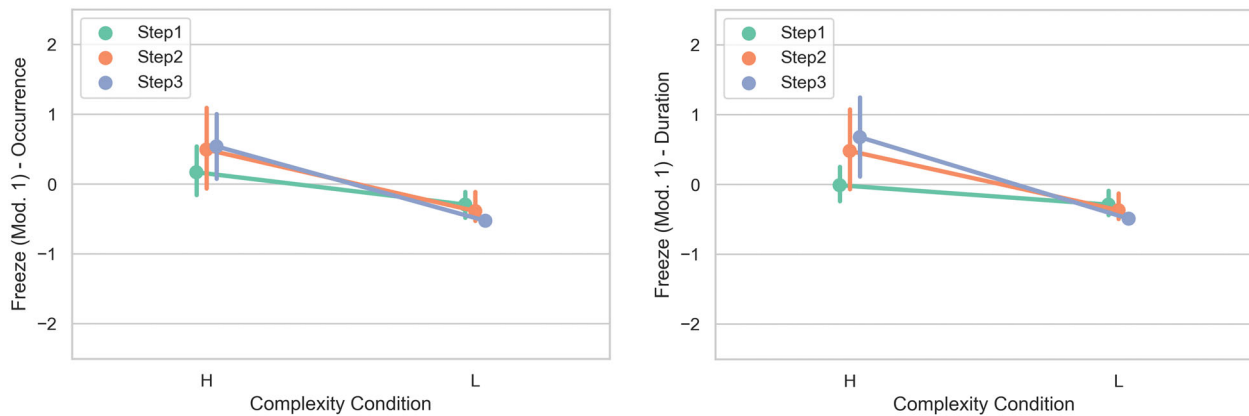


Figure 14. Occurrence and duration of 'Freeze (Modifier 1)', expressed in z-scores.

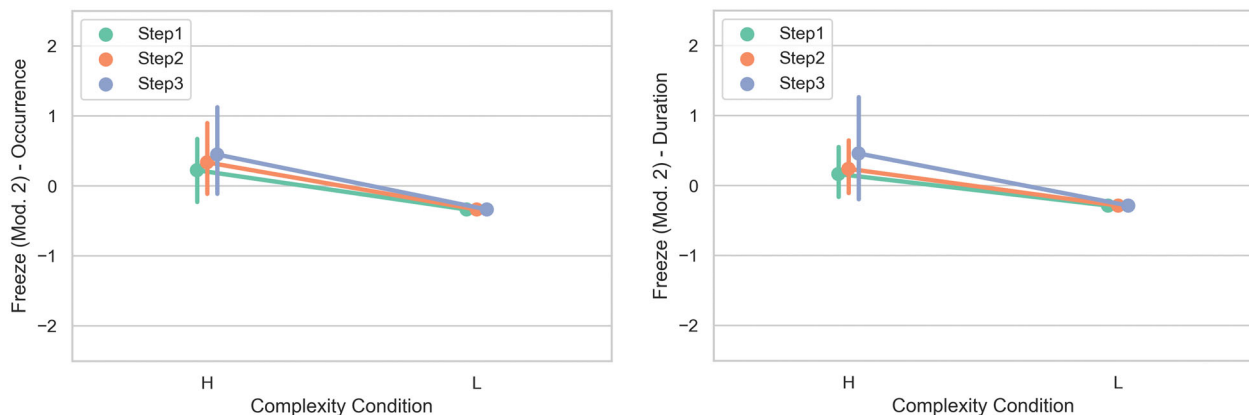


Figure 15. Occurrence and duration of 'Freeze (Modifier 2)', expressed in z-scores.

'Gaze redirection' did not depend on Condition, nor the Steps (see Figure 16). Only Dexterity showed a positive correlation ($p < .05$). The total explained variance of the full model (V) was nevertheless low ($R^2_{\text{model V}} = .06$).

Finally, also 'Relative head position change' did not differ per Condition (see Figure 17). The total explained variance of the full model (V) for this code

was also low, only explaining 5% the total variance (of which 4% by the IV's).

6. Discussion

The current work focussed on the 'Employee Work Behaviour'-level as presented in the conceptual MWL-framework of Van Acker and colleagues (2018),

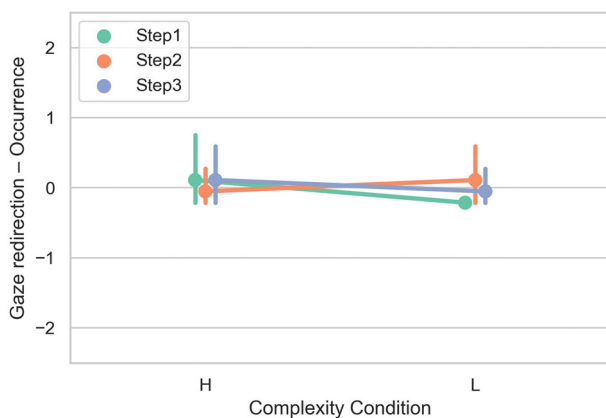


Figure 16. Occurrence of 'Gaze redirection', expressed in z-scores.

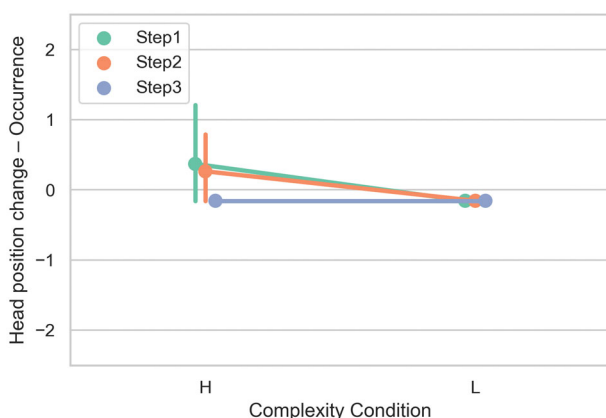


Figure 17. Occurrence of 'Relative head position change', expressed in z-scores.

thereby focussing on the underrepresented behavioural component of MWL. Iterative processes of deductive and inductive development were finalised into a behavioural video coding scheme defining 11 observable indicators of behaviours potentially revealing upper red zone MWL in assembly. An experiment was deployed to validate these codes, i.e. to answer the question whether these codes indeed measure what they should measure.

Multilevel analyses showed that only the occurrence and duration of the codes 'Parts collection' and 'Positioning', and the occurrence of 'Part rotation', 'Positioning attempt' and 'Freeze (Modifier 2)' statistically significantly differed between conditions - thereby partly confirming our hypothesis. The behaviours not differing significantly, were; 'Part touched', 'Verification of a fixed position', 'Correction of a wrong position', 'Inspection of the assembly-in-progress', 'Freeze (Modifier 1)', 'Gaze redirection' and 'Relative head position change'. Based on this first presented work, five behavioural codes (out of eleven) can thus be withheld as indicative of upper red zone MWL in assembly.

In other words, these results suggest that upper red zone MWL can be observed as expressed during a complex assembly task in specific behavioural manifestations such as slower and/or more (1) collecting, (2) positioning, (3) rotating and (4) positioning attempts of/with assembly parts, and (5) freezing of the hands and arms.

The six non-significant codes that could not be indicative of MWL, in this context, could use more scrutiny or might reflect that behavioural expression of upper red zone MWL is partly idiosyncratic and might differ substantially between human beings. Indeed, some people might express different behaviours indicating fluctuations in MWL than others, so that for some certain behaviours might be very indicative, while other behaviours would not, or very rarely, occur at all. Also, it might be that upper red zone MWL elicits in some people rather covert human reactions (e.g. emotional, cognitive rumination) than the overt behaviours we aimed to observe. Below, we refer to some exploratory suggestions on personality traits in this respect. Next, the participant sample size might not have been sufficient to find all effects expected in this more real-life experiment. In line with this, it might also have been the case that the desired effects were not present as strongly as expected. As we show and elaborate upon below, most participants only experienced moderate levels of MWL. Under higher levels of MWL also some of the now non-significant behaviours might therefore become indicative of MWL as well. Inadequate task manipulation and raters' lack of familiarity with behavioural coding or judgmental bias as potential explanations for our non-significant findings can be excluded as we checked our experimental task manipulation and the raters involved were experienced senior researchers, well instructed and trained.

Interestingly, we did see that some main effects of Step might allude to some codes rather revealing accumulated cognitive fatigue towards the third step (Step 2 in the analyses) and the fifth step (Step 3 in the analyses) out of the seven in total (for a possible example of such fatigue effects in pupillometry, see Van Acker et al. 2020; also see Hockey 1997), whereas for other codes main effects could point to a more stressful, startled response-like effect at the onset of the assembly. The interaction effects of certain steps could nevertheless point in the same direction of our hypothesis, in that some codes occurred more and longer during the high complexity condition, but only for certain steps. Overall, main effects of Steps, the interaction effects found in the full models and the

main effects of Condition disappearing after the interaction effects were included (in model III, cf., Freeze – Modifier 1) suggest that the complexity manipulation was not equally strong per step. The steps thus also varied in the MWL they induced. This is intelligible, since manipulating complexity in a real-world assembly with consecutive steps entails this challenge (also see Van Acker et al. 2020). Altogether, all codes might also have been underestimated because of negative confounding due to the low complexity condition yielding moderate levels of task engagement (as compared to significantly higher task engagement levels during the high complexity condition).

Of our control variables we found that spatial intelligence did not show any effect and dexterity only very weakly (see the modest amounts of explained variance). Exploratively, we were able to also measure three personality traits for which we thought they could relate to our codes, this for a subsample of $n = 17$. We subjectively gauged 'Impulsivity', i.e. the tendency of acting before thinking in work situations (based on two items measuring 'individual action propensity' in Vera et al. 2014), and we gauged the Big Five personality traits *Neuroticism* and *Conscientiousness* (each measured with 4 items out of a short form of a Big Five scale; Donnellan et al. 2006). We found that only Impulsivity was negatively correlated ($p < .05$) with the duration of the code 'Verification of a position'. Future work could address these factors more profoundly.

In relation to previous work on mental overload as outlined by, i.a., Young and colleagues (2014), the subjective results showed that the observed behaviours on average did not indicate overload as envisioned in Figure 2, because both MWL and EL remained neutral (note that, however, different measures do not always correlate; Hancock and Matthews 2019; Gerald Matthews et al., 2015). Here, we can at most speak of potentially *impending* overload (i.e. AOI 1 in Figure 2). Future work could explore whether overload could be defined by specific behaviour, or by a long sequence and/or duration of behavioural codes. For impending overload, the code 'Freeze' could for example be differentiated into 'decelerating movement' (i.e. automatised motor execution behaviour, such as fetching, slowing down) and 'contemplation-style freeze' (i.e. the freeze reflects thinking, without negative affect; cf., potentially our Freeze – Modifier 2). While overload per se could be defined by a 'startle-like freeze' (i.e. a freeze associated with negative affect; cf., potentially our Freeze – Modifier 1 or 3) (cf., freezing as a defensive musculo-skeletal response to an abrupt stimulus, related to negative affect in, Lang, Davis, and Öhman 2000).

Differently, nine positioning attempts or a sequence of long-lasting contemplation-style freezes could as well indicate overload. This way, MWL-levels within the upper red zone could be objectively defined as a function of performance - as called for in earlier work - and could even help define, e.g. a 'maximum permissible cognitive load' constraint for assembly work (Grier et al. 2008; Hart and Wickens 2008).

In all, the proposed MWL measure thus showed to be valid within this specific context to measure impending overload (and potentially mental fatigue and startle-like responses) with five behavioural codes. Future work could also explore effects of overload per se to cover the full spectrum of upper red zone MWL and will hereto need to address possible crucial moderating variables such as interpersonal differences in behavioural expressions, personality, intelligence and experience.

6.1. Limitations

The operationalisation of some codes depended on the participant's eye-gaze for the annotation of their onset and end, or to define them (e.g. redirecting eye gaze). It should nevertheless be possible to redesign eye gaze out of the coding scheme, as we tested this with a sample dataset. Also using regular stationary camera's instead of the frontal camera of eye-tracking glasses should be well feasible and could even provide richer datasets since more behaviours are captured.

We decided not to focus on (impending) underload, as the behaviour observed in our piloting iterations did not show an adequate amount of code occurrences such as sighing or gazing away, while such behaviours can also indicate (impending) overload. Future work could additionally explore this construct, underrepresented in the literature (Young et al. 2015). We also found that 'Freeze' showed low interrater-reliability for two participants. Next, the fact that raters were not blind to the conditions might have allowed for some subjectivity. Future work could address this better.

Finally, the proposed coding scheme only applies for our specific assembly context. We believe the designed codes can however be customised. Future work can hence explore the generalizability and external validity of these codes when applied in other contexts and with operators (instead of a with a student sample), finding out that, e.g. for some contexts some codes will not be indicative, will not occur, will have to be redefined or that new codes arise. In the early iterations of the current coding scheme we for instance also included sighing as previous work linked such utterances to high MWL (see Vlemincx, Van Diest, and Van Den Bergh 2012; Vlemincx et al. 2011). Here, we found that our respective code was

too unreliable to code manually. Other behaviours that might apply more in other contexts could be; changing the task execution sequence, re-consulting instructions, verbal expressions such as cursing, ironic laughter, thinking out loud, asking for help, or non-verbal utterances as shaking one's head or fidgeting, and more elementary motor execution such as hovering of the hands over parts or a lower velocity of motor execution in general (cf., Stork and Schubö 2010). The authors therefore look forward to iterations on our method in a diversified set of contexts with a diverse sample of operator profiles, in which the current codes will be customised and new behavioural codes could arise. This future work will eventually show to what extent the presented codes are generic already and easily customisable.

6.2. Implications for research and practice

Our results are well in line with earlier work assessing, for example, computer mouse activity and behavioural entropy. By designing a behavioural coding scheme for MWL detection in manual assembly, we hope to inspire research further developing the method into a measurement system applicable in (real-life industrial) contexts requiring unobtrusiveness, ease-of-use and a straightforward way to map MWL fluctuations directly onto redundant or even dangerous behaviour. A method with such ecological, external and face validity could hence be of added value to practitioners analysing and (re)designing assemblies, instructions, assistive technology and training methods (cf., Error Management Training; Keith and Frese 2008). This might also be relevant for situations in which the consequences of hesitant behaviour can be detrimental (cf., the petrochemical industry, surgery).

Concurrent and incremental validity of the proposed behavioural coding method of and beyond other in literature proposed MWL measures (i.e. physiological measures) is recommended as well. Research further scrutinising physiological measures could also benefit when triangulating by narrowing down to coded events, so that the sensitivity of measures (cf., Matthews et al. 2015) could raise significantly. Also, the aim should be to explore and extend the method's 'group-to-individual generalizability' (Fisher, Medaglia, and Jeronimus 2018). That is, to investigate to what extent the method can be used at the individual level (instead of at the group level as validated here) and how to promote this further. An experimental approach with many repeated measures within the same subjects but over time (instead of cross-sectional) will be needed for this (Fisher, Medaglia, and Jeronimus 2018).

The practice of coding requires intensive training, is very labour-intensive and is even prone to attentional blindness (i.e. by focussing on certain behaviours, not perceiving other behaviours). Future research could aim to simplify codes, to make codes generic (cf., freezing) or to develop behavioural recognition algorithms applied on video images to automatically detect, e.g. freezes or positioning attempts. Only then our method could reach the level of widespread industrial applicability. Finally, as Virtual Training Systems (implementing virtual environment, virtual reality or augmented reality) becomes increasingly valuable (cf., Al-Ahmari et al. 2016; Langley et al. 2016), a MWL-measure for such environments could be developed by deriving, e.g. freezes or positioning attempts from the gyroscope data of the controllers.

7. Conclusion

The presented work endeavoured to develop a non-obtrusive MWL-measure with high ecological and face validity, as current research on physiological measurement faces reliability challenges in applied settings. A behavioural video coding scheme was developed and revealed to be able to detect multiple assembly behaviours indicative of upper red zone MWL. That is, the occurrence and duration of the behavioural codes 'Parts collection' and 'Positioning', and the occurrence of 'Part rotation', 'Positioning attempt' and 'Freeze - Modifier 2' was significantly higher during the execution of a high complexity assembly, as compared to a low complexity assembly. The authors aspire to hereby initiate a novel line of measurement validation to decisively help practitioners and operators optimise MWL-levels on the shop floor.

Disclosure statement

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Notes

1. Note that participants had all the time they needed to complete each step, so that the length of data differed per participant.
2. Note that we had 25 participants in total, but for one participant the video was corrupted and therefore not usable, because of a technical malfunction.
3. Because we did not have the spatial intelligence data for one participant, we ran the analysis with 24 participants to assure complete comparability.

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Appendices

Appendix A. Overview of coding instructions

Category, Code (Unit)	Definition	Coding instructions
<i>I. Selecting Behaviour</i>		
1. Parts collection (state event)	Time needed to select all the perceived correct parts.	From first glance on parts, for at least 2 s, until onset positioning (starting at first glance for at least 2 s on the assembly-in-progress).
2. Part touched (point event)	Number of new parts that are touched.	Code until onset positioning. Nested in 'Parts collection'.
3. Part rotation (point event)	Number of times the operator is manipulating a part (here rotating, from velocity is 0 to velocity is 0).	Also rotating part back to original position counts as rotation. Code until onset positioning. Nested in 'Parts collection'.
<i>II. Positioning Behaviour</i>		
4. Positioning (state event)	Time to select perceived right position. Includes rotation and alignment.	From eye gaze switch from selected part (defined as part that will be positioned) to assembly-in-progress fixating on assembly-in-progress for at least 2s, until onset first screw being inserted or eye-gaze at not-yet selected parts in case a new 'Parts collection' occurs.
5. Positioning attempt (point event)	Number of positions tried (defined by velocity = 0, part touches assembly-in-progress or is being held above, below or aside from it) on assembly-in-progress.	Positions already tried count as a new attempt if part has been moved from position. Parts selected in previous steps count as well. Code until the perceived right position (defined by the final position that precedes completely screwing a part) is achieved of the part on the assembly-in-progress. Nested in 'Positioning'.
6. Verification of fixed position (state event)	Time needed for the operator to verify if a position (i.e. orientation, alignment, position) is correct after a component has been fastened, for at least 2 s.	From finishing screwing (one of the screws of a part) until the next assembly behaviour, such as inserting the next screw, or until eye-gaze for at least 2 s on next part to be collected or positioned, until onset next step (here from onset turning around towards laptop with instructions), until checking steadiness of fastening, etc. Not nested in 'Positioning'.
7. Correction of perceived wrong position (state event)	Time the operator needs to correct a (set of) perceived wrong fastening(s) and perform a perceived correction, for at least 2 s.	From onset completely unfastening the perceived wrong fixation(s) until onset of screwing the last component of a perceived correction, for at least 2s. Not nested in 'Positioning'.
<i>III. Transition Behaviour</i>		
8. Inspection of assembly-in-progress (state event)	Time the operator needs to familiarise with or verify the assembly-in-progress including touching and rotating assembly-in-progress, for at least 2 s, in between visual intake of instructions and onset 'Parts collection' or 'Correction of perceived wrong position'.	Can only occur after a first step has been performed, since from then on an assembly-in-progress is present. Code from start gaze position on assembly-in-progress for at least 2 s, until start 'Parts collection'.
<i>IV. Generic Behaviour</i>		
9. Freeze (state event)	Number of times both operator's hands and arms stop moving or only move very minimally (the latter not as a function of selection or positioning), at a fixed place in the work space for at least 2 s.	From start movement stops (minimally) until onset movement.
Modifier 1	Head freezes, eyes move	
Modifier 2	No freeze of eyes and head	
Modifier 3	Both eyes and head freeze too	
10. Gaze redirection (point event)	Number of times operator gazes away from work table for at least 2s.	Code until switching back to eye-gaze on work table for at least 2 s.
11. Relative head position change (point event)	Number of times operator's head is repositioned closer to or further away from parts or assembly-in-progress, because of the operator moving the upper body or oppositely, the parts or assembly-in-progress.	Moving back from coded position does not count as new code (e.g. moving closer to the parts or assembly-in-progress while moving back to original position 10s later on, counts as one point event).

Appendix B. Overview of attention points

Category, Code (Unit)	Attention points
<i>I. Selecting Behaviour</i>	
1. Parts collection (state event)	1. Can also alternate with 'Positioning', in case of 'Positioning' already started but participant gazes back at parts not yet touched (i.e., parts still on display at outer side of work table). In this case code from first glance on parts until first next glance on assembly-in-progress for at least 2s. 'Parts collection' can hence also only include visual scanning.
2. Part touched (point event)	1. The assembly-in-progress does not count as a part, except during the first step in which there is no assembly-in-progress yet. 2. Parts already touched hence do not count. 3. Can also occur during 'Positioning' or 'Fastening'.
3. Part rotation (point event)	1. Exceptions: rotating assembly-in-progress (this is included in Positioning).
<i>II. Positioning Behaviour</i>	
4. Positioning (state event)	1. Can alternate with 'Parts collection' (reminder: if eye-gaze fixates on assembly-in-progress or at not-yet selected parts for at least 2 s). 2. In case operator positions two parts at once: code stops at inserting first screw of first part and next 'Positioning' code starts from switch of gaze on second part to at least 2 s on assembly-in-progress and stops at inserting first screw of the second part. 3. For the first step of the assembly, the assembly-in-progress is defined as the part on which the other two parts are being positioned on. 4. Can also occur with parts selected in previous steps.
5. Positioning attempt (point event)	/
6. Verification of fixed position (state event)	1. Includes twisting the component just screwed for alignment and orientation. 2. Checking screws and components for tightness does not count, even if component is being twisted in function of this check-up. 3. Includes visually checking the component in relation to the other components (already fastened). 4. Visually checking other components on the assembly-in-progress for at least 2s without gazing back at original component counts as 'Positioning' instead. 5. Manipulating other components after the respective component has been screwed does not count, but instead counts as a new 'Positioning' code.
7. Correction of perceived wrong position (state event)	1. Can also occur at the onset of a step, with parts assembled in previous steps. 2. Can alternate with 'Parts collection' and 'Positioning' (of newly selected parts). In case component is put aside to complete later on, code should be stopped at point of putting aside and starts again when picking up this component.
<i>III. Transition Behaviour</i>	
8. Inspection of assembly-in-progress (state event)	/
<i>IV. Generic Behaviour</i>	
9. Freeze (state event)	/
Modifier 1	/
Modifier 2	/
Modifier 3	/
10. Gaze redirection (point event)	/
11. Relative head position change (point event)	/

Appendix C. Overview of results per behavioural code

1. Parts collection – occurrence					
	I	II	III	IV	V
Spatial intelligence		−0.018			−0.018
Dexterity		0.12			0.12
Condition			−0.786***	−1.347***	−1.347***
Step 2			−0.206	−0.786**	−0.786**
Step 3			−0.187	−0.449	−0.449
Condition × Step 2				1.160**	1.160**
Condition × Step 3				0.524	0.524
Constant	0	0	0.524**	0.804***	0.804***
Observations	144	144	144	144	144
R ²	0.02	0.02	0.24	0.31	0.31

The values in the table are standardized weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

1. Parts collection – duration					
	I	II	III	IV	V
Spatial intelligence		0.014			0.014
Dexterity		0.101			0.101
Condition			−0.908***	−1.465***	−1.465***
Step 2			−0.863***	−1.235***	−1.235***
Step 3			−1.099***	−1.562***	−1.562***
Condition × Step 2				0.745*	0.745*
Condition × Step 3				0.926**	0.926**
Constant	0	0	1.108***	1.386***	1.386***
Observations	144	144	144	144	144
R ²	0.00	0.01	0.43	0.47	0.48

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

2. Part touched – occurrence

	I	II	III	IV	V
Spatial intelligence		0.123			0.123
Dexterity		0.160*			0.160*
Condition			–0.308*	–0.482	–0.482
Step 2			–0.793***	–0.944***	–0.944***
Step 3			–1.014***	–1.124***	–1.124***
Condition × Step 2				0.301	0.301
Condition × Step 3				0.221	0.221
Constant	0	0	0.756***	0.843***	0.843***
Observations	144	144	144	144	144
R ²	0.00	0.03	0.24	0.25	0.25

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

3. Part rotation – occurrence

	I	II	III	IV	V
Spatial intelligence		0.02			0.02
Dexterity		0.033			0.033
Condition			–0.498***	–0.614*	–0.614*
Step 2			–0.988***	–1.054***	–1.054***
Step 3			–1.094***	–1.201***	–1.201***
Condition × Step 2				0.133	0.133
Condition × Step 3				0.214	0.214
Constant	0	0	0.943***	1.001***	1.001***
Observations	144	144	144	144	144
R ²	0.00	0.00	0.31	0.31	0.31

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

4. Positioning – occurrence

	I	II	III	IV	V
Spatial intelligence		0.056			0.056
Dexterity		0.018			0.018
Condition			–0.911***	–1.236***	–1.236***
Step 2			0.325	–0.13	–0.13
Step 3			0.228	0.195	0.195
Condition × Step 2				0.911*	0.911*
Condition × Step 3				0.065	0.065
Constant	0	0	0.271	0.434*	0.434*
Observations	144	144	144	144	144
R ²	0.00	0.00	0.23	0.27	0.27

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

4. Positioning – duration

	I	II	III	IV	V
Spatial intelligence		–0.025			–0.025
Dexterity		0.038			0.038
Condition			–1.348***	–1.114***	–1.114***
Step2			–0.009	–0.094	–0.094
Step3			0.286*	0.721***	0.721***
Condition × Step 2				0.17	0.17
Condition × Step 3				–0.872**	–0.872**
Constant	0	0	0.582***	0.465**	0.465**
Observations	144	144	144	144	144
R ²	0.00	0.00	0.48	0.55	0.54

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

5. Positioning attempt – occurrence

	I	II	III	IV	V
Spatial intelligence		0.006			0.006
Dexterity		0.009			0.009
Condition			–1.068***	–1.222***	–1.222***
Step 2			–0.267	–0.524*	–0.524*
Step 3			–0.121	–0.096	–0.096
Condition × Step 2				0.512	0.512
Condition × Step 3				–0.051	–0.051
Constant	0	0	0.663***	0.740***	0.740***
Observations	144	144	144	144	144
R ²	0.00	0.00	0.30	0.32	0.32

The values in the table are standardized weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

6. Verification of position – occurrence

	I	II	III	IV	V
Spatial Intelligence		–0.003			–0.003
Dexterity		0.003			0.003
Condition			–0.149	–0.448*	–0.448*
Step 2			0.168	–0.056	–0.056
Step 3			–0.560**	–0.784**	–0.784**
Condition × Step 2				0.448	0.448
Condition × Step 3				0.448	0.448
Constant	0	0	0.205	0.355	0.355
Observations	144	144	144	144	144
R ²	0.09	0.09	0.22	0.24	0.24

The values in the table are standardized weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

6. Verification of position – duration

	I	II	III	IV	V
Spatial Intelligence		–0.045			–0.045
Dexterity		0.092			0.092
Condition			–0.481**	–0.323	–0.323
Step 2			0.101	0.409	0.409
Step 3			–0.467*	–0.538*	–0.538*
Condition × Step 2				–0.616	–0.616
Condition × Step 3				0.141	0.141
Constant	0	0	0.363*	0.284	0.284
Observations	144	144	144	144	144
R ²	0.12	0.11	0.27	0.30	0.30

The values in the table are standardized weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

7. Correction of wrong position – occurrence

	I	II	III	IV	V
Spatial intelligence		0.057			0.057
Dexterity		0.053			0.053
Condition			−0.678***	−0.062	−0.062
Step 2			0.586**	1.233***	1.233***
Step 3			0.216	0.493	0.493
Condition × Step 2				−1.295***	−1.295***
Condition × Step 3				−0.555	−0.555
Constant	0	0	0.072	−0.236	−0.236
Observations	144	144	144	144	144
R ²	0.00	0.00	0.18	0.28	0.27

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

7. Correction of wrong position – duration

	I	II	III	IV	V
Spatial intelligence		0.054			0.054
Dexterity		0.190*			0.190*
Condition			−0.470**	0.026	0.026
Step 2			0.359	0.763**	0.763**
Step 3			0.398*	0.738**	0.738**
Condition × Step 2				−0.808*	−0.808*
Condition × Step 3				−0.680*	−0.680*
Constant	0	0	−0.017	−0.265	−0.265
Observations	144	144	144	144	144
R ²	0.10	0.08	0.21	0.25	0.24

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

8. Inspection of assembly-in-progress – occurrence

	I	II	III	IV	V
Spatial intelligence		−0.009			−0.009
Dexterity		0.113*			0.113*
Condition			−0.188*	0.042	0.042
Step 3			0.104	0.333**	0.333**
Condition × Step 3				−0.458**	−0.458**
Constant	0.281**	−0.068	0.323***	0.208*	−0.141
Observations	96	96	96	96	96
R ²	0.00	0.08	0.07	0.17	0.20

The values in the table are standardized weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 2 were used as reference categories.

8. Inspection of assembly-in-progress – duration

	I	II	III	IV	V
Spatial intelligence		−0.077			−0.077
Dexterity		0.878			0.878
Condition			−1.851*	−0.704	−0.704
Step 3			0.706	1.853	1.853
Condition × Step 3				−2.295	−2.295
Constant	1.917***	−0.665	2.489***	1.916*	−0.666
Observations	96	96	96	96	96
R ²	0.00	0.06	0.06	0.08	0.14

The values in the table are standardized weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 2 were used as reference categories.

9. Freeze (Modifier 1) – occurrence

	I	II	III	IV	V
Spatial intelligence		−0.099			−0.099
Dexterity		0.011			0.011
Condition			−0.802***	−0.463	−0.463
Step 2			0.116	0.324	0.324
Step 3			0.069	0.37	0.37
Condition × Step 2				−0.417	−0.417
Condition × Step 3				−0.602	−0.602
Constant	0	0	0.339*	0.17	0.17
Observations	144	144	144	144	144
R ²	0.00	0.01	0.16	0.18	0.19

The values in the table are standardized weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

9. Freeze (Modifier 1) – duration

	I	II	III	IV	V
Spatial intelligence		−0.034			−0.034
Dexterity		0.071			0.071
Condition			−0.764***	−0.278	−0.278
Step 2			0.205	0.491	0.491*
Step 3			0.243	0.688*	0.688*
Condition × Step 2				−0.571	−0.571
Condition × Step 3				−0.889*	−0.889*
Constant	0	0	0.233	−0.01	−0.01
Observations	144	144	144	144	144
R ²	0.00	0.01	0.16	0.19	0.20

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

9. Freeze (Modifier 2) – occurrence

	I	II	III	IV	V
Spatial intelligence		0.033			0.033
Dexterity		−0.004			−0.004
Condition			−0.673***	−0.561*	−0.561*
Step 2			0.056	0.112	0.112
Step 3			0.112	0.224	0.224
Condition × Step 2				−0.112	−0.112
Condition × Step 3				−0.224	−0.224
Constant	0	0	0.280	0.224	0.224
Observations	144	144	144	144	144
R ²	0.01	0.01	0.17	0.17	0.17

The values in the table are standardized weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

9. Freeze (Modifier 2) – duration

	I	II	III	IV	V
Spatial intelligence		–0.053			–0.053
Dexterity		–0.012			–0.012
Condition			–0.574***	–0.451	–0.451
Step 2			0.037	0.074	0.074
Step 3			0.147	0.294	0.294
Condition × Step 2				–0.074	–0.074
Condition × Step 3				–0.294	–0.294
Constant	0	0	0.226	0.164	0.164
Observations	144	144	144	144	144
R ²	0.00	0.00	0.10	0.11	0.10

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

10. Gaze redirection – occurrence

	I	II	III	IV	V
Spatial intelligence		–0.024			–0.024
Dexterity		0.184*			0.184*
Condition			–0.107	–0.322	–0.322
Step 2			0.081	–0.161	–0.161
Step 3			0.081	0	0
Condition × Step 2				0.484	0.484
Condition × Step 3				0.161	0.161
Constant	0	0	0	0.107	0.107
Observations	144	144	144	144	144
R ²	0.07	0.04	0.07	0.09	0.06

The values in the table are standardized weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.

11. Relative head position change – occurrence

	I	II	III	IV	V
Spatial intelligence		–0.026			–0.026
Dexterity		0.018			0.018
Condition			–0.316	–0.526	–0.526
Step 2			–0.053	–0.105	–0.105
Step 3			–0.263	–0.526	–0.526
Condition × Step 2				0.105	0.105
Condition × Step 3				0.526	0.526
Constant	0	0	0.263	0.368	0.368
Observations	144	144	144	144	144
R ²	0.00	0.00	0.04	0.05	0.05

The values in the table are standardised weights (Beta's).

* $p < .05$; ** $p < .01$; *** $p < .001$.

$N = 24$.

Low spatial intelligence, low dexterity, high complexity and Step 1 were used as reference categories.