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Socially Interactive Agents as Cobot Avatars: Developing a Model to Support Flow Experiences and Well-Being in the Workplace

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ABSTRACT

This study evaluates a socially interactive agent to create an embodied cobot. It tests a real-time continuous emotional modeling method and an aligned transparent behavioral model, BASSF (boredom, anxiety, self-efficacy, self-compassion, flow). The BASSF model anticipates and counteracts counterproductive emotional experiences of operators working under stress with cobots on tedious tasks. The flow experience is represented in the three-dimensional pleasure, arousal, and dominance (PAD) space. The embodied covatar (cobot and avatar) is introduced to support flow experiences through emotion regulation guidance. The study tests the model's main theoretical assumptions about flow, dominance, self-efficacy, and boredom. Twenty participants worked on a task for an hour, assembling pieces in collaboration with the covatar. After the task, participants completed questionnaires on flow, their affective experience, and self-efficacy, and they were interviewed to understand their emotions and regulation during the task. The results suggest that the dominance dimension plays a vital role in task-related settings as it predicts the participants' self-efficacy and flow. However, the relationship between flow, pleasure, and arousal requires further investigation. Qualitative interview analysis revealed that participants regulated negative emotions, like boredom, also without support, but some strategies could negatively impact well-being and productivity, which aligns with theory.

KEYWORDS

Human-Robot Interaction, Socially Interactive Agents, Affect Modeling, Emotion Regulation, Flow, Boredom, PAD Model

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1 INTRODUCTION

Socially Interactive Agents (SIAs) combined with the exponentially growing market of collaborative robots (Cobots) [21] may be effective in supporting workers' emotion regulation during their stressful and tedious activity in the production line. They can thus be applied to move away from technology-driven approaches towards a value-driven era that, besides efficiency, focuses on the workers' well-being and involvement [43], the so called the "fifth industrial revolution" [46]. SIAs in the role of social and embodied collaborative companions represented in the physical space of the production line may help to address negative experiences, especially those related to robotic manipulators and the consequent increase in production rates. However, such an SIA presupposes an Avatar-Cobot behavioral model that anticipates and combats negative emotional experiences.

Current research focuses on exploring these concepts, to define design principles of mental-health-friendly work cells for operators working together with Cobots [35]. Principles of supporting social interaction through SIAs combined with robots/cobots must be defined based on theory and be transparent to be tested systematically. End-to-end systems do not allow isolating and empirically testing individual aspects of the interaction. Existing literature does not offer any analysis focusing on these aspects for non-humanoid industrial robots, making this study a first-time attempt.

An approach to this explored the effect of the integration of the physical capabilities of a robot with the SIA's verbal and nonverbal skills on user perception of the system as a social entity [36]. The objective of the present study is to develop and evaluate a transparent theory-based real-time emotional modeling method based on boredom, anxiety, self-efficacy, self-compassion, and flow. In short, BASSF reacts socially and promotes self-efficacy and flow for well-being in the production line [37]. Here, we zoom in and empirically test the relation of dominance to self-efficacy and flow.

1.1 Robots, Cobots and SIAs as Embodied Companions at the Workplace

Virtual agents that support emotion regulation are limited. D'Mello et al. [11] presented AutoTutor and Affective AutoTutor, two intelligent tutoring systems trace emotional states to increase engagement and flow for learning. Pagalyte et al. [38], introduce the idea of incorporating Dynamic Difficulty Adjustment (DDA) through the use of Reinforcement Learning (RL) in turn-based battle video games to induce game flow. Samrose et al. [42], investigated whether an empathetic conversational agent can mitigate boredom. These test different interaction settings and deal with virtual agent behavior. Additional difficulties arise when combining avatars with cobots who co-habit and work in the physical space of the production line [24].

Analysis of human-human interaction highlights the importance of verbal and non-verbal communication. In every socially interactive scenario, motor correlates such as lip-syncing, head nods, deictic gestures, and gaze movements are abundant and play a great role in expressing emotions, intentions and establishing common ground in communication [27]. However, such capabilities are missing in current industrial cobot installations, increasing the risk for social isolation of their operators. There is scarce knowledge regarding how industrial robots can be adapted to improve the emotional experience and reduce health risks. There is evidence that people project themselves onto non-humanoid robotic devices [2], and preliminary studies [36] are trying to understand how humans perceive them and what roles they ascribe to them. Virtual SIA could act as mediators between cobots and their operators, promoting a lifelike social experience. SIA can move in human-like ways with sets of actions impossible for today's industrial robots, while physical embodiment and presence may increase the salience of lifelike perceptions and the importance compared to two-dimensional entities [20]. The combination of both is promising.

2 RELATED WORK

2.1 Flow, Emotion Regulation and Guidance

Flow describes a pleasurable and effective state in which a person is highly engaged in an activity [8]. Six flow components are described: Merging of action and awareness, centering of attention, loss of self-consciousness, feeling of control, coherent non-contradictory demands, and autoletic nature.

There are additional preconditions of flow. Maybe the most important one is the skill-to-challenge ratio which is strongly connected to the feeling of control. A balanced ratio [9, 25] shall facilitate flow, whereas a mismatch can lead to boredom/apathy or stress, anxiety, and shame. To react to the individual emotional experiences of boredom and anxiety in a way perceived as relevant to the workers, we also need to dissect boredom, which is a complex construct. The experience of boredom may have different origins and functions.

Here, we further differentiate between boredom that may be experienced due to under-challenge, common conception, and over-challenge, which can be experienced in our setting due to time pressure and competitiveness among workers or due to failure at the organizational level. Over-challenge can occur due to task-focused boredom, commonly when the task is tedious and meaningless, like in the production line, or due to Self-focused boredom, when individuals focus on feelings of dissatisfaction and frustration with themselves [16]. Self-focused boredom is seen as a defense mechanism against prolonged high-stress levels. Individuals tend to subconsciously reduce negatively experienced and self-threatening emotions by entering a state of boredom [34]. This aligns with the relationship between over-challenge boredom and anxiety and identity [9, 16]. Negative and self-referential emotions increase self-directed attention, potentially resulting in boredom. Additionally, lack of self-knowledge may predict boredom as individuals may attempt to avoid perceived negative emotions[4]. Finally, over-challenge boredom correlates with lower self-efficacy concerning self-regulation and lower achievement, but under-challenge does not [45].

Regulating negative emotions removes obstacles from experiencing flow. It may also elevate a perceived imbalance of the skill-to-challenge ratio. Cognitive reappraisal could help reappraise the demands of the situation and, therefore, simultaneously influence the emotion and the perceived skill-to-challenge ratio [29]. Guidance to emotion regulation can be beneficial but depends on the context, the individual's emotional experience, and individual differences. Implicit guidance is often viewed as less obstructive [19]. In contrast, explicit guidance typically interrupts the process, i.e., by giving prompts for action [23]. Although guidance may exhibit aspects of both, this distinction helps make decisions for particular applications, like the production line, where task attention is very important.

2.2 Emotion Modeling

The PAD model posits that all emotional states can be located and differentiated using three dimensions (pleasure - displeasure, degree of arousal, and dominance - submissiveness) [30, 32, 41]. Values on each axis range from -1 to 1. Mehrabian [31] dichotomizes the dimensions into positive and negative values, e.g., +P and -P for pleasant and unpleasant states (Table 1, resulting in 8 octants of the PAD Space, also called ESM (Eight States Model) [6] or Octant Space.

The PAD Model is used extensively across disciplines [3], but there is controversy arises about the dominance dimension. Some researchers have suggested that dominance is an unclear construct [3, 5], and not necessary emotions [44].

Concerning flow, Gilroy et al. [18] offered a representation of flow in the PAD space. Pleasure is considered an indicator of flow. Arousal is associated with a task or interface's level of stimulation. Dominance generally relates to feelings of control and influence, so it relates to the skill-to-challenge ratio. Not having enough skill for the task would create a submissive (-D) state, although challenging tasks may also be stimulating. Thus, flow is associated with a pleasurable, aroused, dominant state, the +P, +A, +D octant.

3 THE BASSF MODEL

The BASSF Model operates as a control loop for monitoring and influencing worker affective state towards achieving the flow state. It employs social signal interpretation on live video footage captured by multiple cameras to track the worker's affective state, which is classified within the Octant Space (see Table 1). Through a decision algorithm, appropriate interventions are selected to assist the participant in reaching the desired flow state. For a detailed description see [37].

In BASSF, the affective experience of the worker is monitored continuously by assigning a subspace in an adapted PAD-Flow space, based on the PAD Model [6, 32], and [18]. This consists of a three-dimensional space, with the axes pleasure, arousal, and dominance. To make the BASSF model decisions more transparent, adaptable to user needs, and testable, we look into differential causes of boredom and connect those to stress and anxiety, common emotional experiences at the workplace and related to flow [25]. In our experiment, we induced prolonged stress, which can be regulated through boredom [16, 34]. We operationalised prolonged stress, caused by overwhelming time pressure, as anxiety in the PAD space (-P, +A, -D). We can then test if anxiety, a low-dominance experience itself, eventually leads to low-dominance regulated boredom. Since also [18] defines -P, -A, -D as boredom, we define the whole low pleasure low arousal space as regulated, overwhelming boredom (O-Boredom). We differentiate that from underwhelming boredom (U-Boredom) [17] that is connected with -P, -A, and +D. Table 1 shows a summary of emotion representations in PAD.

Octant Names			
Value	Mehrabian (1996)	Gilroy et al. (2009)	This work
+P +A +D	Exuberant	Flow	Flow
+P +A -D	Dependent	Impressed	Awe
+P -A +D	Relaxed	Relaxed	Relaxed
+P -A -D	Docile	Hopeful	Hopeful
-P +A +D	Hostile	Hostile	Hostile
-P +A -D	Anxious	Anxious	Anxious
-P -A +D	Disdainful	Disdainful / Dismissive	U-Boredom
-P -A -D	Boredom	Apathy	O-Boredom

Table 1: Overview of the different names used for the octants.

BASSF then defines covatar reactions for emotional experiences represented in PAD that are not conducive to Flow (Table 2). Reactions constitute guidance to emotion regulation, and are used for all boredom and anxiety experiences. Each Flow-PAD octant has its own set of interventions. If a worker regulates their emotions in a productive manner, there is no need for intervention. We opted for implicit guidance to avoid destruction at the workplace, where task-focus is required.

4 METHODS

4.1 Research Questions and Hypotheses

The goal of the study was to systematically evaluate the theoretical transparent assumptions on of the BASSF Model. We empirically tested the possibility of representing flow in the PAD space, to be able to provide continuous input to the BASSF model and enable socially interactive behavior for the covatar. To achieve this, we needed to define the relationship between flow and PAD. Hypotheses H1 to H3 test this relationship: **H1:** Self-reported self-efficacy will predict flow. **H2:** Dominance will predict self-efficacy. **H3:** There will be a significant linear relationship between pleasure, arousal and dominance as predictors and flow as outcome.

H1 examines the theoretical connection between self-efficacy [26] and flow, considering self-efficacy's association with the subjective challenge-to-skill ratio. **H2** explores the relationship between

Affect/ Intervention	Avatar verbal beh.	Avatar/Cobot nonverbal beh.	Theoretical justification
Self-Efficacy against Anxiety	"Look at that! We have already done so many pieces!"	A: Surprised Expression	Focus attention on the shared achievement to increase Skill-to-Challenge Ratio and ease the pressure by reminding them that they are a team [22].
Self-Awareness against U-octant	"Are you okay over there? Let me know if you need anything!"	A: Head tilted to the right, Bending hips/ C: Increase acceleration & velocity	Increase Self-Consciousness and Task-Awareness to reduce boredom via socio-cognitive conflict & increased challenge, while remaining caring [4, 7].
Self-Compassion against O-Boredom	´´You are doing great! Everybody would be stressed at this speed"	Moderate zoom in: Short compassionate smile	Increases Self-Compassion to facilitate self-regulation and cognitive reappraisal [22].

Table 2: Example Interventions. A = Avatar, C = Cobot. Original interventions were in Italian, these are translations.

self-efficacy and dominance, validating the potential representation of self-sfficacy through Dominance in PAD [18]. Finally, **H3** tests the relation of all three PAD variables to flow and its representation in the three-dimensional PAD space. The connection between flow and PAD is investigated by checking the assumption that flow can be represented in the ESM, namely the +P,+A,+D quadrant, as predicted by [18].

Further, to gain insight into emotional experiences related to flow with respect to working in the production line, we used a semi-structured interview and exploratory look into the research question: Which emotions do participants feel during the task, and how do they regulate them?

The study employed a mixed-methods design. Participants performed an assembly task together with an interactive Covatar (cobot plus avatar) during two phases, a slow and a fast (boring and stressful) (Section 4.4.1). After the working phase, participants re-watched video clips from their working phase, and completed six self-reported questionnaires on their affective experience, flow, and self-efficacy during the task (Section 4.3). A semi-structured interview on their emotion regulation strategies was performed [36] in between the questionnaires.

4.2 Participants and Procedure

The experimental setup was first piloted with two subjects to fine-tune the duration of each phase and to verify the correct working of the whole system. The final data collection involved a total of 20 participants. All participants were healthy adult volunteers (12M-8F, 25-48 years old). The interview was conducted with the first four participants.

After an introduction and training of the subject to the task, each experimental session lasted 50 minutes, of which 30 minutes in phase 1 (slow phase) and then 20 more minutes with the setup in phase 2 (fast phase). In order to avoid any bias that may arise and to promote an even stronger reaction in the participants, the switch between the two phases was performed through a "fake failure" of the system. In practice, after 30 minutes, the robot would stop assembling, and the operator would "fix" the situation by changing the setup and asking the participant to try and keep up with the new rhythm of the robot.

After the working phase, the participants were led into a separate room. The experimenter and the participant watched six scenes of the working session together. For each scene, a questionnaire was answered (by all participants), and a semi-structured interview was conducted (only on the first four participants). This lasted about 45 minutes when questionnaire and interview were conducted and 20 minutes when only the questionnaire was administered.

For this study, a simplified version of the BASSF Model was used to isolate and test its assumptions. The interventions by the Covatar were timed a priori. First, interventions against O-Boredom were displayed, then Anxiety, and lastly U-Boredom. The first intervention in the slow task started 15 minutes after the start of the experiment. The first intervention against Anxiety was started 5 minutes into the slow task, and the interventions against O-Boredom were started 12 minutes later.

4.3 Instruments and Interview

The semantic differential [32] was used to measure pleasure, arousal, and dominance. For each dimension, there are six adjective pairs with nine spaces in between. Subjects indicate their emotional state by the position of their mark on the line. The flow short scale [14, 40] measured Flow on ten sub-components. State self-efficacy was measured with a single item [26].

A semi-structured interview was conducted with the first four participants. They watched the footage of six recorded videos depicting three pre-selected interventions. They were asked to describe their feelings and thoughts about the task and avatar and the effects of the intervention. A deductive category assignment was used the analyze the material [28].

4.3.1 Interview Coding Rules. Two category systems were used: Affective experience and emotion regulation. For affective experience, the categories were related to the ESM to see whether the quantitative and qualitative descriptions would align. All ESM octants were used, and two additional ones: Shame and NI ("not inferable").

For the emotion regulation system, the most common emotion regulation strategies were used: cognitive reappraisal, distraction, acceptance, rumination, and disengagement [12, 29]. Additionally, three strategies from the compass of shame were selected: attack other, attack self, and avoidance. Withdrawal was not chosen because the experimental setup did not leave room to withdraw from the situation without aborting the experiment [12, 34]. We differentiate avoidance, disengagement, and distraction the following way: We understand distraction as an act where the participant is aware of the negative stimuli and willingly or unwillingly refocuses their attention to a more pleasant stimulus [29]. Avoidance and behavioral disengagement both manipulate the relevance of the stimuli but differ in the acknowledgment of the averse feelings. We define behavioral disengagement as the willful and conscious withdrawal of efforts due to the difficulty of a task. In avoidance, the negative experience is not acknowledged, but the relevance of the stimuli is nonetheless reduced, i.e., by reducing interest [12, 34].

4.4 Experimental setup

An industrial collaborative work cell was reproduced in a lab environment. As shown in Figure 1, two tables are positioned in an L-shape formation to realize two distinct workspaces: one for the operator and one for the cobot. The industrial task under analysis is a collaborative assembly of the product [39], where some of the components are put together by the robot, some by the operator, and the final joining is performed collaboratively. Looking at Figure 1, a Fanuc CRX10iA/L collaborative robot is placed in front of the operator together with a tablet for the visualization of the virtual agent. The co-location and interplay of these two entities have been the focus of the study in [36] to promote a perception of embodiment. A detailed description of the Covatar can be found here[36].

4.4.1 Assembly task. To elicit different reactions in the volunteers, two phases of the experimental session were prepared. The first phase (boring phase) exploited the full assembly capabilities of the cobot, with the manipulator looking for the necessary parts using a detection camera, picking them up, and assembling them together before bringing the completed subassembly to the operator. This process takes around 50-60 seconds, during which the operators have plenty of time to finish their tasks and, therefore, may experience boredom and frustration after some time. A second phase (fast phase) was, instead, designed to elicit a feeling of stress in the operator. In fact, as shown in the right side of Figure 1, the spare components on the cobot's table are substituted by an array of preassembled subassemblies. The cobot must only reach a predefined position to get the subassembly and bring it toward the user. This process only takes around 10-15 seconds, which is not enough for the operators to complete their part of the task, and they will often see the robot waiting for them. Participants were instructed to complete as many assemblies as possible during the experimental session but without starting to work on a new product before finishing the previous one.

5 RESULTS

Descriptive Statistics for all measured variables can be found in Table 3. For hypotheses 1 and 2, the connection between dominance, self-efficacy, and flow was analyzed using Mixed Effect Models with Random Intercept, due to the nested structure of the data. The participant was used as a grouping variable to account for the correlations between repeated measurements [10]. The tests were done with and without centering around the group mean [13]. Centering did not affect the results on the relationship between dominance and self-efficacy. However, in the relationship between, self-efficacy and flow, centering had a significant impact on the results; self-efficacy was a significant predictor of flow, while centered self-efficacy was no significant predictor of flow (see Table 4).

For hypothesis 3, several mixed effect models were used to examine the relationship between PAD and flow (for a visualization see Figure 2). Multiple regression was not usable due to the nested structure of the data. Centering did not affect the significance of the results. The mixed effect models showed no significance for any one of the predictors when used together (see Table 5). However, strong correlations between the predictors were found (Pleasure

Figure 1: Left: Phase 1 setup - The robot and the operator have completed their subassembly and the collaborative joining is ongoing. Right: Phase 2 setup - The robot has brought the subassembly towards the operator, who is still working on his parts.

Summary Statistics					
Construct	Mean	Median	SD	Min	Max
Pleasure	0.078	0.063	0.304	-0.833 (-1)	0.833 (1)
Arousal	-0.099	-0.125	0.292	-0.75 (-1)	0.583 (1)
Dominance	0.134	0.167	0.31	-0.792 (-1)	0.833 (1)
Flow	4.995	5	0.687	2.9 (1)	6.5 (7)
Self-Efficacy	4.042	4	0.614	2 (1)	5 (5)

Table 3: Summary statistics of all constructs measured with the questionnaire. Round brackets in the “Min” and “Max” Columns denote theoretically possible min and max values.

Results of Hypothesis 1 & 2				
Formula		SE ~ D (Cent.) + (1 | ID)	Flow ~ SE (Cent.) + (1|ID)	Flow ~ SE + (1|ID)
REML criterion		135	175.7	171.5
N observations:		120	120	120
N groups		20	20	20
Fixed effects:				
Intercept	Estimate	4.042	4.995	3.976
	SE	0.118	0.133	0.421
	t-stat.	t(19) = 34.14	t(19) = 37.678	t(106) = 9.437
	p	p < 0.001 ***	p < 0.001 ***	p < 0.001 ***
Coeff.	Estimate	0.686	0.099	0.252
	SE	0.181	0.112	0.101
	t-stat.	t(99) = 3.8	t(99) = 0.881	t(115) = 2.512
	p	p < 0.001 ***	p = 0.381	p = 0.013 *
Method of t-test		Satterthwaite's method	Satterthwaite's method	Satterthwaite's method
AIC		143.039	183.719	179.511
BIC		154.189	194.869	190.661

Table 4: Note: SE = Self-Efficacy, D = Dominance, ID = Participant; Sig: p < 0.001 ‘*’; p < 0.01 ‘**’; p < 0.05 ‘*’; p < 0.1 ‘.’**

Results of Hypothesis 3					
Formula		Flow ~ P + A + D + (1 | ID)	Flow ~ P + (1 | ID)	Flow ~ A + (1 | ID)	Flow ~ D + (1 | ID)
REML criterion		171.1	171.6	175.4	170.5
N observations:		120	120	120	120
N groups		20	20	20	20
Fixed effects:					
Intercept	Est.	4.995	4.995	4.995	4.995
	SE	0.133	0.133	0.133	0.133
	t-stat.	t(19) = 37.678	t(19) = 37.678	t(19) = 37.678	t(19) = 37.678
	p	p <0.001 ***	p <0.001 ***	p <0.001 ***	p <0.001 ***
Coeff.	Est.	P: 0.274 A: 0.003 D: 0.367	0.400	-0.002	0.461
	SE	P: 0.274 A: 0.254 D: 0.269	0.209	0.199	0.211
	t-stat.	P: t(97) = 1.001 A: t(97) = 0.016 D: t(97) = 1.364	t(99) = 1.913	t(99) = -0.011	t(99) = 2.182
		P: p = 0.319 A: p = 0.988 D: p = 0.176	p = 0.059 .	p = 0.992	p = 0.032 *
Random effects:					
Intercept	Est.	0.326	0.325	0.324	0.326
	SD	0.571	0.570	0.570	0.571
Res. Var.	Est.	0.156	0.157	0.163	0.155
	SD	0.395	0.396	0.403	0.394
Method of t-test		Satterthwaite's method	Satterthwaite's method	Satterthwaite's method	Satterthwaite's method
AIC		183.055	179.622	183.352	178.535
BIC		199.780	190.772	194.503	189.685
VIF		P: 1.73 A: 1.70 D: 1.61			

Table 5: Note: P = Pleasure, A = Arousal, D = Dominance, ID = Participant; Sig: p < 0.001 ‘*’; p < 0.01 ‘**’; p < 0.05 ‘*’; p < 0.1 ‘.’**

& Arousal: r = -0.59; Pleasure & Dominance: r = -0.55, Arousal & Dominance: r = 0.54). When the predictors were on their own, dominance was a significant predictor (see Table 5).

An in-depth investigation of the relationship of PAD and flow for each time frame was attempted, but the statistical power for n=20 data points was too low (below 0.8).

5.1 Qualitative Results

After performing deductive category assignment on the dataset, we calculated several descriptive statistics to better understand the results of the two main category systems: "Affective Experience" and "Emotion Regulation" (see Table 6)

The high SD in the Affective Experience column indicates that the distribution of observations across categories within each system is centered around some variables, which is unsurprising since all participants participated in the same experimental setup.

The affective experience and regulation strategies will be summarized here: Participant A (also called AV_C4QPF as reference for Figure 2) felt relaxed at first during the slow phase. When the speed increased at the start of the fast phase, the participant started

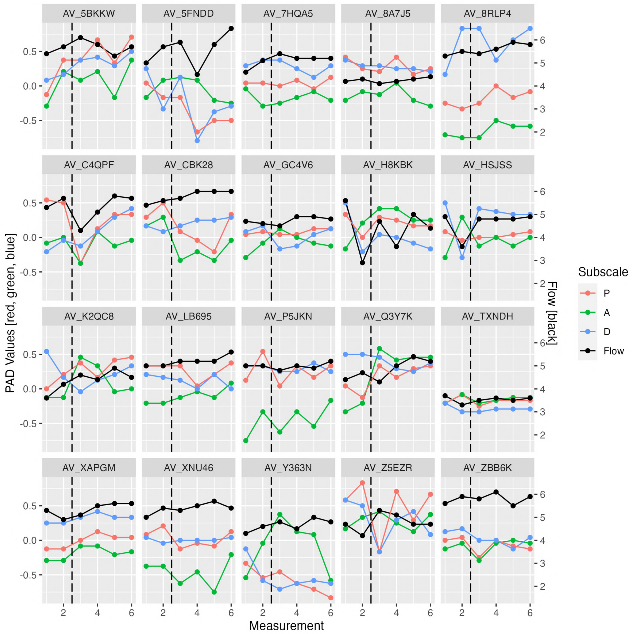

Figure 2: Flow and PAD values over time for each participant. The dotted vertical line represents the change from the slow to the fast phase.

	Affective Experience	Emotion Regulation
Mean Obs. per Category	3.7	1
SD	4.27	1.12
Min. Obs. per Category	0 (“Flow”, “Awe”)	0 (“Attack Self”, “Acceptance”, “Rumination”, “NI”)
Max. Obs. per Category	14 (“Relaxation”)	3 (“Cognitive Reappraisal”)
Proportion of Obs.	33.72%	9.45%

Table 6: Descriptive Results for Deductive Category Assignment. Note that the proportion of observation is an estimation. Timestamps, Ids, comments, translated passages, and multiple codings have not been removed.

feeling many different feelings such as anxiety, o-boredom, hostility, shame, and hopefulness. The participant felt stressed because they[1] are slowing the assembly down. They decided to reduce their efforts and to go at their own rhythm. “It’s enough for it to be repetitive; I don’t need it also to be to be fast.” This behavioral disengagement did not, however, instantly alleviate the pressure. Before it caused relaxation, it caused feelings of shame for not being able and not willing to keep up with the robot.

Participant B (AV_GC4V6) felt relaxation and u-boredom. They unintentionally distracted themselves by thinking about their work, which led to them doing a mistake while assembling. When the fast phase started, the participant started to feel stressed by the speed of the robot. The participant then tried to reappraise the situation: “I was like, no, this is my job and the robot is just a robot. So he has no feeling he can wait. [...] Also because I was kind of telling myself that I had to do the most difficult part like matching the gears going, with the clips and stuff.”[2] The participant kept their speed and reported feeling more relaxed after half of the “fast phase” had passed.

Participant C (AV_LB695) described only feeling relaxed and no boredom in the beginning because they felt they were doing a purposeful commitment that would eventually end. In the “fast phase”, the participant described not feeling rushed: “ I thought that since the number of movements that the machine had to do was smaller then what I had to do was just completing the task earlier than I. [...] It was just waiting for me, but it was not a problem.” Notably, when asked how they dealt with unsolvable tasks, the participant believed that in such a case, the blame lies with the person who gave them the task, not them. (“Yeah, probably, especially if it was in a real situation then I would have thought that the whole planning of the operation was bad because even if I strived, I wouldn’t have managed to be so quick and be always on time for the robot. So yeah, I would be angry in case it would always be like that.”)

Finally, Participant D (AV_ZBB6K) described themselves as being relaxed. However, they distracted themselves by thinking about how to improve the work cell and the task. This tactic ended around the middle of the “slow phase” when Participant D started to feel bored. This was coupled with some short interruptions where the system experienced errors that needed to be fixed. When the “fast phase” started, the participant did not increase their speed. When asked about the reason for this, the participant said they didn’t care anymore. Further investigation no reason for this could be found as the participant said they didn’t know why they felt that way. Therefore, we categorized this as a case of avoidance.

While the self-ascribed feelings of the participants usually matched the results of the semantic differential. 13 times one of the self-ascribed states matched the result of the semantic differential. However, six times there was a mismatch. Most often (4 of 6) it involved the ascription of awe and hopefulness from the semantic differential. In the interviews, they were described as relaxation (2 of 4) but also as anxiety.

6 DISCUSSION

Based on the mixed results on H1, a clear conclusion could not be reached; further research is necessary (see below for an in-depth discussion). H2 showed significant results and is therefore accepted. H3 showed no evidence of a connection between PAD as a whole and flow. The hypothesis will be rejected. However, the connection between dominance and flow is significant and will be investigated further.

Uncentered self-efficacy predicted flow, which strengthens the association between self-efficacy and the challenge-to-skill ratio, which was known to be a predictor of flow [33]. However, group-centered self-efficacy is not. One possible explanation for this would be that self-efficacy remained relatively stable, and the centering thereby caused many zero values. While the scale was validated [26] it contained only one item, and therefore only integer values

[1]To protect the privacy of the participants, only gender-neutral pronouns will be used

[2]Multiple words, fillers, and incomplete sentences have been removed from all the participant’s citations.

were possible. A possible solution to this would be to use a scale that contains more than one item or increase the sample size.

Dominance predicted self-efficacy. This stresses the role of dominance in the PAD model, especially for task-related settings. Continuous monitoring of dominance could capture how workers feel about a task and whether they see themselves as capable of handling the task or if they feel overwhelmed by it and plan interventions for well-being. Additionally, dominance has the strongest connection to flow from all models tested. The model that only used dominance had the lowest AIC and BIC and therefore seem to offer the best fit to the data. From all known variables in this experiment, dominance is best suited for flow estimation and should be included in its modeling.

The results on the connection between flow and PAD are mixed. Surprisingly, and against previous theoretical definitions [1, 15], the results show that pleasure and arousal were not connected to flow in this experiment. Our results suggest that the presence of pleasure in the model strongly influences the estimations for dominance, which is not unlikely due to the strong correlation between pleasure, arousal, and dominance.

The lack of significance of pleasure on flow taps into the discussion of enjoyment in flow [1]. Given the assumption that flow is an enjoyable experience, an increase in flow should have also led to an increase in pleasure. We found no evidence for this claim. However, we can also not rule it out based on our results, as it only describes a partial one-directional relationship, which our model cannot test. Increases in flow predict increases in enjoyment; however, increases in enjoyment do not predict the flow level.

In the literature, high arousal was associated with flow [15]. In our scenario, this would association would be hard to support, as high levels of arousal can be associated with stress, which is more likely to occur in shifts of up to 8 hours.

6.1 Discussion of Qualitative Results

All participants described the tasks as relaxing and positive while acknowledging their repetitiveness. This positive feeling faded in the fast phase when the task became more stressful for 3 of the 4 participants.

After the introduction of the fast phase, none of the participants were able to keep up with the robot. A fluctuation of different emotions was noticed by 3 of the 4 four participants, which may indicate that they were not sure how to properly adapt to the situation and is an indicator of stress. However, all participants found a way to deal with the stress and reached a constant state towards the end of the experiment. This was relaxation for three of them and hostility and boredom for one of them. All participants that felt stressed by the speed of the covatar reduced its intensity by regulating their emotions through reappraisal, avoidance, or disengagement. However, two reduced their performance, and one did not enjoy their affective state towards the end. This indicates that while participants were able to deal with stressors, their strategies used did not always yield the most optimal results in terms of productivity and well-being in the production line.

Boredom was regulated less often than stress and anxiety. However, this might have been because participants knew about the length of the experiment and thereby did not feel any pressure to regulate boredom. Still, all regulation strategies used were not optimal as they distracted themselves from the task, leading to errors, and were not sustainable for longer periods. This highlights the importance of positive guidance to emotion regulation.

6.2 Limitations and Future Work

Small sample size and predictor correlation limited exploring the flow-PAD relationship statistically in detail. Few interviews hinder generalizations but provide insights into participants' task experience, aiding quantitative data comprehension. Future work may test replicability and explore mediation effects between self-efficacy, dominance, and flow.

7 CONCLUSION

This study contributes to developing a socially interactive virtual agent which embodies a cobot in the production line. Combined they can support workers in emotion regulation and flow experiences during collaboration. The results provide valuable insights into the assumptions underlying the BASSF Model, the real-time continuous emotional modeling method, and the aligned behavioral model to support emotion regulation. Surprisingly, the findings suggest that the dominance dimension of the PAD model plays a crucial role in predicting flow. Furthermore, the study highlights the importance of guidance in emotion regulation, as some strategies used by participants negatively impacted their well-being and productivity. This is the first attempt to reevaluate the significance of the dominance dimension of PAD. Further validation is needed to consolidate these results and theory-based interpretations and provide differential SIA reactions based, e.g. on the dichotomous cause of boredom. Overall, this study adds to the growing body of research on the use of technology to support emotion regulation in the workplace.

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