

## What is buzzing around me?

### Assessing the Influence of Indoor Unmanned Aerial Vehicles on Human Cognitive Performance and Well-Being\*

Olga Vogel<sup>a,c,†</sup>, Raphael Dyrska<sup>b,c</sup>, Jens Müller<sup>b,c</sup>, Martin Mönnigmann<sup>b,c</sup>, and Annette Kluge<sup>a,c</sup>

<sup>a</sup>*Work, Organizational, and Economic Psychology, Ruhr-Universität Bochum, Germany*

*olga.skrebec@rub.de, annette.kluge@rub.de*

<sup>b</sup>*Automatic Control and Systems Theory, Ruhr-Universität Bochum, Germany*

*raphael.dyrska@rub.de, jens.mueller-r55@rub.de, martin.moennigmann@rub.de*

<sup>c</sup>*Research Center for the Engineering of Smart Product-Service Systems (ZESS), Hans-Dobbertin-Str. 8, 44803 Bochum, Germany*

#### Abstract

Unmanned Aerial Vehicles (UAVs) are becoming increasingly common in both everyday life and professional contexts. The present study investigates the human factors that have to be considered in the adoption of UAVs in practice. In a one-factorial design, the impact of UAV indoor flights on human cognitive performance and well-being were analyzed. Forty-eight participants were divided into an experimental (EG) and a control group (CG) and completed the Work Efficiency Test. In the EG, UAVs flew different path trajectories indoors behind a safety net. Additionally, flow experience, mental effort, and mental strain were measured. Results show that the EG performed marginally worse on the Work Efficiency Test than the CG and experienced less flow during task processing. Additional qualitative interviews showed that participants felt distracted by UAV noise and flight trajectories. Our results corroborate that the human factor cognitive performance should be considered in the implementation of UAV technology in the workplace.

**Keywords:** Cognitive performance; Noise; Trajectories; UAV indoor applications; Unmanned aerial vehicles

#### 1. Introduction

Due to their flexibility and agility, there exists a variety of indoor applications for UAVs. The application areas include logistics, the construction sector, manufacturing, the steel sector, and the chemical and pharmaceutical sector (Rejeb et al., 2023; Nwaogu et al., 2023; Stroud & Weinel, 2020). The diversity of potential applications results from four dimensions of action (Maghazei & Netland, 2020): UAVs can “See” to perform visual inspections of facilities or monitor safety-related and ergonomic human factors. They “Sense” to assess damages on plants with thermal-imaging devices or sound inspection. A widespread use of UAVs involves the ability to “Move” objects, such as transporting small parts between adjacent areas or last-mile delivery (Moshref-Javadi & Winkenbach, 2021). The connection of the first three dimensions of action results in “Transforming”, where the data are converted into valuable information while the UAV performs physical operations.

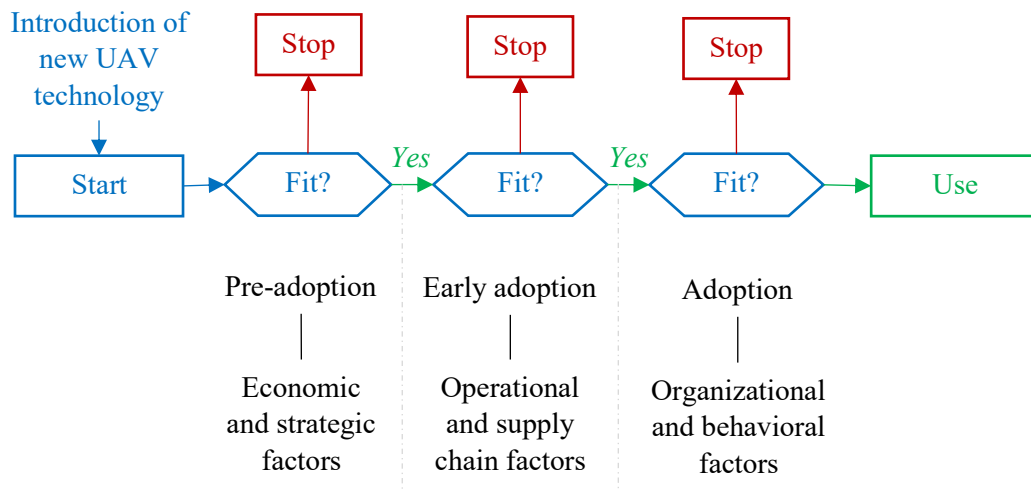
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<sup>†</sup>corresponding author

Despite the large potential of UAV deployment, to date there are only individual use-cases of real-world indoor applications with varying degrees of success (Mourtzis et al., 2021). For example, in 2021, the global furniture manufacturer and retailer IKEA implemented UAVs in five warehouses, which were responsible for recording inventory stocks and reconciling them with the warehouse management system (Maghazei et al., 2022). After only two years, the number of UAVs in use at IKEA increased to 100 in a total of seven different countries (INGKA Holding B.V., 2023). In contrast, Geberit, a leading manufacturer of sanitary equipment in Europe, has stopped the inspection of facilities using UAVs after only two pilot projects in 2018 (Maghazei et al., 2022).

Successful adoption of UAVs as Advanced Manufacturing Technology (AMT) depends on sequential decision-making processes, which are illustrated in Figure 1.



**Figure 1.** Fit framework for UAV indoor adoption (adapted from the conceptual fit framework for AMT adoption (Maghazei et al., 2022))

The least attention in the UAV adoption literature has been paid to organizational and behavioral factors (Malang et al., 2023), which focus on acceptance and human-machine fit. Maghazei and colleagues (2022) identify these factors as the key step for AMT adoption, especially if the new technology poses risks to employees. They evaluate UAVs as a technology that is highly different from existing AMTs in industrial companies and currently assume a poor fit in human-machine interaction. The outcomes of the case studies at IKEA and Geberit underline these assumptions. In the Geberit case, adoption was discontinued before UAVs were flown near humans. The responsible managers assumed that the employees would be annoyed by the noise of the UAVs and would not have trust in the safety of the technology (Maghazei et al., 2022). At IKEA, UAVs are exclusively used when no employees are present in the warehouses due to safety concerns.

The objectives of the present study are 1) to investigate which human factors are impacted by UAVs in indoor adoption and 2) to identify UAV features that have a significant impact on human experience at work. In an experimental design, we examine how the presence of UAVs influences cognitive performance, well-being, and ergonomics. The results expand the fit framework for UAV adoption including mental factors. Thus, this contribution serves as one of the necessary steps to integrate UAVs in indoor environments together with human workers, as it evaluates factors necessary to cope with for a successful implementation. For the experiments, we used the Crazyflie 2.1 manufactured by Bitcraze, which we introduce in more detail in Section 3.2 and Appendix A. Due to their small size and low weight, UAVs of this type are a popular choice for use in indoor environments, e.g., for gas detection (Castro et al., 2018), in rescuing scenarios (Paliotta et al., 2021), to generate 3-dimensional maps for assessing the quality of radio signals (Mendes et al., 2022), and for the mapping of indoor environments as a preparation for disaster management approaches (Karam et al., 2022).

## 2. Theoretical Background

The Industry 4.0 strategic initiative aims to change the manufacturing and logistics industry by implementing holistic production lifecycles through the Internet of Things, cyber-physical systems, industrial robotics, and cloud-based systems (Zhong et al., 2017). Thus, the role of humans as manual operators is to be transformed to knowledge workers who primarily engage in cognitive activities. These tasks encompass a range of responsibilities, such as overseeing assets from a strategic perspective, collaborating with digital systems, and developing creative solutions to overcome technological limitations (Margherita & Bua, 2021; Wan & Leirimo, 2023). Changes in work tasks are accompanied by the necessity to adapt work characteristics to the employees' needs to increase their well-being, motivation, and therefore productivity (Parker & Grote, 2022). The emerging industrial revolution 5.0 even calls for a human-centered design of sociotechnical systems (Xu et al., 2021), including the evaluation of newly deployed technologies in terms of their impact parameters on human factors (Alves et al., 2023). The European Commission states that a key prerequisite for a socially sustainable transition to Industry 5.0 is that technological implementations serve the people involved in terms of motivation, well-being, and ergonomics (Breque et al., 2021).

Neumann and colleagues (2021) categorize human factors in the context of Industry 4.0 as mental, physical, psychosocial, and perceptual. Mental factors include cognition, knowledge, learning, and memory. Physical factors are primarily related to physical safety and ergonomics, but also incorporate fatigue and well-being. Psychosocial factors are a broad area focusing on interaction with team members and leaders as well as personal job satisfaction and job identity. Perceptual factors refer to information processing. Previous research on the impact of UAVs has addressed some relevant human and ergonomic factors. UAVs produce characteristic noises (Christian & Cabell, 2017). Even if these are within the range of legally required indoor noise level, they can result in cognitive distraction (Hui et al., 2021).

In general, noise may affect cognitive performance. According to the model of human information processing, performance in work tasks requires several cognitive processes (Wickens et al., 2022). First, the information from the environment is perceived sensorily. Processing of the received information involves a combination of attentional and working memory processes, as well as selection of congruent and divergent information from long-term memory. The operation results in the selection and execution of a response to the presented information. Since the beginning of industrialization, effects of noise on information processing have been extensively studied (Landström et al., 1995; Liebl et al., 2012). Based on their meta-analysis, Szalma and Hancock (2011) categorize noise as an environmental stressor that has a negative impact on various cognitive processes such as performance accuracy, attentional selectivity and working memory performance, impairing information processing. In a warehouse-like setting, Callanan and colleagues (2020) found that both, loud and quiet UAVs' sounds led to difficulties in listening comprehension of complete sentences. Key findings show that the distance of the UAV from the human has an effect on listening test performance but not on self-reported perception. Volume, in contrast, has an effect on both listening tests and annoyance and ability to understand the speaker's voice. Other unique features of UAVs belong to their flight capabilities. Hui and colleagues (2021) found that noise from low-flying UAVs is perceived as more annoying.

In addition, UAVs can cause distraction as an infrequent visual stimulus by shifting attention away from the relevant information processes (Jeelani & Gheisari, 2021). So far, the influence of light on cognitive performance and well-being has mainly been examined as a visual environmental stressor (Lamb & Kwok, 2016). Liebl and colleagues (2012) investigated the effects of dynamic and static light on performance in four different cognitive tasks in addition to noise in the workplace. Despite the absence of objective performance differences caused by variations in light as a visual distractor, self-reported performance was influenced. The authors claim that since the lighting conditions were only moderately modified, workplace analyses should still encompass visual distractors. These results suggest that UAVs in the same space as humans negatively impact cognitive performance parameters at work.

Environmental stressors such as auditory and visual distractors also have negative impacts on the physical human factors well-being and ergonomics (Kari et al., 2017; Liebl et al., 2012). When engaging in cognitive tasks, flow experience, as an intrinsically motivated state, serves as a central indicator of well-being (Hohnemann et al., 2022; Peifer & Wolters, 2021; Rivkin et al., 2018). It involves intense concentration, absorption, a strong sense of control, and a perceived alignment between one's skills and the task demands (Peifer et al., 2022; Rheinberg et al., 2007). During an optimal flow state, individuals experience heightened cognitive efficiency, reduced stress, and positive affect, which in turn positively impact job satisfaction and leads to reduced absenteeism and lower employee turnover (Maeran & Cangiano, 2013; Peifer et al., 2022). Following the Brixey Model of Interruption (Brixey et al., 2007), Peifer and Zipp (2019) showed in an experimental design that interruptions at work can lead to a reduced flow experience. Interruptions occur, among other things, when attention is shifted away from a task without switching to a new task (Brixey et al., 2007).

Furthermore, physical factors depend on the task design and characteristics of the implemented technology (Robelski & Wischniewski, 2018). Against this background, Callanan and colleagues (2019) found that the loudness of UAVs significantly affected the participants' workload by increasing annoyance and decreasing listening comprehension. The authors call for further research on the effects of UAVs on mental workload in indoor and outdoor environments to better understand the individual cognitive components. Mental workload comprises the resources and capacities that a worker applies to a task (Kramer, 2020). It is a broad concept that includes the components mental effort and mental strain (Cain, 2007). Mental effort describes the efficiency and depth of cognitive processing, reflecting the interaction between perceived task demand characteristics, self-efficacy, and working memory capacity (Kirschner & Kirschner, 2012). The additional activation of affective resources to meet task demands depends on perceived mental strain (Mayerl et al., 2016). Functional strain refers to positive emotions and experience of competence. Dysfunctional strain, on the contrary, reflects negative emotional states and physical discomfort (Wieland & Hammes, 2014).

The influence of human-machine interaction on ergonomics is subject to user experience, that is, positive and negative attitudes towards the technology, as well as the acceptance of working with it in a shared context (Prati et al., 2021). Baytaş and colleagues (2019) summarize the relevance of user-centered design in human-drone-interaction in their review on design characteristics of social drones. In addition to proxemics, control methods and appearance, noise, and flight patterns are among the central characteristics that influence human positive and negative perception. However, previous studies have focused mainly on the effects of distance and gesture control on ergonomics, whereas studies on environmental stressors are lacking (see also Cauchard et al., 2015).

The present study aims to add relevant findings to the discussion on indoor UAV use and related Human Factors aspects. We see a research gap regarding, e.g., the generalizability of results and external validity of previous research and want to address how indoor UAVs affect objectively measured performance in complex cognitive real-world tasks performed by workers in manufacturing and logistics as well as human-centered ergonomic factors. Moreover, we want to identify the additional characteristics of UAVs, besides noise and motion, that affect task processing. In summary, our hypotheses and our research question are:

*H1: Cognitive work task performance is lower when UAVs are flying in the workspace than when UAVs are not present.*

*H2: Indoor flights of UAVs have a negative impact on flow experience, functional strain, user experience and a positive impact on mental effort and dysfunctional strain.*

*RQ1: What characteristics of UAVs are perceived as distracting during the processing of cognitive work tasks?*

### 3. Methodology

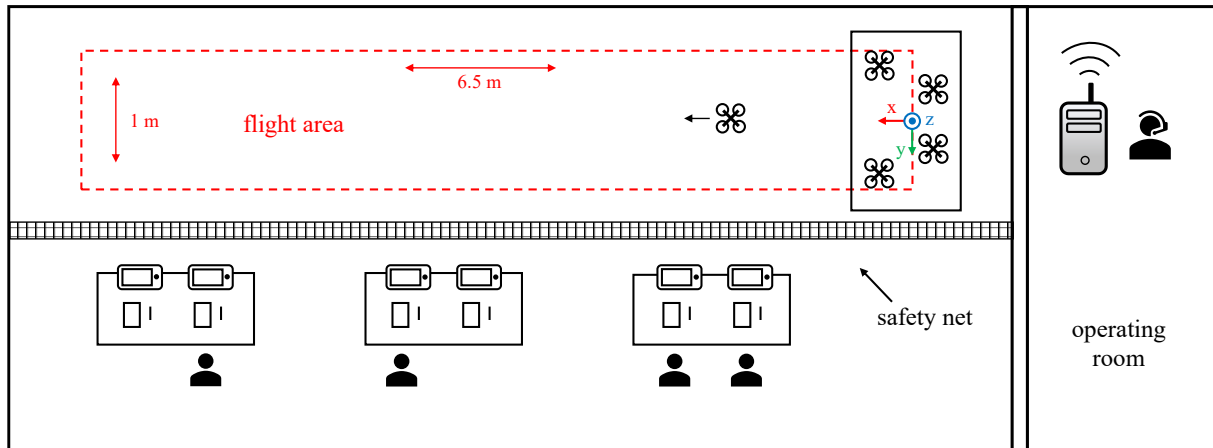
#### 3.1 Sample

Participants were recruited on the campus of the Ruhr-Universität Bochum through flyers and messages in WhatsApp student groups and Moodle lectures as well as from the authors' private networks (for a detailed description of the sample, see Appendix B).

The study was approved by the local ethics committee of the faculty of Psychology (No. 812 as of October 10, 2022). Participants were informed about the general setup and sequence of the study and told that they could discontinue participation at any time (in terms of informed consent). They received 20€ for participating in the experiment. Psychology students could instead receive credit for one and a half trial volunteer hours, which must be collected as part of their curriculum. A total of 48 participants took part in the pseudo-randomized study allocated to the experimental (EG,  $N = 24$ ) and control (CG,  $N = 24$ ) groups. The age of participants ranged from 18 to 49 years ( $M = 25.91$ ,  $SD = 6.38$ ). Sixty-three percent ( $N = 30$ ) of the participants were women.

#### 3.2 Laboratory Setup

An experimental laboratory design with two conditions (EG/CG) was set up to test the hypotheses. The experiments were conducted in the flight laboratory operated by the authors inside the Research Centre for the Engineering of Smart Product Service Systems (ZESS) research building of the Ruhr-Universität Bochum. The laboratory setup is sketched in Figure 2.



**Figure 2.** Top view on the laboratory setup consisting of a flight area (top, see also Fig. 3 (a)), an operating room (right), and the space for the participants (bottom, see also Fig. 3 (b)). A safety net separates the participants from the flight area that is marked by the red dashed line. UAVs are depicted by the black crosses and circles. The overall dimension of the flight lab, i.e., excluding the operating room, measures 10 x 5 m. Note that the flight area shown in red is sketched larger for readability and thus not true to scale.

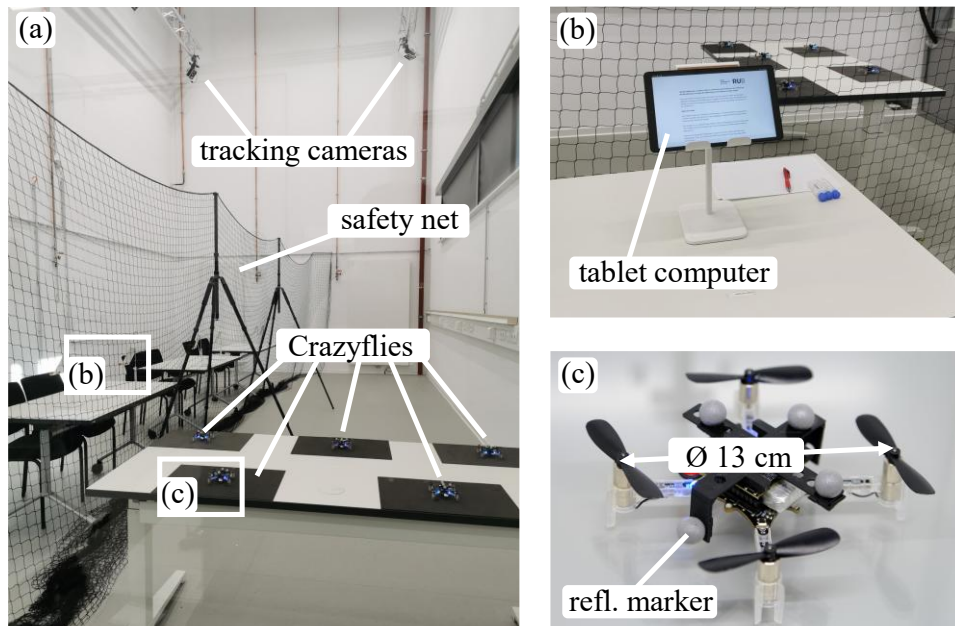
One experiment trial lasted 90 minutes. EG and CG both worked on a cognitive work efficiency task for 12 minutes. After a familiarization period with the task of 2 minutes, UAVs flew in the EG for the remaining 10 minutes in the same room where the participants worked on the task. In the CG, no UAVs were present. Before and after the WET, participants completed several questionnaires (see Table 1 for the experimental design).

**Table 1**  
Experimental Design

Pre-Survey <i>15 minutes</i>	Experimental Trial <i>12 minutes</i>	Follow-Up Survey <i>30 minutes</i>
Previous Experiences with UAVs (self-invented items)  Cognitive Failures Questionnaire (Klumb, 2001)  Scale of Trust in Automated Systems (Jian et al, 2000)	EG: Performance of the WET (Conzelmann & Kersting, 2012)  UAVs fly behind the safety net	Distracting Factors (qualitative question)  Flow Short Scale (Rheinberg et al., 2019)  Mental Effort (Tausch & Kluge, 2022)  Wuppertal Mental Strain Screening Instrument (Wieland & Hammes, 2014)  User Experience (Laugwitz et al., 2008)  Demographical Data (baccalaureate grade)
	CG: Performance of the WET (Conzelmann & Kersting, 2012)  No UAVs were present	

For safety reasons, the lab space was separated by a safety net, hanging at a height of approximately 2.5 m (see Fig. 2). The participants were seated at tables equipped with tablets, looking towards the flight area during the whole experiment. Up to six participants were tested in parallel. Due to cancellations at short notice, the number of participants fluctuated between one and five in each experimental session.

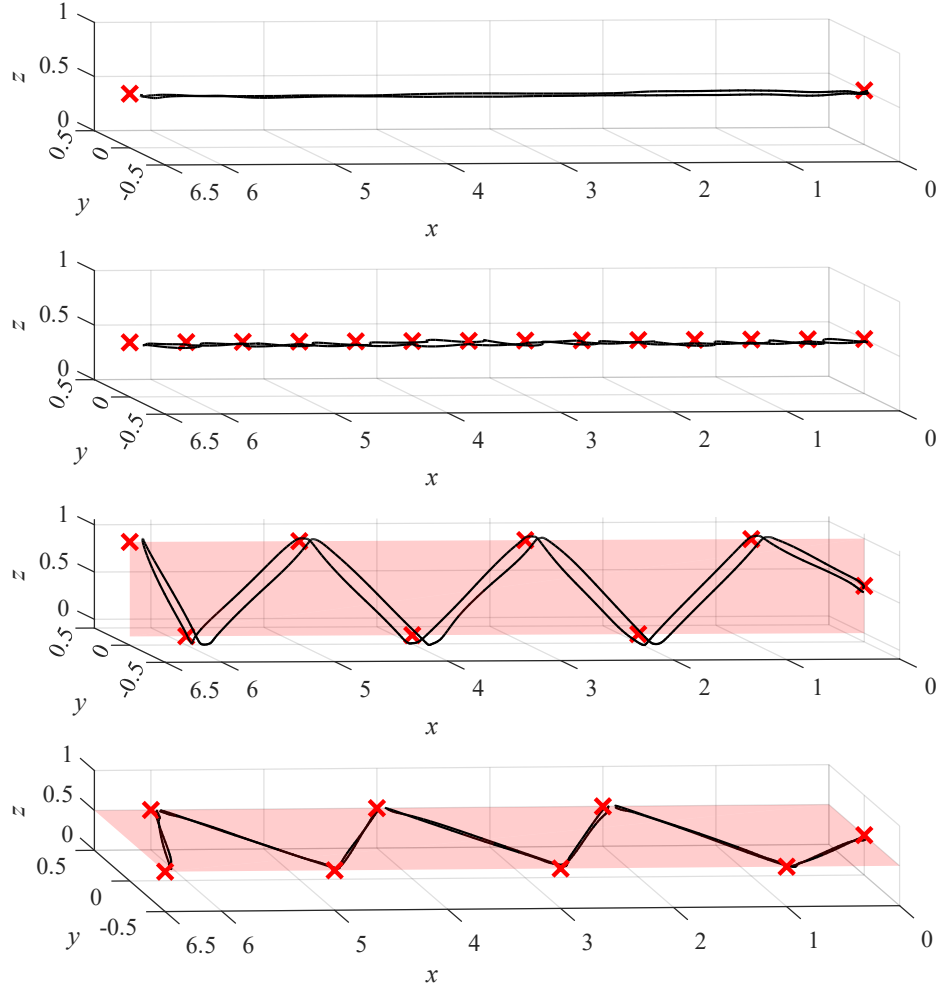
The UAVs (sketched by crosses and circles in Fig. 2) were operated by the ground station located in the operating room, which is divided from the laboratory by windows. Figure 3 shows photos taken from the perspective of the operators (a) and the participants (b), as well as a photo of the UAV (c) used in the EG.



**Figure 3.** (a) Laboratory design from the operators perspective including the motion capture (tracking) cameras and the safety net. White boxes mark one of the desks spaces at which participants worked at a tablet computer (b) and to the take-off and landing position of the UAV equipped with reflective markers (c).

The UAV was a Bitcraze Crazyflie 2.1 (see Fig. 3 (c)), which flew autonomously as described in Appendix A (see Giernacki et al., 2017) for an introduction to the Crazyflie project). The UAV weighs 27g and has a rotor-to-rotor diameter of 130 mm. UAVs of this type are often used in the field of automatic control, to implement and test control algorithms (see, e.g., Candan et al., 2018; Carlos et al., 2020; Kooi & Babuska, 2021) or to evaluate tuning algorithms for existing controllers (see, e.g., Dyrska et al., 2023). With a weight of below 250 g, the UAV is part of the category with the least regulations, making an incorporation into the everyday business easier and thus more attractive for companies, also with upcoming regulations transferred to the indoor case.

To ensure a flight time of 10 minutes, four UAVs performed flights sequentially. The fifth UAV shown in Figure 2 was added as a backup. All UAVs started from a table and landed at their starting point after the flight. At first, each UAV took off up to a height of 0.5 m above the table and moved to its center marked by the coordinate system shown in Figure 2. Subsequently, the UAVs performed flights following the trajectories illustrated in Figure 4. The autonomous flights were performed in the area sketched in Figure 2 (6.5 x 1 m), and in a height ranging between 0 and 1 m with respect to the center of the table. Flights were conducted both with constant and varying height (see Fig. 4).



**Figure 4.** Trajectories for the flight experiments. Red crosses mark reference points that define the trajectories. Black lines show sample trajectories of the UAV that were measured by the motion capture cameras during actual flights. From the participants' point of view, all trajectories started from the right and were passed twice, i.e., the UAV followed the reference points backwards after reaching the reference point at  $x = 6.5$  m.

Figure 4 shows the flight patterns from the participants' perspective, i.e., starting from the right at coordinate  $(0,0,0.5)$  with respect to the center of the table. The first two patterns show straight flights over a span of 6.5 m. While the first one consists of starting point and end point only, the second trajectory contains several reference points. Since the autonomous flights were realized by point-by-point flights, the approach towards a new reference point always includes an acceleration at the beginning and a deceleration when reaching the new reference. Thus, the two patterns differ with respect to the noise and the pattern of motion of the UAV. The third trajectory varies in height. The fourth trajectory lies in a plane of constant height, but moves back and forth from the participants' perspective, adding another type of motion to the flight behavior. All patterns were performed from right to left and left to right before switching to the next trajectory. The order in which the trajectories shown in Figure 4 were performed changed for each UAV to prevent habituation of participants to repeating flight patterns.

### 3.3 Variables

The independent variable was the presence of UAVs. In the EG, UAV flights were conducted as described above while participants performed the Work Efficiency Test (WET). Dependent variables were assessed with multiple scales (see below).

#### 3.3.1 Cognitive Task Performance

The module salary determination of the WET by Conzelmann and Kersting (2012) was used to measure cognitive task performance. The test battery comprises complex problem-solving tasks that occur in typical office activities and can be applied in technical and industrial occupations. Solving the task requires simultaneous reasoning, processing speed and working memory capacity. The module consists of 44 individual tasks. For each correct solution, the participants received one point (minimum possible correct solutions = 0; maximum possible correct solutions = 44). In the original test description, participants have 18 minutes to solve as many tasks as possible. A detailed description of the WET is provided in Appendix C. In our design, participants had 12 minutes. Since the flight time of the UAVs amounted to 10 minutes, the participants had time to familiarize themselves with the task in the first two minutes. From the third minute, the UAV flights started in the experimental group.

#### 3.3.2 Physical Factors Well-Being and Ergonomics

Flow, mental effort, mental strain, and user experience were surveyed after the WET was completed. An overview is given in Table 2.

To measure flow experience, the subscales Fluency, Absorption, Worry, and Skill Demand Fit of the German version of the Flow Short Scale were used (Rheinberg et al., 2019). The scale was selected because it has already been used in studies on flow and cognitive performance and represents mental components of flow experience (Palomäki et al., 2021). Fluency refers to experiencing the course of action as smooth and cohesive. Absorption describes a complete involvement in the activity. Worry measures concerns about one's performance in the task and is an inverted component of flow, as experiencing flow leads to a fading out of all cognitions that are not focused on the task. Skill Demand Fit refers to an optimal level of demand for the activity. Due to the too low internal reliability of  $\alpha < .70$  of the Absorption subscales, the Fluency and Absorption scales were combined into the higher order Flow Short Scale (FSS) for analyses, as is common in flow surveying (Harris et al., 2021).

Mental effort was assessed using the Mental Effort Questionnaire by Tausch and Kluge (2022). This instrument was developed to examine how industrial robots need to be designed to reduce mental effort in human-machine interaction. Experience of affective tasks was measured using the German-language Wuppertal Mental Strain Screening Instrument (WSIB, Wieland & Hammes, 2014). This instrument was selected as it measures mental stress specifically in the work context and is distinct from clinically relevant constructs of mental stress. Positive and negative experiences with UAVs were measured using the German version of the User Experience Scale (Laugwitz et al., 2008), which is characterized by high economy and a focus on the affective evaluation of systems (Schrepp et al., 2017). 17 out of the 26 original items were surveyed. Nine items were excluded since they could not be adapted to UAV technology (e.g. organized - cluttered).

**Table 2**

Questionnaire parameters of predictors and control variables

Scale	Example Item	No. Items	Range	Cronbach's $\alpha$
Flow Short Scale	I feel just the right amount of challenge	10		.86
Fluency	My thoughts/activities run fluidly and smoothly	6	7-point likert scale	.89
Absorption	I do not notice time passing	4	1 = not at all; 4 = partially; 7 = very much	.54
Worry	I was worried about a failure	3		.72
Skill Demand Fit	For me personally, the requirements of the WET are...	3	9-point likert scale 1 = too low; 5 = just right; 9 = too high	.60
Mental Effort	I had to concentrate a lot	7	7-point likert scale 1 = not at all; 7 = completely	.79
Functional Strain	During the processing of the WET I felt "full of energy"	4	7-point likert scale 1 = barely; 2 = a little; 3 = somewhat; 4 = pretty; 5 = strong; 6 = very strong; 7 = extraordinarily	.80
Dysfunctional Strain	During the processing of the WET I felt "nervous"	4		.75
User Experience	Please rate the drone based on the following statements: 1 = "annoying"; 7 = "enjoyable"	17	7-point likert scale	.85
Cognitive Failures	I could not remember something that I had been told some time ago	32	5-point likert scale This happened to me in the last 6 months: 0 = never; 1 = rarely; 2 = sometimes; 3 = often; 4 = very often	.92
Trust	Drones are reliable	6	7-point likert scale 1 = not at all; 7 = extremely	.78
Baccalaureate grade	With what grade did you complete your university entrance qualification (Abitur)?	1	1.0 - 3.4 <sup>a</sup> (EG: 1.0 - 3.1; CG: 1.0 - 3.4)	.

Note. <sup>a</sup> refers to the range of grades in the data set

### 3.3.2.1 Distracting Characteristics of UAVs

Distracting factors of UAVs were measured in the EG with the open question "What aspects of drones did you find distracting?". In the CG, participants were shown a short video of the drone flights after the WET, which was previously recorded in the laboratory. The video was presented on the tablet at the same volume for all participants. They then answered the question "What aspects of drones do you think are distracting at work?". In addition, participants in the experimental group were asked whether and which flight trajectories they noticed during the WET processing. The question was asked based on the exploratory assumption that distracting trajectories are more likely to be noticed. All qualitative questions were presented to the participants via Qualtrics. The answers were given by filling free text fields.

### 3.3.3 Control Variables

Based on theoretical considerations, the following control variables were included in the analyses.

#### 3.3.3.1 General Intelligence

For cognitive performance and especially working memory, general fluid intelligence is the most powerful individual predictor (Ackerman et al., 2005; Burns et al., 2006; Colom, 2004). In their meta-analysis, Roth and colleagues (2015) interpret the significant relationship found between school grades and intelligence of  $\rho = .54$  as substantial. Thus, for the measurement of general intelligence, participants were asked about their baccalaureate grade.

#### 3.3.3.2 Cognitive Failures

Attentional processes at work are influenced by cognitive failures. This cognitive style causes a person to fail to perform a task adequately even though they have the ability to do so (Wallace, 2004). In this case, limited cognitive resources are directed to an external irrelevant stimulus, rather than to the task (Lange & Süß, 2014). Cognitive failures were measured with the German version of the Cognitive Failures Questionnaire (Klumb 1995; Klumb, 2001).

#### 3.3.3.3 Trust

Trust is a factor that does not directly affect cognitive performance, but substantially influences the use and acceptance of UAVs in industrial processes (Maghazej & Netland, 2020). Trust in UAV technology was measured with a shortened German translation of the Scale of Trust in Automated Systems (Jian et al., 2000, German translation by Tausch & Kluge, 2022). Items attributing personality traits to UAVs (e.g. "The drone is deceptive") were excluded.

### 3.4 Statistical Analyses

Almost all statistical analyses were performed using the IBM SPSS Statistics program (version 29). Control variables that correlated with the outcome variables were included as covariates in group comparisons to test H2 using R package *lsmeans*. To compare the EG and the CG on the dependent variables, one-sided T-tests for independent samples were calculated. For non-normally distributed variables, the Mann-Whitney-U test was calculated instead. To address the Research Question, the qualitative responses were rated and clustered by two independent experts. Intraclass correlations (ICC) were calculated to determine interrater reliability. Results were analyzed descriptively by frequency distribution. The awareness of the flight trajectories was evaluated with a chi-square test.

## 4. Results

### 4.1 Descriptive Results

At the beginning of the study, participants were asked about their previous experience with drones. The term drone was used throughout the questionnaire instead of UAV because it is more widely used, ensuring that participants were familiar with it. No participants possessed a drone pilot license. Some participants had piloted drones that do not require a license. The remaining results of the pre-survey are presented in Table 3 and show that the level of experience is approximately equally in both groups.

**Table 3**  
*Participants' Previous Experience with Drones.*

Variable	total sample <i>N</i> = 48		experimental group <i>N</i> = 24		control group <i>N</i> = 24	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
<b>Experience level with drones</b>						
no experience	2	4.2	0	0.0	2	8.3
experiences from television or media	5	10.4	3	12.5	2	8.3
already seen a drone in the free time	29	60.4	13	54.2	16	66.7
flown a drone once	8	16.7	5	20.8	3	12.5
already engaged with drones in the context of work/study	1	2.1	1	4.2	0	0.0
interacted with a drone several times	2	4.2	1	4.2	1	4.2
already worked with a drone	1	2.1	1	4.2	0	0.0
<b>Number of own drones</b>						
0	43	89.6	21	87.5	22	91.7
1	4	8.3	2	8.3	2	8.3
2	1	2.1	1	4.2	0	0.0
<b>Drone piloting frequency<sup>a</sup></b>						
never	32	66.7	14	58.3	18	75.0
very rarely	8	16.7	5	20.8	3	12.5
rarely	4	8.3	2	8.3	2	8.3
occasionally	1	2.1	1	4.2	0	0.0
frequently	1	2.1	0	0.0	1	4.2
very frequently	2	4.2	2	8.3	0	0.0

*Note.* <sup>a</sup> Scale ranged from 0 = never to 5 = very frequently;

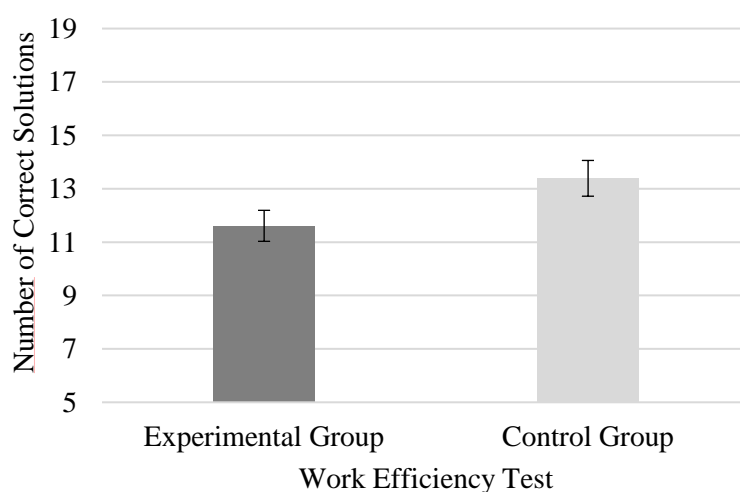
Spearman correlation analyses were performed across all control and dependent variables to ascertain the inclusion of specific control variables within the hypothesis testing framework. The control variable cognitive failures shows no significant correlations with the dependent variables. Trust correlates positively with the Flow Short Scale in the EG ( $r_{\text{SEG}}(22) = .430, p = .036$ ) but not in the CG ( $r_{\text{SEG}}(22) = .251, p = .237$ ) and in both groups with user experience ( $r_{\text{SEG}}(22) = .447, p = .029$ ;  $r_{\text{SCG}}(22) = .620, p =$

.001). The baccalaureate grade shows only a positive correlation with worry in the experimental group ( $r_{sEG}(22) = .432, p = .044$ ;  $r_{sCG}(22) = -.313, p = .146$ ). Based on the intercorrelations, the control variables that showed a significant correlation with the respective outcome variable in at least one group were included in the analysis of H2 (see 4.2.3).

## 4.2 Inferential Statistics

### 4.2.1 H1: Group Comparisons in Cognitive Task Performance

The number of correct solutions in the WET was compared between the groups to determine differences in cognitive task performance. After initial outlier analyses using boxplot and stem-leaf diagrams, one participant per group (31 correct solutions in EG and 23 correct solutions in CG) was excluded from the analysis. Subsequently, the range of correct solutions was between 5 and 20 correct answers ( $range_{EG}$ : 5 -20;  $range_{CG}$ : 7 - 20). The mean number of correct solutions was  $M = 13.39$  ( $SD = 3.30$ ) in the CG and  $M = 11.61$  ( $SD = 4.08$ ) in the EG. The difference between groups is marginally significant at a level of  $\alpha < .05$  with  $t(44) = 1.91, p_{one-sided} = .055, r = .24$  (see Fig. 5). The first hypothesis could not be confirmed.



**Figure 5.** Number of correct solutions in the WET.

*Note.* Error bars represent one standard error above and below the mean.

### 4.2.2 H2: Group Comparisons in Well-Being and Ergonomics

As displayed in Table 4, only the group differences in the Flow Short Scale were significant. Here, the control group reported a higher flow experience (see Tab. 4), thus H2 could be partially confirmed.

**Table 4**  
Group Comparisons

Scale	Experimental group <i>N</i> = 24		Control group <i>N</i> = 24		<i>T</i> <sup>c</sup>	<i>Z</i> <sup>d</sup>	<i>p</i> <sup>e</sup>	<i>r</i> <sup>f</sup>
	<i>M</i> <sup>a</sup>	<i>SD</i> <sup>b</sup>	<i>M</i> <sup>a</sup>	<i>SD</i> <sup>b</sup>				
Flow Short Scale	4.69	1.05	5.29	1.00	1.98		.027	.30
Mental Effort	3.77	1.03	3.57	0.65	0.81		.210	.12
Skill Demand Fit	3.26	1.47	3.08	0.91	0.51		.310	.08
Dysfunctional Strain	2.02	0.9	2.1	0.87		0.37	.357	.05
Functional Strain	4.73	0.84	4.65	1.11	0.29		.385	.04
User Experience	4.05	0.84	4.1	0.75	0.19		.424	.03
Worry	3.13	1.44	3.22	1.63		0.04	.486	.01

*Note.* <sup>a</sup> *M* = Mean; <sup>b</sup> *SD* = Standard Deviation; <sup>c</sup> *T* = T-value; <sup>d</sup> *Z* = Z-value according to the Mann-Whitney-U test for non-normally distributed variables; <sup>e</sup> *p* = p-value; <sup>f</sup> *r* = correlation effect size *r* according to Rosenthal et al. (2000)

#### 4.2.3 H2: Influence Effects of the Control Variables

For the analysis, all interval-scaled predictors were z-standardized. The results in Table 5 show that flow is still significantly explained by the group difference after controlling for trust. No other effect was found.

**Table 5**  
*Analyses of Covariance*

	Effects on Flow Short Scale				
	<i>B</i>	<i>B</i>	<i>SE</i>	<i>T</i>	<i>p</i>
Intercept	5,31	.	0,2	26,55	< .001
Group	-0.54	-0.26	0,28	-1.92	.031
Trust	0.40	0,34	0,16	2,53	.008
<i>F</i> (2,45) = 5.49, <i>p</i> = .007, <i>R</i> <sup>2</sup> = 0.16					
	Effects on Worry				
	<i>B</i>	<i>B</i>	<i>SE</i>	<i>T</i>	<i>p</i>
Intercept	0,37	.	0,48	-0.03	.487
Group	0,09	0,03	0,19	0,19	.424
Grade	-0.19	-0.09	0,34	-0.57	.288
<i>F</i> (2,42) = 0.20, <i>p</i> = .82, <i>R</i> <sup>2</sup> = -0.04 <sup>a</sup>					
	Effects on User Experience				
	<i>B</i>	<i>B</i>	<i>SE</i>	<i>T</i>	<i>p</i>
Intercept	4,06	.	0,13	30,32	< .001
Group	-0.00	-0.00	0,19	-0.02	.494
Trust	0.50	0,57	0,11	4,67	< .001
<i>F</i> (2,45) = 11.00, <i>p</i> = < .001, <i>R</i> <sup>2</sup> = 0.30					

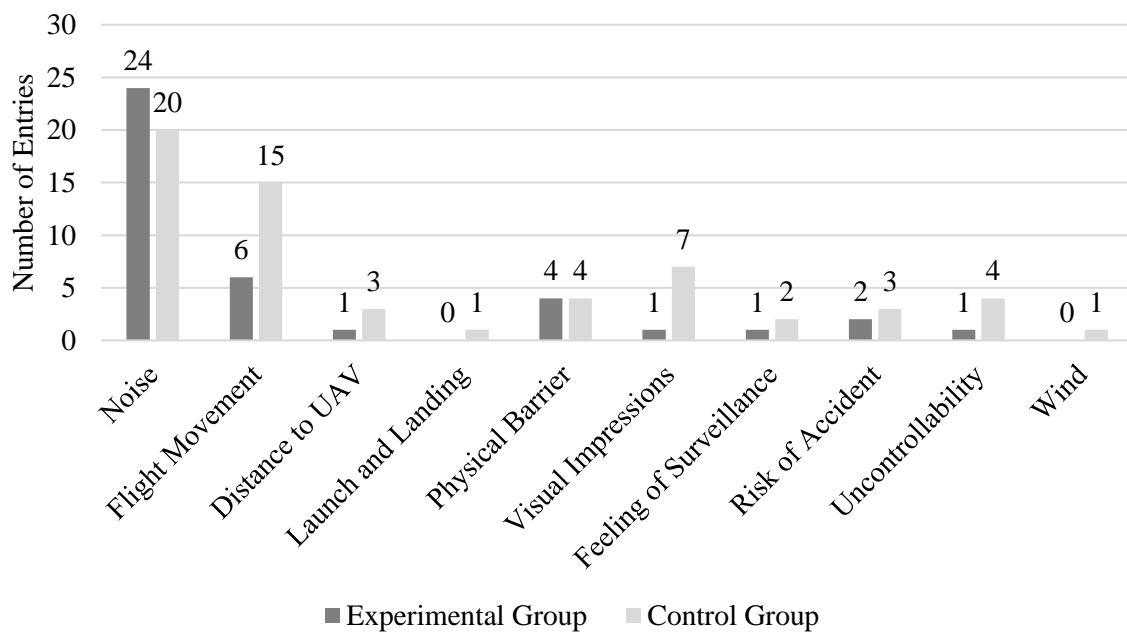
*Note.* *B* = standardized beta weight; *β* = unstandardized beta weight; *R*<sup>2</sup> = adjusted R-square;

<sup>a</sup> There are 42 degrees of freedom because 3 people did not enter their grade

#### 4.2.4 RQ: Distracting Characteristics of UAVs

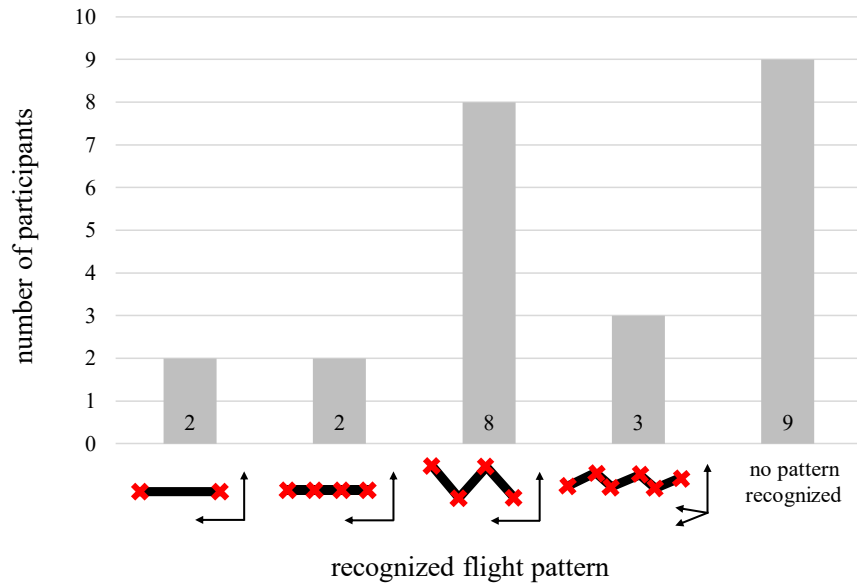
Following the thematic analysis approach (Braun & Clark, 2012), two independent rater derived categories for the qualitative results. Categories were created step by step based on the participants'

written responses. With each emerging aspect, an additional category was chosen. The raters had similar sample characteristics to the test sample. They began by reading the first statement and assigning it to a category. For the next statement, they decided to assign it to the previously created category or to create a new one. Similar answers like “noise“ or “loud” were grouped into superordinate categories. The descriptive results are presented in Figure 6. In the first round, a total of ten categories of confounding factors emerged, with Rater 2 introducing the tenth category, i.e., "Wind." The remaining nine identified categories were similar between the raters. To perform ICC, all responses were assigned to categories 1 to 10. Some participants reported multiple distracting factors. Each of these was scored individually. In total, the 48 participants named 100 factors.  $ICC_{just}$  shows good agreement with  $ICC = .783$  [.672, .856],  $p < .001$  (Koo & Li, 2016).



**Figure 6.** Number of distractions mentioned divided by categories built by raters.

Figure 7 shows which flight trajectories were noticed by the participants in the EG ( $N = 24$ ). The chi-square test confirmed the assumption that there were frequency differences ( $\chi^2(4,24) = 9.75, p = .045$ ).



**Figure 7.** Number of participants (not) recognizing the patterns of the flight trajectories introduced in Figure 5.

## 5. Discussion

The purpose of this study was to identify key factors for UAV adoption in organizations in terms of human factors according to the AMT adoption model of Maghazei and colleagues (2022). The first hypothesis (H1), that the presence of indoor UAVs inhibits work performance in complex cognitive tasks, could not be confirmed, as only a marginally significant difference was found. This effect is likely underestimated in our sample due to the small sample size. Several contributions classified UAVs with respect to, e.g., their size (see Hassanalian & Abdelkefi, 2017; Adoni et al., 2023). According to the classification by Adoni and colleagues (2023), the UAV used in our experiments is considered *very small*, while the ones applied in use cases in logistics such as Ikea are of category *small*. As in general a higher noise emission can be expected by increasing the size of the UAV, we assume that the higher noise level in the industrial application of larger UAVs will limit cognitive performance to a greater extent.

Another aspect that could have led to the marginal statistical effect was the duration of exposure to the UAV. Due to the current short battery lifetime, there are only laboratory studies with short-term exposure that measure the influence of UAV noise on cognitive performance (Schäffer et al., 2021). The effects of noise on cognitive performance are subject to the duration of exposure (Szalma & Hancock, 2011). Short-term noise pollution can enhance adaptability in task performance by increasing concentration and commitment to effort (Matthews et al., 2002). In contrast, long-term impairments in cognitive performance are moderated by factors such as fatigue, which arise after prolonged exposure (Szalma & Hancock, 2011). Jafari and colleagues (2019) examined the effect of different levels of noise on mental workload and cognitive performance. With an experimental duration of 15 minutes, the reduction in cognitive function was only observed at a level of 95 dB, while Crazyflie 2.1 reached a maximum frequency of 83 dB in the present study.

A significant difference was shown in self-reported performance for flow (H2). Although participants in the experimental group trusted the UAV technology, they experienced lower flow states during the UAV flights. Notably, the presence of UAVs did not impact two flow characteristics: skill-demand fit and worry about individual performance. Fluency and absorption represent the mental components of flow and are a predictor of cognitive performance and an integral aspect of positive performance encounters (Palomäki et al., 2021). This result shows that motivation and well-being during cognitive performance are reduced by UAVs. To prevent negative effects of UAVs on work characteristics mediated by flow,

distracting UAV features need to be identified and mitigated. No group differences were observed for mental effort, mental strain, and user experience. Overall, participants reported rather high functional strain, low dysfunctional strain, and a moderate mental effort during task processing. This indicates that the cognitive task employed in our study stimulated motivational and mental resources (Wieland & Hammes, 2014). If applicable, the influences of the UAVs were mitigated by the positively perceived task characteristics. The lack of effect on the user experience can be explained by the distracting factors. The CG rated user experience after reception of the UAV video. This presented a new stimulus that influenced the subsequent measurement.

Consistent with previous research (see Sec. 2), we identified noise and movement as the primary sources of distraction among UAV features (RQ1). Exploratory results suggest that UAV trajectories can have varying effects on visual attention. Despite the use of very small UAVs, we also identified seven other relevant factors, such as distance, that we anticipate will gain increased significance in the context of small UAVs. For example, Acharya and colleagues (2017) showed that people feel more comfortable at a greater distance from a 54 cm<sup>2</sup> large AscTec Hummingbird than from ground robots.

Our results show that even in the short period of 10-12 minutes of UAV exposition, there are indications for a relevant impact on cognitive performance and flow. In their investigation of UAV adoption in the AMT fit framework, Maghazei and colleagues (2022) found that there is a mainly poor fit for organizational and behavioral factors due to psychosocial and physical human factors. We contribute to the body of empirical research by expanding the framework to include mental human factors as well as distracting technical characteristics.

## 6. Conclusion

In the following, we reflect the results against the background of the study's limitations. Finally, we contextualize the results within the current practical and scientific discourse on UAV use.

### 6.1 Limitations

We acknowledge that the study has some relevant limitations. Regarding the experimental stimulus, one limiting factor is the flight duration of the UAV, which amounted to only 10 minutes. Additionally, due to safety reasons, we used very small UAVs, and a safety net was employed to protect the participants. As a consequence, the stimulus of the UAVs regarding noise and visual distraction might have been limited and not sufficiently salient to produce larger effects. The test environment was subject to further restrictions. It was predominantly quiet in the laboratory. Only noise from construction sites and roads in front of the building could be heard alongside the UAVs. In a warehouse, by contrast, noise emissions from equipment and conversations are greater and interfere with one another (Hui et al., 2021).

Following the approach of Liebl and colleagues (2012), we examined the combined effects of UAV-related distractions to enhance the external validity of our results. However, this approach constrains our ability to interpret the specific impact of each individual distractor (e.g., flight trajectories) on the dependent variables. Regarding the sample, 48 participants were sampled, which corresponds to a power of  $\beta = .57$ . To ensure that an effect is uncovered in the hypotheses examined, a power of  $\beta = .80$  should be aimed for in future studies. The sample consisted of (mainly young) students, who are used to perform cognitive tasks for the studies. It is also known from research in developmental and cognitive psychology, that young persons are able to perform cognitive tasks better under influence of auditive distractors than older persons (Beaman, 2005).

## 6.2 Implications for Further Research

Based on the limitations of our study, we see implications for further research. The environmental stressors of UAVs should be studied individually to determine which factors need to be technically changed to ensure cognitive performance and comfort at work. It can be assumed that, in addition to noise, movement and wind might influence ergonomic factors. While noise and distance have been studied as individual factors (Callanan et al., 2020; Lieser et al., 2021), the isolated effects of other environmental stressors related to UAVs remain largely unexplored. Future studies could assess the impact of visual stimuli from UAVs by equipping participants with noise-canceling earplugs to minimize auditory distractions. Studies with small and medium-sized UAVs are planned to compare the effects of UAV features on cognitive performance and thus determine to what extent the effects were underestimated in this study. To do this, additional safety measures must be implemented to enable UAV flights without a safety net and, for example, above the head of participants. To increase external validity, a manufacturing environment should be established in terms of noise and visual stimuli. In a real-world application scenario, workers are exposed to external influences from UAVs for hours or the entire day (Liebl et al., 2012). Therefore, influences on ergonomic parameters should be tested in longer lasting studies to simulate a real-world situation.

## 6.3 Implications for Practice

Collaboration between humans and UAVs in shared spaces is not yet possible. To achieve this, UAVs must become quieter on the technological side and have the possibility to fly outside the scope of human vision. In addition to human factors, the fit framework for indoor adoption addresses further challenges on the strategic and operational level. So far, there are no specific laws or regulations in Europe regarding the deployment in indoor operations (EASA, 2022). A risk assessment is required for each specific use case, leading some companies to wait for the introduction of regulatory approvals for indoor use (Malang et al., 2023).

A main assumption based on qualitative data is that noise poses the greatest environmental stressor. We note that hearing protection that is often required in industrial settings can affect how workers would perceive the presence of UAVs. However, while the noise will in general not be suppressed completely by the protection device, the visual component and the associated fear of a collision remain as distracting factors (Jeelani & Gheisari, 2021). Recent results presented in (Radun et al., 2024) show that while noise perception decrease due to hearing protection, cognitive task performance and perceived workload do not differ compared to the condition without hearing protection. In contrast, since the hearing sense will be limited to perceive environmental information, a higher attention for potential dangers could be observed. Therefore, we expect that the use of hearing protection in areas with frequent UAV flights will even increase the negative effects on the well-being of human workers (see, e.g., Kari et al., 2017).

Moreover, the implementation of UAVs as part of existing supply chain management and logistics management systems is subject to complex assessments. For example, the hardware of UAVs has to be extended by other systems (for example, RFID and barcode scanner) to perform operations such as stock management or inspections (Maghazei & Netland, 2020; Malang et al., 2023). Furthermore, the interaction of UAVs with industrial robots (multi-robot systems) and smart systems (e.g., data transfer and storage) requires accurate planning and coordination (Maddikunta et al., 2021; Sinnemann et al., 2022). The challenges impede the calculation of the return on investment (Maghazei et al. 2022). Thus, strategic planning is only possible through careful consideration of each step in the fit framework and by considering multiple perspectives from management, employees, and social accident insurance companies.

UAVs offer many advantages for processes in manufacturing and logistics. To ensure appropriate technological implementation, challenges must be identified and addressed. For human factors, there is considerable uncertainty about the potential for humans and UAVs to work together in indoor

environments. We identified cognitive performance and well-being as key issues that needs to be integrated into adoption processes in the future. This challenge must be considered from the technological as well as the organizational perspective to find holistic solutions with and for the employees who will work with UAVs in the Industry 5.0.

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## Appendix

### Appendix A. Technical description of the autonomous flights of the UAVs

For the autonomous flight implemented in the study, a realtime feedback of the UAV's position and orientation was used. Specifically, a motion capture system consisting of 10 Vicon Vantage V5<sup>1</sup> infrared cameras and the software Tracker 3 to track the UAV during flight was used. UAVs were equipped with reflective markers mounted on a 3D printed deck (see Fig. 3(c)). The communication and exchange of information between the ground station that evaluates the position information and the UAV was established through the Bitcraze Crazyradio PA<sup>2</sup> on a 2.4 GHz ISM band. For autonomous flights using the position information of the motion capture system, parts of the Python code provided by the CrazyFlie-SdGN<sup>3</sup> Github project were modified to implement a point-by-point flight using given reference points. Both reference points and position information are processed by the cascaded PID controller implemented on the UAV. More technical details can be found in Giernacki and colleagues (2017).

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<sup>1</sup> <https://docs.vicon.com/display/Vantage/Vantage+documentation>

<sup>2</sup> [https://www.bitcraze.io/documentation/hardware/crazyradio\\_pa/crazyradio\\_pa-datasheet.pdf](https://www.bitcraze.io/documentation/hardware/crazyradio_pa/crazyradio_pa-datasheet.pdf)

<sup>3</sup> <https://github.com/slim71/CrazyFlie-SdGN>

## Appendix B. Detailed overview of the study sample

**Table 6**  
*Demographical Data*

	total sample <i>N</i> = 48		experimental group <i>N</i> = 24		control group <i>N</i> = 24	
Variable	<i>M</i> <sup>a</sup> (range)	<i>SD</i> <sup>b</sup>	<i>M</i> (range)	<i>SD</i>	<i>M</i> (range)	<i>SD</i>
<b>Age</b>	25.91 (18-49)	6.38	24.45 (18-40)	5.38	27.36 (19-49)	7.06
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
<b>Gender</b>						
female	30	63.0	12	50.0	18	75.0
male	18	37.0	12	50.0	6	25.0
<b>Education Degree</b>						
vocational training qualification	3	6.3	2	8.3	1	4.2
baccalaureate degree	26	54.2	16	66.7	10	41.7
Bachelor degree	13	27.1	4	16.7	9	37.5
Master degree	6	12.5	2	8.3	4	16.7
<b>Current employment</b>						
unemployment	1	2.1	0	0.0	1	4.2
part-time employment	7	14.6	2	8.3	5	20.8
full-time employment	2	4.2	1	4.2	1	4.2
university studies	37	77.1	11	45.8	16	66.7
Ph.D.	1	2.1	0	0.0	1	4.2

Note. <sup>a</sup> *M* = Mean; <sup>b</sup> *SD* = Standard Deviation

## Appendix C. Detailed description of the Work Efficiency Test (WET)

The module salary determination consists of 44 individual text passages on employees of the GlobalCom company (example: Ms. Seifert is divorced and has a son from her first marriage. She sells 300 cell phone contracts per month. She has worked for GlobalCom for 12 years and is 42 years old. Ms. Seifert only uses the company car as part of her job at GlobalCom). For each of the statements, a salary group must be selected on a scale from 0 to 9. Participants have a total of two tables and a note on the company car. To solve the task, salary points must be taken from the tables using the following information: Age, work experience in years, sales volume of cell phone contracts, management tasks, and use of the company car. This results in a salary point value between 1350 and 4149, which must be converted to the salary group using a third table. In the assessment using the test manual, the number of correct solutions is counted and then compared with nomination samples. The reference group with a baccalaureate solves an average of 25.33 tasks. In our sample, the solution rate was  $M = 12.50$ , as the participants had a third less time available.