Investigating Body Gestures as Means of Input Modalities in Crowdsourced Microtasks

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Abstract

Microtask crowdsourcing has grown in popularity in recent years. Microtasking is a form of crowdsourcing in which typically small, simple tasks are distributed over the Internet to a large number of people, also known as workers. Workers are highly susceptible to developing musculoskeletal disorders due to prolonged computer use and the monotonous, performance-oriented nature of microtasking. Fortunately, it has been demonstrated that exercise can remedy these health issues. Since some body gestures resemble low-intensity exercise, the use of gestures as input in crowdsourced microtasks has the potential to improve the health of the worker. The purpose of this study was to determine which gestures are effective for controlling microtask workflows in terms of health benefits and usability. In an effort to maximize the positive impact on health, a total of 12 gestures were developed for four distinct microtask workflow elements. Then, we incorporated these gestures into a survey to evaluate the subjective perceptions of usability. On the basis of the survey results, we ranked these gestures for each workflow element and proposed three gesture-command dictionaries optimized for maximum efficiency. Due to the numerous limitations of this study, it is strongly recommended that the outcomes be enhanced. The primary contribution of this study is, therefore, the establishment of new research directions for gestural input in microtasking and in all human-computer interaction.

1 Introduction

Microtask crowdsourcing is increasingly being adopted to efficiently outsource simple but non-automated tasks. The individuals who complete these tasks, commonly know as workers, are required to repeatedly perform the same actions over long periods of time. Due to the monotonic nature of solving microtasks workers might be highly susceptible to developing long term health problems [24].

The proportion of office workers having musculoskeletal disorders is prominent [31], [30] especially among IT professionals and computer workers [23]. Kothapalli found that 67 percent of the participants experienced discomforts in a time span of one week [23]. Pain in the neck, shoulder and upper and lower back are the most prevalent musculoskeletal discomforts based on many findings [30], [23], [15]. According to Jensen et al. prolonged mouse use develops hand wrist and shoulder symptoms [21]. Furthermore, research suggest that the duration of computer work correlates with the prevalence of musculoskeletal disorders [31], [21]. Moreover, based on the findings of Coles-Brennan et al. digital eye strain is associated with incomplete blinking. [17]. To prevent or reduce the impact of these health problems it is suggested to exercise or change posture during prolonged computer work [14], [15], [25], [23].

Therefore, adopting body gestures in microtask crowdsourcing might replace the need for exercise or reduce the amount of exercise needed to preserve the worker's health. This study aims to answer the following research question: *In terms of health benefits and usability, what gestures of the body serve as an effective form of input for crowd-sourced micro-tasks?*

In this study, we established criteria for appropriate gestures and defined gestures for four microtask workflow elements. The design of the gestures took into account their potential health effects. Using a survey to evaluate the usability of these gestures, we established a ranking for gestures assigned the same workflow elements. As a final response to the research question, we created three gesture-command dictionaries based on our findings.

First, Chapter 2 describes the methodology. In Chapter 3, relevant work and additional context are discussed and reviewed. Chapter 4 presents our contribution as a part of the survey's design process. After presenting the results of the survey in Chapter 5, we then discuss them in Chapter 6. Additionally, limitations and future work are included in that section.

2 Methodology

2.1 Qualitative literature analysis

To gain a deeper understanding of the possibilities for gestural input in microtasking, we first conducted a literature review. The previous work on microtask taxonomies, gestures in human-computer interaction, gesture recognition technologies, and the health problems of computer work and their exercise-based treatment were investigated. Our primary resources for peer-reviewed research articles were Scopus, Science Direct, Web of Science, and Google Scholar.

Using the findings of the literature review as a guide, a survey was designed to assess the usability of twelve specific gestures. After selecting the appropriate recognition technology, we determined which workflow elements of microtasks are applicable for gesture control. For each workflow element, we designed three gestures based on body movements that have been demonstrated to effectively treat musculoskeletal disorders of typically affected body regions. This process of this qualitative analysis is described in detail in Chapter 4, as it is based on the findings of the literature review. The survey included only the gestures that were presented in that chapter.

2.2 Measuring usability

To evaluate the perceived usability of the gestures, we chose three criteria: ease of use, error tolerance, and efficiency, in order to compare the various gestures associated with the same system functionality. Therefore, we asked participants to rate each gesture on these characteristics using a 7-point Likert scale. Respondents were asked to evaluate each item by answering the following questions:

- Q1 How easy was it to use this gesture? (ease of use)
- Q2 How likely is it to unintentionally make this gesture? (tolerance for error)

Q3 How productive did you feel while using this gesture? (efficiency)

The possible responses for Q1 ranged from very difficult to very simple, while the seven responses for Q2 ranged from very unlikely to very likely. For Q3, respondents could select responses ranging from very unproductive to very productive.

Instead of analyzing gestures based on all three aspects of usability separately, we compared gestures based on their overall usability scores. These scores for usability were determined using the average of individual ratings for ease of use, error tolerance, and effectiveness. To account for the fact that, in contrast to ease of use and effectiveness, small tolerance for error scores (close to 1) were associated with positive perceptions and large tolerance for error scores (close to 7) were associated with negative perceptions, we subtracted the scores from 8. In addition, each factor was given equal weight.

2.3 Conditions of the survey

The survey was hosted using Google Forms; consequently, the data was collected and stored on third-party servers provided by Google, with access restricted to the researchers of the study. A link to the survey was shared on the crowdsourcing platform Prolific, where participants were recruited.

Participants were screened beforehand to ensure that only English-speaking individuals with at least five previous valid submissions would complete the survey on a laptop or desktop computer. The study was distributed to all Prolific participants, and participation was permitted in all countries where Prolific is available.

The exact copy of the survey can be found in Appendix A.

3 Literature review

3.1 Workflow and control in microtasks

Gadiraju et al. proposed a categorization scheme for typically crowdsourced microtasks based on the tasks' objectives and workflows [19]. In this study, we employ their findings to determine which workflows and how they can be controlled via gesture commands. In this section, we classify these processes depending on the type of actions required to complete the microtasks to which they belong. It should be noted that our classification includes overlaps across groupings and excludes specific workflows that do not fit into any of our categories. Nevertheless, the classification is adequate for identifying which workflows are ideal for gesture control.

The first category consists of microtasks for which inputting text was a strict requirement. Typically, these require the worker to type text in various circumstances. Media transcription, data collection and enhancement, content feedback, translation, demographics, and tagging fall under this category.

In tasks of the second category, the worker is asked to visit an external website and perform tasks or find information on an unknown user interface. This typically necessitates the use of a mouse-like input device with a pointer. Classes of microtasks belonging to this category are promoting, testing, metadata finding, and ranking.

In the third case, workflows can be condensed into yes-no questions. This type of microtask is frequently used in content moderation, where workers are required to review and approve or reject content based on a set of guidelines. In spam detection, users are asked to review and report spam content.

Lastly, certain tasks require the worker to select from a predetermined list of options to categorize and classify content, and can therefore be transformed into multiple-choice questions. In addition to categorization and classification, similar representations can be found for content moderation, sentiment analysis, data collection and enhancement, spam detection, data selection, and quality evaluation.

3.2 Gestures in Human Machine Interaction: Taxonomy

In Human Machine Interaction, gestures are typically employed to send commands to a system with the intent of directly influencing its internal state. This is referred to by Carfi and Mastrogiovanni as a functional human-machine interaction [16]. Consequently, they refer to the gestures used in functional HMI as functional. On the basis of this distinction, two researchers have recently developed a functional-gesture taxonomy as part of a more comprehensive conceptual design framework that aims to ensure the efficacy of development efforts in gesture-based HMI. They classified gestures on the basis of four primary characteristics: effect, time, focus, and space. This section introduces this taxonomy in order to define gestures later in this paper. Due to the fact that their work is recent, exhaustive, and addresses the shortcomings of previous gesture taxonomies, we decided to rely solely on their taxonomy.

The state of a system can be continuous or discrete. Effect distinguishes gestures based on the effect they have on the system's state. Continuous gestures yield data that is mapped at each time instant to a state change in the system. Discrete gestures automatically associate a change in the system with the entire gesture.

Time can also be used to categorize gestures. The three phases of a gesture are preparation, stroke, and retraction. In the preparation phase, the body part is moved to its initial position. Static gestures are those in which the stroke phase entails maintaining the pose in the starting position for a period of time and the retraction phase entails moving to the next pose. Dynamic gestures, on the other hand, are those in which both the stroke and retraction phases are dynamic, with body parts having velocity and acceleration. Continuous system states cannot be associated with static gestures.

The third characteristic, focus, describes which body parts are the focal point of the gesture. This essentially describes which movements or positions of body parts convey meaning. Carfi and Mastrogiovanni contend that these are properties of gestures, not categories per se.

Finally, gestures can be classified according to space. Spatially related gestures are those in which the gesture's meaning is tied to the physical location of the body parts. In contrast, spatially unrelated gestures are those in which the meaning of the gesture is not associated with the physical location of the body part but rather with the orientation, inclination and the body part that appeared.

3.3 Health issues and exercises

In the introduction, we argued that using gestures as input in microtask crowdsourcing has the potential to replace exercising, thereby improving the physical health of workers. To be able to determine the types of gestures that have a positive health impact, it is necessary to identify the body regions most commonly affected by musculoskeletal discomfort and to determine which exercises are the most effective at alleviating discomfort in these regions.

Kothapalli investigated the prevalence of self-reported work- related musculoskeletal disorders (WRMSDs) among software professionals [23]. They found that the most frequently reported symptoms are neck (65.0%), upper back (56.4%), lower back (62.6%), right shoulder (41.4%), left shoulder (35.4%) and right thigh (41.4%). Less extreme but still significant proportion (more than 25%) of the participants reported upper arm, lower arm and wrist pain. Berényi and Sasvári investigated the undesirable health impacts of computer work and found that workers experience milder or stronger back and shoulder pain (78.5%), eye strain (75%), neck pain (65.5%), waist pain (59%), pain in the hands and arms (43.5%) and fingers (40%). [14]. (put the info about eye strain in the intro can go into). Shariat et al. also investigated the prevalence and severity of WRMSDs [30]. Their findings indicate that office workers are more vulnerable to body aches in the neck, shoulders and lower back then pain in other parts of the body. Furthermore, Cagnie found that 45.5% of office workers experience neck pain [15]. They highlighted that results of many other studies also indicates a high prevalence of neck pain among office workers.

According to Jensen et al. prolonged mouse use develops hand, wrist and shoulder symptoms [21]. Wærsted also found that computer mouse and keyboard time relates to a diagnosis of wrist tendonitis and can cause forearm disorders [33]. Ali and Sathiyasekaran found that the prevalence of wrist symptoms (Carpal Tunnel Syndrome) was 13.1% among the participants. The same research it was shown that higher risk for Carpal Tunnel Syndrome was found with higher exposure to computer work [12].

The aforementioned data suggests that employing gestures based on exercises that target the neck, shoulders, lower back and waist, hands and fingers and the wrists are the most effective in terms of their health effects.

The following exercises are useful to reduce neck pain and disorders: tilting the head sideways [25] [1] [2] [10], bending head up and down [25], dropping the head down so that the chin touches the chest, rotating from side to side [25] [1] [2], turning head left and right [2] [10].

The following exercises treat shoulder symptoms: raising the shoulders to the ears [25] [1] [10], rotating shoulders them forward or backward [25] [1] [2] [10], cross-body stretch [10], overhead shoulder stretch [2] [10].

To tackle discomforts in the wrists the following activities are advised: stretching the wrist by pulling the hand upward and downward at the wrist [25] [8] [2] [10], banding wrist from side to side [2] [10], forearm flexors (putting palms together and raising elbows) [10], starting with hand being in a handshaking position and rotating palm up and down [10].

The following hand and fingers exercises are commonly mentioned in sources: thumb flexion and extension [8], extended finger stretch (bending all fingers at the knuckles) [8] [2] [10].

The following exercises focus on the back: reaching towards the ceiling [2], [10], straightening out arms in front with the fingers interlaced [10], executive stretch (hands behind the head bring elbows back as far as possible leaning back and stretching) [25] [2] [10].

Lastly, according to Kumar and Coles-Brennan, blinking helps with tackling eye strain [25] [17].

3.4 Gesture recognition

Gesture recognition technologies are used to interpret human gestures through mathematical algorithms [22]. This technology enables computers to recognize human gestures as input, enabling users to control applications without the use of conventional input devices such as keyboard or mouse.

There are two major categories of gesture recognition technologies: sensor-based and vision-based [28], [11]. Others call the former as physical-based or wearables in reference to the fact that, unlike vision-based devices, they are worn or held by the user [32]. According to Al-Shamayleh et al., vision-based solutions are overwhelmingly preferred over their sensor based alternatives; they are used in 77.2% and 22.8% of the cases respectively [11].

Numerous studies attempted to further classify technologies and devices in both categories [28], [16], [11], [32]. Commonly mentioned wearables include inertials that employ accelerometers and gyroscopes to utilize the Earth's magnetic field, mechanicals such as gloves and body suits, electromyogram (EMG) based devices that measure electrical activity in response to nerve stimulation of the muscle. Other non-wearable sensor-based devices include haptics, devices that use radio frequency, ultrasound, and electric field sensing. The more widely researched [16] vision-based technologies are typically based on regular video cameras, depth sensing cameras and motion capture systems. Regular video camera-based techniques extract depth information from 2D sensory data using either a single camera, such as a webcam, or multiple cameras. Using infrared light, depth capture cameras recognize the three-dimensional structure of an object.

Wearables have many disadvantages but only a few benefits. Due to being attached to the body, the use of wearable might result in greater degree of fatigue, discomfort and consequently divert users' attention away from the gestures [32]. Furthermore, their operation and configuration require user experience [11]. Most of these technologies are still in early stages of development making them unaffordable to the general public [29]. On the other hand, the absence of noise in sensing and the relatively high precision make it more appealing [29]. However, other sources state that they are still less precise than their vision based counterparts [13], [11].

On the contrary, most vision-based solutions have numerous benefits and relatively few major drawbacks. They are inexpensive, user-friendly, readily available [11] and the devices are portable [32]. The use of bare hands, the simplicity of their use, and lack of interference with the users' gestures align well with the objective of achieving intuitive interface interaction [32]. Although Vuletic at al. think they often lack consistent and sufficient precision, and despite having overcome many obstacles (such as problems with rotation, scale and illumination invariance, and cluttered backgrounds), potential occlusion and having insufficient real world data to train machine learning models are still open issues [29].

Comparing recognition technologies demonstrates that vision-based solutions are more affordable, convenient, and accessible than sensor-based alternatives. Furthermore, having a small gesture dictionary with simple, intuitive gestures mitigates the risks associated with using vision-based technologies.

When selecting the right gesture recognition technology that enables gesture control in microtask crowdsourcing, it is essential to take into account the specific circumstances of the crowdworkers. According to research, equipment affordability is one of the primary reasons workers participate in crowdwork [18]. Moreover, a study conducted by Newlands and Lutz found that 99.5% of workers in the US and 98.9% of workers in India complete microtasks using their laptop or desktop computer [27]. Since most laptops are equipped with a camera (79%) [9] and the price of new webcams is low compared to other devices, it makes webcams adequate enablers of gesture control in microtasking. Additionally, open source libraries such as MediaPipe [26], GRT [20] and Human Library [3] enable developers to create gesture webcam-based recognition systems.

More specifically, MediaPipe is a graph-based framework for constructing multimodal applied machine learning pipelines [4]. It also facilitates the integration of machine learning technology into applications on a vast array of different hardware platforms (e.g., Android, iOS, workstations). They provide solutions for a variety of applications that can be utilized in developing software for gesture control in microtasking, such as real-time hand tracking [7], real-time body posture tracking [6] and simultaneous hand, face, and posture perception [5]. Their real-time body pose tracking approach is capable of tracking 33 human body key points, including multiples on the face, hands, and feet, which makes it suitable for gesture dictionaries that omit finger and face gestures. Their holistic approach, however, can identify up to 21 hand and 468 facial landmarks in addition to the 33 body key points. Each toolkit is available in Python, JavaScript, and C++.

4 Beyond the literature: Survey design

This chapter describes in depth how the gestures tested in the survey were constructed. Additionally, we provide justification for our selection of gesture commands and gesture recognition technology.

4.1 Controlling workflows with gestures

In Chapter 3.1, we introduced four types of microtasks based on the required control actions. In this section, we determine which workflow elements are applicable to gesture control.

To answer a yes-no question, the worker must issue commands corresponding to answering yes or answering no and submissions of answers. Submission of answers facilitates progression to the next question.

In the case of multiple choice questions, the worker must select one of an arbitrary number of options. The random number of available options prevents us from associating a specific action with a specific option. However, the workflow can be reduced to two symmetrical navigation control actions for moving left and right in the list, as well as a giving a third command for answer submission, as previously mentioned.

To complete other kinds of microtasks, the workers are required to input text and move a pointer to complete tasks. The technologies that enable performing mouse actions and typing with gestures are still in the early stages of development and, consequently, are less accurate and less efficient than conventional input methods. As a result, we are focusing our efforts completely on developing gesture commands for the workflows described above.

In addition, workers are frequently required to examine diverse content before responding to a question. Large or multiple images and embedded websites cannot always be displayed in their entirety on-screen. Given their prevalence in microtasks, our gesture-based interface must also support web page scrolling. Consequently, in this project, we also investigate gesture commands for the scrolling functionality.

4.2 Gesture Control System

We mentioned in section 3.4 that webcams and open source frameworks like MediaPipe are suitable for developing gesture-based control systems for microtasking. However, due to the limited time available, we decided not to develop software for this research. Instead of using a real gesture control system to test the gestures, participants were asked to imitate the gestures seen in recordings and thus experience using a real gestural interface vicariously. Regardless, gestures were designed to be compatible with webcam recognition capabilities.

4.3 Selecting Gestures

In section 4.1, we determined which microtask categories are adequate for gesture control and described their workflow. In this section, using the gesture taxonomy presented in section 2.2, we establish criteria for suitable gestures for elements of these workflows and construct three specific gesture commands for each workflow.

The choice of gesture recognition technology restricted the available gestures to those that could be performed while seated within the webcams' field of view.

In addition, prior research identified neck, shoulder, and lower back pain, in addition to eye strain, as the most prevalent conditions. As sitting makes movements of the lower back difficult, we concentrate on the neck, shoulders, and eyes when deriving gestures. Hand and wrist symptoms are less common. However, because hand gestures are typically very user-friendly, we also investigate gestures involving the wrist and fingers.

Answering yes or no (move the marker one to the right or left)

In order to answer yes-no questions, the worker must place the marker on one of the options. It should also be possible to move the marker from one option to the other.

Discrete static or discrete dynamic gestures that are spatially related or unrelated are best suited for this purpose. Discrete since we need to associate a whole gesture with distinct commands. When dynamic spatially unrelated gestures are employed, the movement itself carries meaning. When we prefer to associate meaning with the positioning of a static posture, static spatially related gestures are the most appropriate. Additionally, static spatially unrelated gestures are most effective when the meaning is conveyed through the body part's tilt or rotation.

The following gestures were selected for evaluation for this workflow component:

- G1.1 Lifting the arm, showing palm to camera, swiping arm towards center of body while showing hand to camera
- G1.2 Showing palm to the camera, bending the wrist to the left and right.
- G1.3 Taking an executive stretch and bending the entire upper body to the left and right.

All of these gestures are discrete dynamic and spatially unrelated since we aim to associate meaning with the movement of the body parts. Although, depending on the characteristics of the gesture recognition system, meaning could also be associated with the physical position, inclination, or rotation of the body parts, hence making G1.1 static spatially related; G1.2 and G1.3 static spatially unrelated.

G1.1 focuses on shoulder muscle and joint activation, G1.3 resembles an executive stretch with side and back muscle activation, and G1.2 was designed to activate the wrist joint and stretch the forearm.

Submitting answers and move to the next question

In dichotomous or multiple choice questions, the action must be confirmed to move to the next question. This prevents unintentional marker placement as an answer.

This task is best suited to discrete dynamic or discrete static spatially unrelated gestures. A single command must be linked to a gesture. We believe that as long as it is simple and usable, either conveying information in the movement or associating meaning to the position of body parts are equally reasonable choices for this functionality.

We decided to test three discrete spatially unrelated gestures: two static and one dynamic.

- G2.1 Raising both shoulders to the ears and holding them for at least half a second.
- G2.2 Closing the eyes for more than 2 seconds.
- G2.3 Extended finger stretch. (raising both hands so that they are visible to the camera and bending the fingers at the knuckles).

G2.1 was designed to activate shoulder muscles, whereas G2.2 was created to relieve eye strain by incentivizing users to close their eyes. Finally, G2.3 aims to reduce hand and fingers discomforts while incorporating shoulder movement.

Moving the marker an arbitrary number of times to the right or left

To select an option in multiple choice questions, the marker needs to be moved an arbitrary number of times to the right or left. Commands for answering yes or no can be used for taking a single step. The marker is assumed to be placed on the middle option.

For this purpose, discrete static gestures, spatially related or unrelated, or continuous dynamic spatially related gestures can be used. With the former, the duration of holding a posture is associated with the degree of the marker's movement (the marker moves syncronously). The direction of movement can be indicated by performing the same action with opposite body parts or performing mirrored actions with the same body part, making the gestures spatially unrelated and spatially related, respectively. We ruled out discrete dynamic gestures as they involve unnecessary stroke and retraction phases. As a result, we ruled them out. In the case of continuous gestures, the extent of movement is associated with the degree of the marker's movement.

Two discrete static spatially unrelated and one continuous dynamic spatially related gesture were chosen to be tested for this workflow element:

- G3.1 Bending the head to the sides and holding the posture until the marker moves onto the desired option.
- G3.2 Hand raised with palm orthogonal to screen plane. Holding a bent wrist until the marker moves to the right option.
- G3.3 Bending fingers at the knuckles to grab the marker, then moving the hand to the left and right to move the marker. Straighten fingers to release the marker.

G3.1 is intended to alleviate neck pain by stretching its muscles. In contrast, G3.2 was designed to mimic a specific wrist stretching exercise that also engages the shoulders. Similarly to G2.3, G3.3 also includes an extended finger stretch to alleviate hand and finger discomfort.

Scroll up and down

To facilitate scrolling, discrete static spatially related or unrelated gestures can be used. In this case, the position, orientation, or rotation of a body part can be linked to the direction of scrolling, and the duration of a posture's stroke phase can be linked to the degree of page scrolling. Scrolling for a specific portion of a screen is possible with discrete dynamic gestures. In contrast, for continuous gestures, the extent of movement of the body part can be related to the degree of page scrolling.

A discrete static spatially unrelated, a continuous dynamic spatially related and a discrete dynamic spatially unrelated gesture were tested in the survey:

- G4.1 Pointing thumb up and down to scroll with a constant speed. The forearm is held vertically and parallel to the screen.
- G4.2 Single palm facing the screen, bending knuckles to grab the screen. Moving your hand downwards or upwards with your fingers bent to scroll.
- G4.3 Swiping up with a hand, palm facing up, to scroll up half a page. Swiping down with a hand, palm facing down, to scroll down half a page.

Similar to G1.2, G4.1 requires the user to rotate their wrist to indicate the scrolling direction. In this manner, the wrist joints and forearm muscles are activated. Due to the elevated arm position, the shoulder is also moved. Similar to G2.2 and G3.3, G4.2 addresses hand and finger discomfort by imitating the extended finger stretch. Finally, G4.3 was designed to stimulate the wrist and shoulder.

Later in this paper, we will refer to the unique identifier for each of the gestures presented in this subsection.

4.4 Content of the recordings

Although the recordings used for this survey are not publicly available, their content can be shared so that they can be recreated. Each video depicts a typical interface for each workflow element along with a subject performing the gestures, creating the illusion that he is controlling a real system.

The first recording guides the participant through answering yes-no questions and submitting their answers, allowing them to proceed to the next question. After selecting yes or no with G1.1, the subject used G2.1 to move to the next question. G1.2 was paired with G2.2 and G1.3 was paired with G2.3 to carry out the identical action sequence. The second video introduced G3.1, G3.2, and G3.3 to instruct the respondent on how to mark options in a multiple choice question, while the third video demonstrated scrolling using G4.1, G4.2, and G4.3, respectively.

5 Results

A total of ten individuals participated in the study, with an vast majority of them being between the ages of 18 and 25. The remaining participants were aged 25–30 and 50–60, each contributing 10 percent to the responses. The average respondent had been working on different crowdsourcing platforms for one to two years, and none had been completing microtasks for longer than four years. Only two respondents mentioned additional sites besides Prolific, namely Swagbucks, Lifepoints, YourGov, and Amazon MTurk. In the following sections, we present our findings regarding the usability of gestures.

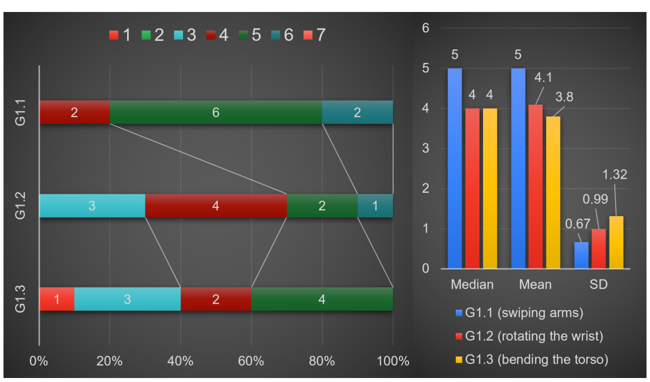

Figure 1: Distribution, median and mean of usability scores of the different gestures designed for answering yes no questions.

We found that the most usable gesture for answering yes and no questions was G1.1, with a median score of 5 and a mean value of 5. The standard deviation for this gesture was 0.67, making arm swipes the only gesture that was unanimously rated positively. The median values for rotating the wrist (G1.2) and bending the torso (G1.3) were both 4, with respective means of 4.1 and 3.8, making G1.2 preferable. Although G1.3 is not the lowest-rated gesture in this study, with a standard deviation of 1.32, it appears to be the most divisive. The order of these gestures is therefore G1.1, G1.2, and G1.3. Figure 1 illustrates the median, mean, and distribution of usability scores for each gesture.

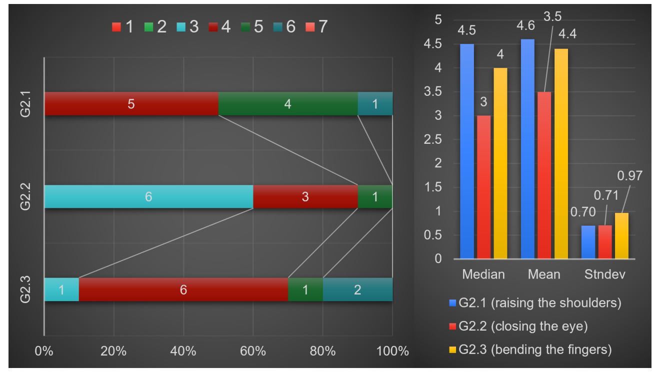

Figure 2: Distribution, median and mean of usability scores of the different gestures designed for submitting an answer.

According to the data, the shoulder-raising gesture (G2.1) is the most suitable for submitting answers, with the highest median usability (4.5), highest mean usability (4.6), and lowest standard deviation (0.70). Due to the fact that the former has a median of 4 and a mean of 4.4, while the latter has a median of 3 and a mean of 3.5, it appears that bending the fingers (G2.3) is a better way to submit an answer than closing the eyes for 1.5 seconds (G2.2). Despite the fact that G2.3 has a slightly larger standard deviation than G2.2 (0.97 versus 0.71), both gestures have a minimum score of 3, therefore the three gestures' usability is ranked as follows: G2.1, G2.3, and G2.2. Figure 2 depicts the median, mean, and distribution of each gesture's usability score.

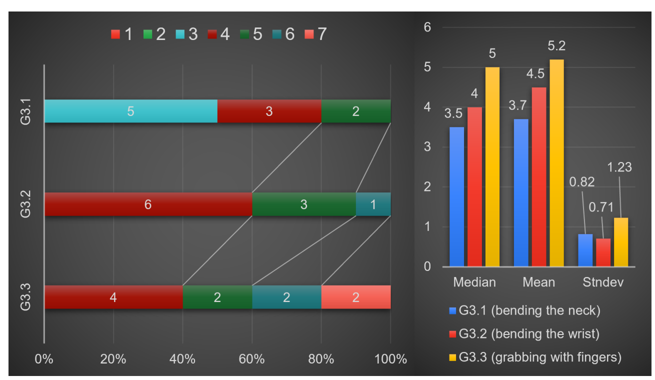

Figure 3: Distribution, median and mean of usability scores of the different gestures designed for answering multiple choice questions.

G3.3 has the highest usability scores in this survey, with a median and mean of 5 and 5.2, making it the most suitable for marking multiple-choice answers. Even though it is the second most divisive gesture in this survey, with a standard deviation of 1.23, it receives only positive responses, confirming its position. Bending the wrist (G3.2) is measurably more effective than bending the neck (G3.1) for answering multiple-choice questions, as evidenced by a higher median (4 to 3.5) and mean (4.5 to 3.7) and a lower standard deviation (0.71 to 0.82). As a result, the usability rankings for these gestures are G3.3, G3.2, and G3.1. Figure 3 portrays the median, mean, and distribution of usability scores for each gesture.

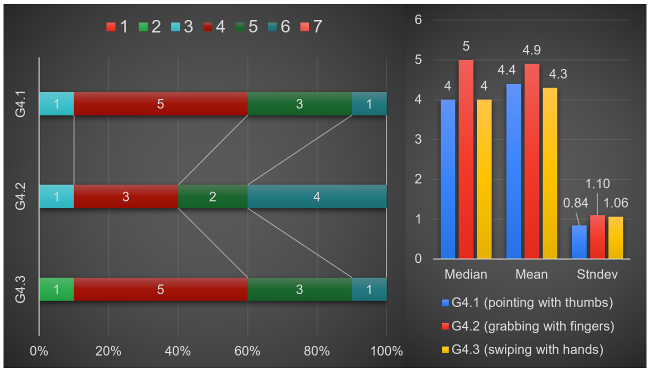

Figure 4: Distribution, median and mean of usability scores of the different gestures designed for scrolling.

The most feasible gesture for scrolling was G4.2, which received a median score of 5 and a mean value of 4.9. Despite a high standard deviation, its usability scores range between 3 and 6, indicating a positive overall impression. The remaining two gestures were rated similarly in terms of usability. However, pointing with thumbs (G4.1) received a higher overall usability score with a median of 4, a mean of 4.4 and a standard deviation of 0.84 than swiping with a hand (G4.3) received a 4, 4.3 and a 1.06 for the same measures. As a result, these gestures are ranked as follows: G4.2, G4.1, and G4.3. Figure 4 depicts the median value, mean value and the distribution of usability scores for each gesture.

The time and effect of the gestures presented in this survey appear to influence the perceived usability of body movements and postures. In general, continuous gestures have been found to be more usable than discrete ones. Similarly, dynamically moving body parts is a more preferred method for selecting multiple-choice answers, submitting answers, and scrolling than maintaining a static posture. The spatial characteristics of these gestures appear to correspond with their effects. Lastly, usability scores indicate that gestures involving the hands, fingers, and arms are generally more usable than gestures involving head, eye, and torso movements.

6 Discussion

In this research we investigated the effectiveness of different gestures. As we discussed earlier, effectiveness conveys both health benefits and usability, therefore, in order to find effective gestures, both factors need to be considered. Here, after elaborating on the limitations of this research, we establish a criteria for effectiveness and provide concrete gesture-command dictionaries to serve as a foundation for future implementations of a gestural interface for microtask crowdsourcing.

Limitations

The current study has several limitations that should be taken into account.

First, we recruited our participants through Prolific, a platform accessible in the majority of OECD nations. This prevents participation in most of the developing world, thereby limiting the applicability of our results to other populations and creating a sampling bias.

Second, participants were compensated for their responses on Prolific. Due to the length of the survey and budgetary constraints, we could only recruit ten individuals. The N = 10 sample size is insufficient, however, to draw valid conclusions from the statistical analysis. Accordingly, there may be issues with statistical power in the study's findings; consequently, they cannot be generalized to the general population.

Thirdly, there has been limited prior research on microtask workflows and taxonomies, making it challenging to select the most pertinent tasks for our study. In addition, because the inclusion of more complex functionalities would have necessitated additional research, we had to impose reasonable limitations on the microtask workflows that were included.

Instead of using a gesture recognition system to test the gestures, participants were asked to imitate the gestures seen in videos and thus vicariously experience using a real gestural interface. As a result, we were unable to collect objective usability data, and the usability ratings of gestures were based solely on the limited subjective perceptions of the respondents.

Fifth, while webcams are a viable option for microtasking, other inexpensive consumer electronics devices may also be capable of supporting microtasking gesture control. Due to time constraints, we were unable to investigate other similarly viable gesture recognition technologies in depth.

The connection between gestures and health-improving exercises is tenuous, so gestures' health benefits are not supported by substantial evidence. We also did not create a ranking of gestures based on their health benefits. We therefore assumed that all gestures were equally effective at remedying musculoskeletal disorders.

To compare the health benefits of various gestures, it would be necessary to quantify the health effects of each gesture, which is beyond the scope of this study. However, gesture-command dictionaries can be created to address a wide variety of bodily discomforts, thereby maximizing the health benefits thereof.

Gesture-command dictionaries

As demonstrated in Chapter 5, certain body regions are favored over others; therefore, in order to construct a sufficiently diverse dictionary of gesture-commands, we must also consider gestures that are less usable. To ensure that none of the selected gestures are specifically unusable, we recommend differentiating between usable and unusable gestures according to the following criteria: With nine out of ten participants giving a score of at least four, the usability score is strictly greater than four. This way, we ensure that the vast majority of individuals rated the gesture positively or at worst, neutrally. In order to prevent the exclusion of certain individuals, we prohibit receiving multiple negative responses.

Based on the aforementioned criteria, the following gestures can be considered for inclusion in future gesture-command dictionaries: G1.1, G2.1, G2.3, G3.2, G3.3, G4.1, G4.2, G4.3. Consequently, we propose the following gesture-command quadruples as effective inputs for crowdsourced microtasks:

- **G1.1-G2.1-G3.2-G4.2**: The combination of G1.1 and G2.1 aims to relieve discomfort in the shoulders. Combining them with G3.2 extends the health benefits to the wrists, whereas the addition of G4.2 improves the ability of this set of gestures to stretch the hand and fingers.
- **G1.1-G2.1-G3.3-G4.1**: This quadruple targets the same body regions as the previous set, with G3.3 focusing on the hand and fingers and G4.2 aiming to alleviate wrist symptoms.
- **G1.1-G2.3-G3.3-G4.3**: G2.3 and G3.3 are designed to alleviate discomfort in the hands and fingers, while G4.4 targets wrist issues. In addition to G1.1, G3.3 and G.4.3 contribute to the treatment of the shoulder by activating muscles and joints.

Improvements and Future Work

These dictionaries are merely illustrative of how our findings may be utilized in future endeavors. This study lays the groundwork for the development of more extensive and thorough dictionaries that take into account the limitations of this research and are tailored to the conditions of a future gestural interface.

More specifically, we recommend modifying the conditions of this experiment to continue investigating effective gestures in microtask crowdsourcing. To increase statistical power, we recommend increasing the number of prospective survey participants. To improve the accuracy of the results, we suggest testing the gestures with a microtasking-specific real-world gesture recognition system. As participants would have direct experience with microtasking, hosting the survey on microtasking platforms may also increase the relevancy of the results.

Moreover, at the dawn of the digital age, as computer use become ingrained in our daily lives, the issue of the negative health effects of computer work is becoming of paramount importance. Therefore, we recommend exhaustively investigating the health-improving potential of gestural input not only in microtasking but in all human-computer interaction.

7 Responsible Research

Since this study includes an experiment involving human participants, the ethical implications of the research have been thoroughly considered. Additionally, we elaborate on the reproducibility of our results in this section.

Participants were selected at random from Prolific and were compensated equally for their participation adhering to Prolific's guidelines. To ensure that each participant was compensated equitably, regardless of their efficiency, we set the estimated completion time for the survey to be longer than what was actually required and compensated respondents accordingly. One response was discarded since the respondent did not devote sufficient time answering the questions. Disqualification was administered in accordance with the platform's rules.

Through informed consent, participants were educated on the objectives and risks of the research. Participants were also informed that their participation in the survey was voluntary and that they were free to leave at any time.

Furthermore, the data collected from respondents was securely stored and handled to ensure confidentiality. The responses were processed and presented without revealing any information about the respondents.

Lastly, the funding institution, Delft University of Technology, had no vested interest in the study's outcome. As long as we published the questionnaire on Prolific and stayed within budget, we had complete authority over the survey's circumstances.

To ensure that the results are reproducible, we have attached the survey questions at the end of this document. Since the recordings from the survey are not publicly available, we described the content of each video in section 4.4. Based on that and the section 4.3 descriptions of the gestures, the recordings can easily be recreated. Furthermore, the exact conditions of the survey, including sampling and prescreening of participants, are also described in section 4.4, allowing for the reproduction thereof.

On the other hand, statistical power issues with our results, stemming from the small sample size, may deter researchers from replicating them, thereby preventing future observations of the same tendencies.

8 Conclusions

Due to poor posture and lack of movement, microtask workers are at a high risk of developing musculoskeletal disorders. However, as we have previously demonstrated, exercise has been shown to reduce bodily discomfort. Consequently, incentivizing microtask workers to exercise is a promising strategy for addressing the computer-related health issues of these individuals. In light of the fact that performing certain body gestures resembles low-intensity exercise, we investigated which body gestures are the most effective means of input for crowdsourced microtasks in terms of health benefits and usability.

To achieve this, we conducted a literature review on microtask taxonomies, gesture taxonomies, gesture recognition technologies, and the health implications of computer work in order to investigate the potential for gestural input in microtasking. Following a review of the relevant literature, a questionnaire was developed to assess the usability of gestures. In order to establish criteria for appropriate gestures, we determined which microtask workflow elements are applicable for gesture control as part of the design process. Finally, we designed specific gestures for the survey, taking into account their impact on health.

The results demonstrated a distinct hierarchy of gestures for each workflow element. Swiping the right and left arms inwards to indicate no and yes, respectively, is the most effective way to respond to yes-no questions. Shoulder-raising is the most preferred method for submitting answers. Two similar gestures, bending the fingers at the knuckles to activate control and moving the hand horizontally to move the marker sideways or vertically to scroll up and down, were found to be the most potent for answering multiple choice questions and scrolling. In general, hand, arm, and finger gestures were proven to be more effective than head, eye, and torso movement gestures. In addition, the findings indicate that continuous and dynamic gestures are preferred over discrete and static ones.

These results, however, must be improved due to the limitations of this study. We recommend combining quantitatively measured health benefits with usability to determine the effectiveness of gestures. Furthermore, we recommend testing a broader set of gestures with a larger number of participants using a real-time gesture recognition system. Finally, we encourage further research into the health-improving potential of gestural input in human-computer interaction.

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A Survey Questions

See the next page.

Investigating gestures as input modalities in microtask crowdsourcing

WARNING! After submitting the survey you need to click the link on the confirmation page that redirects you to Prolific! Otherwise your efforts will not be rewarded.

* Required

1. What is your prolific ID? *

2. Age *

Mark only one oval.

- 18-25
- 25-30
- 30-40
- 40-50
- 50-60
- 60+

3. How long have you been working on microtask platforms? *

Mark only one oval.

- Less than 1 year
- 1 - 2 years
- 2 - 3 years
- 3 - 4 years
- More than 4 years

4. Have you worked on other microtask platforms such as Amazon MTurk, TimeBucks, Clickworker etc. ? If yes, which ones? *

Mark only one oval.

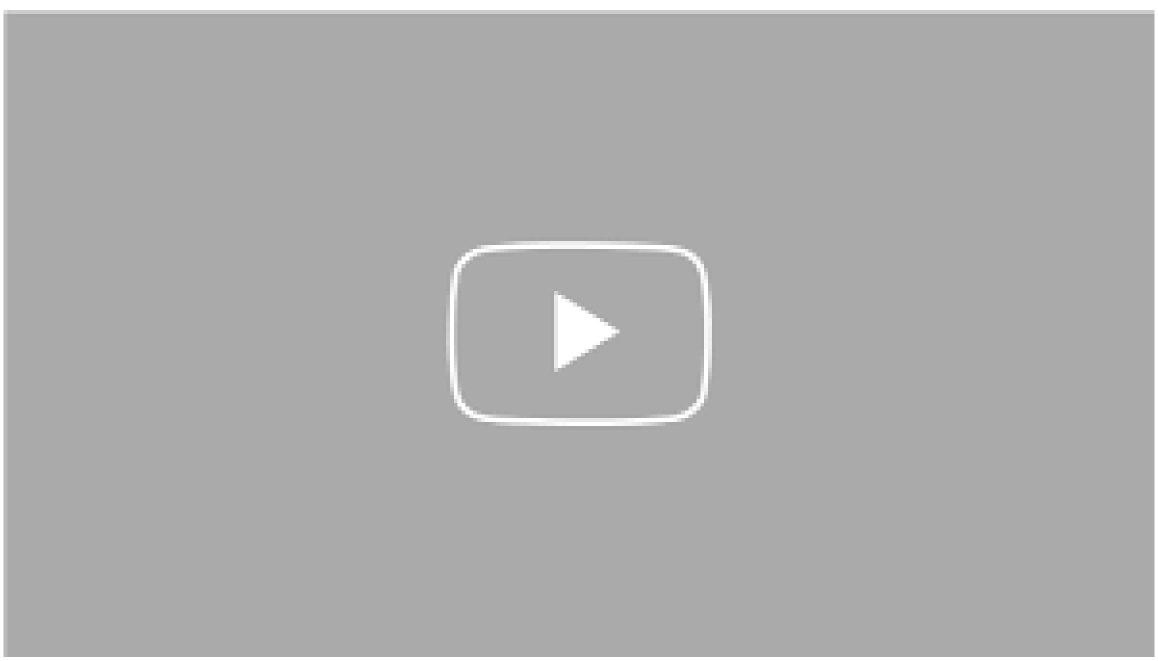
- I have not.
- Other: ______________________

Below are three videos that demonstrate specific gestures for controlling different types of microtask workflows.

Section I.

Please pay attention to every instruction.

In this video we present gesture controls for answering yes & no questions. This coveys answering the question and moving forward to the next question (submitting the answer). Please follow along and imitate the gestures.



5. 1.1 How easy was it to use these gestures (used for marking answers)? [very hard (1) - very easy (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (swiping the arms)							
gesture 2 (rotating the wrist)							
gesture 3 (bending the torso)							

6. 1.2 How likely is it to unintentionally make the gestures (used for marking answers)? [very unlikely (1) - very likely (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (swiping the arms)							
gesture 2 (rotating the wrist)							
gesture 3 (bending the torso)							

7. 1.3 How productive did you feel while using the gestures (used for marking answers)? [very unproductive (1) - very productive (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (swiping the arms)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 2 (rotating the wrist)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 3 (bending the torso)	⬭	⬭	⬭	⬭	⬭	⬭	⬭

8. 1.4 How easy was it to use these gestures (used for moving to the next question)? [very hard (1) - very easy (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (raising the shoulders)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 2 (closing the eyes)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 3 (bending the fingers)	⬭	⬭	⬭	⬭	⬭	⬭	⬭

9. 1.5 How likely is it to unintentionally make the gestures (used for moving to the next question)? [very unlikely (1) - very likely (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (raising the shoulders)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 2 (closing the eyes)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 3 (bending the fingers)	⬭	⬭	⬭	⬭	⬭	⬭	⬭

10. 1.5 How easy was it to fail attention check (attention check: mark only 2s to pass this check)? [very hard (1) - very easy (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (raising the shoulders)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 2 (closing the eyes)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 3 (bending the fingers)	⬭	⬭	⬭	⬭	⬭	⬭	⬭

11. 1.6 How productive did you feel while using the gestures (used for moving to the next question)? [very unproductive (1) - very productive (7)] *

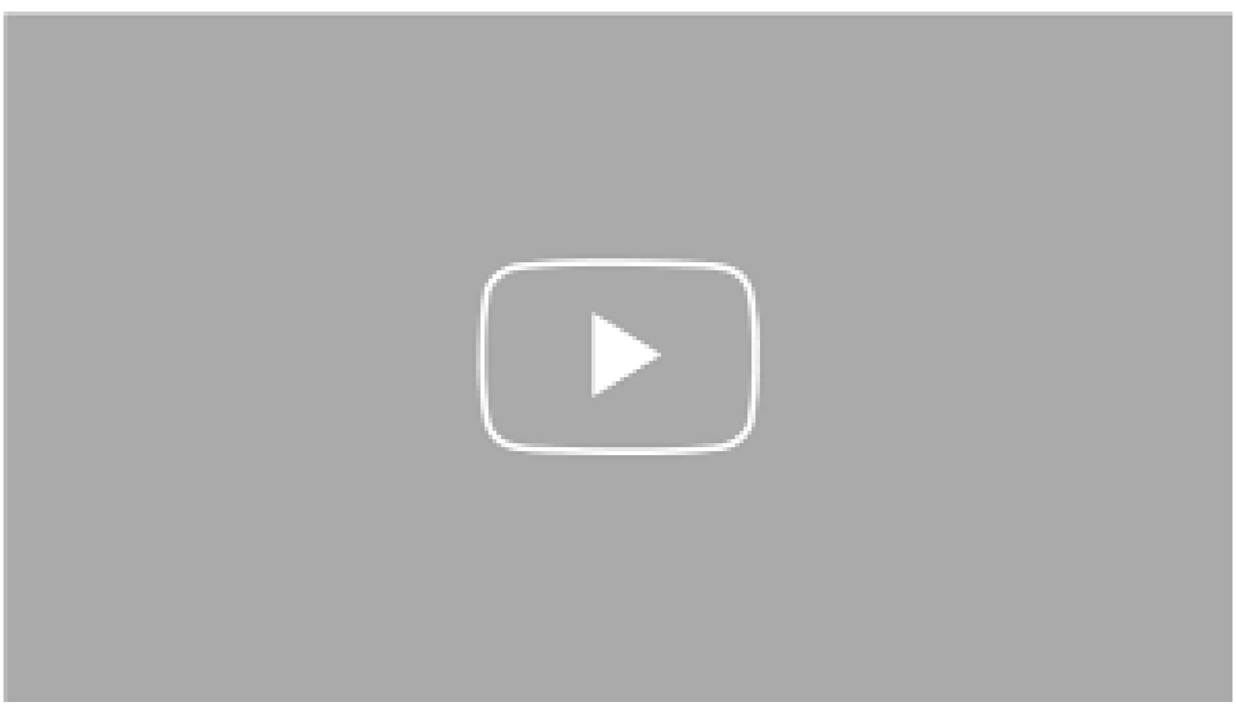
Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (raising the shoulders)							
gesture 2 (closing the eyes)							
gesture 3 (bending the fingers)							

Section II.

It is important to provide valid answers in surveys even if it is hard to prove invalidity.

In this video we present gesture controls for answering multiple choice questions. Please follow along and imitate the gestures.



12. 2.1 How easy was it to use these gestures? [very hard (1) - very easy (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (bending the neck)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 2 (bending the wrist)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 3 (grabbing with fingers)	⬭	⬭	⬭	⬭	⬭	⬭	⬭

13. 2.2 How likely is it to unintentionally make the gestures? [very unlikely (1) - very likely (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (bending the neck)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 2 (bending the wrist)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 3 (grabbing with fingers)	⬭	⬭	⬭	⬭	⬭	⬭	⬭

14. 2.3 How productive did you feel while using the gestures? [very unproductive (1) - very productive (7)] *

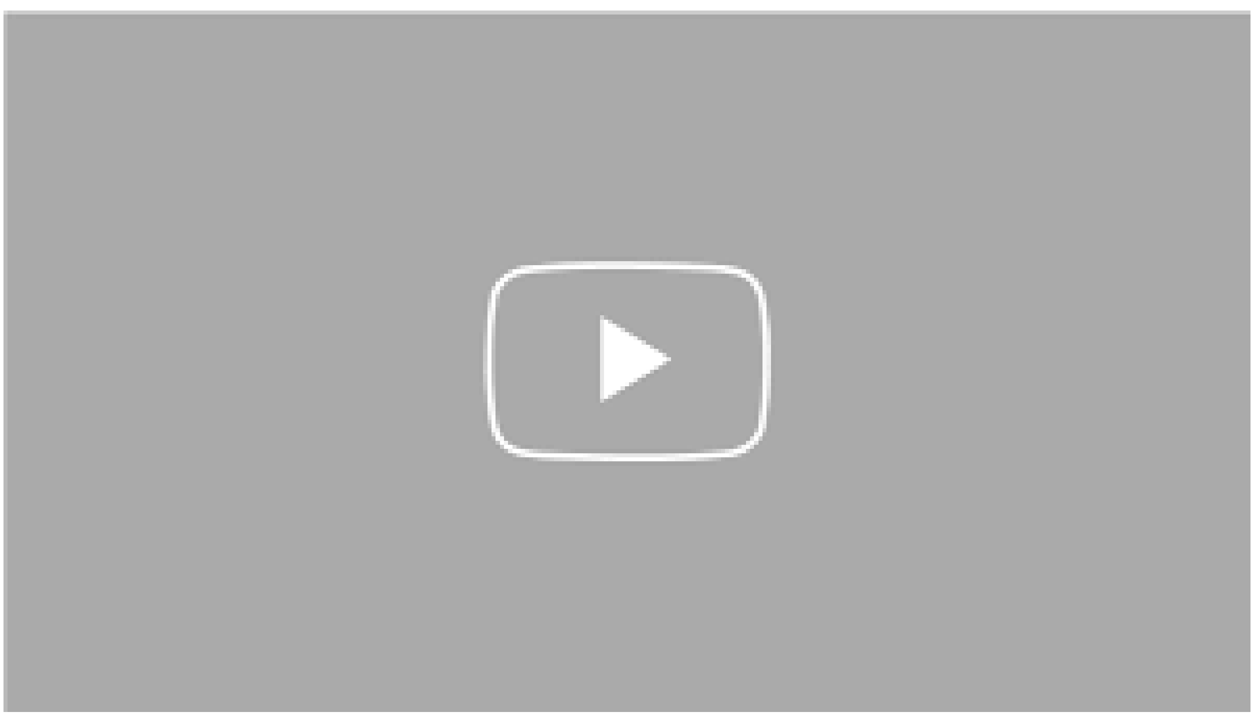
Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (bending the neck)							
gesture 2 (bending the wrist)							
gesture 3 (grabbing with fingers)							

Section III.

In last multiple choice question of this survey answer other... and type "check" in the textbox to pass attention check! It is called "Last Question". Please pay special attention to this!

In this video we present gesture controls for scrolling. Please follow along and imitate the gestures.



15. 3.1 How easy was it to use these gestures? [very hard (1) - very easy (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (pointing with thumb)							
gesture 2 (grabbing with fingers)							
gesture 3 (swiping with hands)							

16. 3.2 How likely is it to unintentionally make the gestures? [very unlikely (1) - very likely (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (pointing with thumb)							
gesture 2 (grabbing with fingers)							
gesture 3 (swiping with hands)							

17. 3.3 How productive did you feel while using the gestures? [very unproductive (1) - very productive (7)] *

Mark only one oval per row.

	1	2	3	4	5	6	7
gesture 1 (pointing with thumb)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 2 (grabbing with fingers)	⬭	⬭	⬭	⬭	⬭	⬭	⬭
gesture 3 (swiping with hands)	⬭	⬭	⬭	⬭	⬭	⬭	⬭

18. Last question *

Mark only one oval.

- gesture 1
- gesture 2
- gesture 3
- Other: ____________

After submitting the survey you must click the link show on the confirmation page!
Thank you for your time!