

Louvain School of Management

Wrist-based Gesture Interaction for Sports: Elicitation and Application

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ABSTRACT

When you're running, it's not always very practical to take out your phone to change music, to answer a call or to monitor your pace. In this thesis, we work on a solution to this problem, Kinemic. This connected bracelet allows you to detect the gestures made by your arm to transform them into actions. The objective of this work is to carry out an elicitation study to determine the most intuitive and natural gestures that should be made for each action. To do so, we chose the 21 most useful actions while running and asked 30 participants which gesture they would do for each action. After that we put together their movements to make a group of 32 gestures, we analysed their characteristics and identified those with the most consensus. Finally we discussed the results obtained and we provided guidelines for the use of these gestures in other applications.

Contents

1	Introduction	1
1.1	Context of the problem	1
1.2	Objective of the thesis	2
1.2.1	Mission statement	2
1.2.2	Research question	2
1.2.3	Working hypotheses	2
1.3	Outline of the thesis	2
2	Related works	4
2.1	Thumb-In-Motion: evaluating thumb-to-ring microgestures for athletic activity	4
2.2	Running Gestures: hands-free interaction during physical activity	5
2.3	Designing concurrent full-body gestures for intense gameplay	6
2.4	Design of an ergonomic gestural interface for professional road cycling	8
2.5	A hierarchical hand gesture recognition framework for sports referee training-based EMG and accelerometer sensors	9
2.6	Global comparison	10
3	Method	12
3.1	Device used	12
3.2	Set of actions	13
3.3	Methodology	14
3.3.1	Demographic form	14
3.3.2	Process of the experiment	14
3.4	Presentation of the participants set	16
3.5	Set of gestures	18
4	Results and discussion	21
4.1	Categorisation	21
4.1.1	Agreement score and agreement rate	21

4.1.2	Most frequent gesture	22
4.1.3	Characteristics of the gestures	23
4.2	Thinking time	30
4.3	Goodness of fit	33
4.4	Ease to perform	36
4.5	Benefits and limits	38
5	Conclusion and perspectives	41
5.1	Summary of the contributions	41
5.2	Future works	42
	Bibliography	43

List of Figures

2.1	Image illustrating the various studies from Boldu et al., 2018	4
2.2	Prototype used for this study Smus and Kostakos, 2010	6
3.1	Device used in the experience Kinemic GMBH, 2024	12
3.2	Example of referent	15
3.3	Representation of the experiment	15
3.4	Graph showing the distribution of professions among participants	16
3.5	Pareto distribution of participants	17
3.6	Graph of the results of the frequency questions	18
3.7	Distribution of categories for each characteristic	20
4.1	Referents in decreasing order of Agreement Score	22
4.2	Referents in decreasing order of Agreement Rate	22
4.3	Most frequent gesture	23
4.4	Frequency of movements by amplitude of movement	24
4.5	Distribution of gestures per range of motion	25
4.6	Frequency of gestures by nature of movement	26
4.7	Distribution of gestures per nature	26
4.8	Frequency of gestures by laterality of movement	27
4.9	Distribution of gesture per laterality	28
4.10	Frequency of gestures by form of movement	29
4.11	Distribution of form per laterality	29
4.12	Frequency of gestures by temporality of movement	30
4.13	Average thinking time per participants in second	31
4.14	Average thinking time for every actions in second	32
4.15	Comparison between the thinking time and the level of approval	33
4.16	Average goodness of fit per participant	34
4.17	Average goodness of fit per actions	35
4.18	Comparison between the goodness of fit and the level of approval	36
4.19	Average ease to perform per actions	37
4.20	Comparison between the ease to perform and the agreement rate	38

4.21	Average IBM PSSUQ score per participant	39
4.22	Average response for all participants	39
5.1	Summary graph	42
5.2	Before touching the Kinemic	45
5.3	Swiping left	45
5.4	Participant doing different gestures	45

Chapter 1

Introduction

1.1 Context of the problem

In recent years, there has been a noticeable increase in the number of people taking up running. This surge in popularity is evident in the growing participation rates at running events and races (Thibaut Hugé, Pierre Jadot, 2024). More individuals are running not only as a form of exercise but also as a social activity and a way to improve overall well-being. This increase is due to the fact that running is very easy to do and requires no special equipment apart from running shoes.

With the number of runners on the rise, we aimed to simplify the use of mobile phone when running. Many people listen to music or answer calls during their workouts. Currently, interacting with your device while running typically involves using headphones, either by tapping them once or multiple times or by sliding on them. However, this system has several drawbacks, such as the possibility of confusing the left and right earphones or miscounting the number of touches.

To address this issue, we considered using gestures recorded by a wristband to interact with the device. This system offers several advantages, including more intuitive and varied gestures compared to headphones. For instance, to change the music, you can use logical gestures like swiping left or touching your ear.

To achieve this, we used a device called the Kinemic. It's a small wristband equipped with an accelerometer that can detect gestures made with the hand and arm. To determine which gestures should correspond to specific actions, we conducted an elicitation procedure with around thirty participants.

1.2 Objective of the thesis

1.2.1 Mission statement

The goal of this work is to observe the intuitive gestures that a person would do to execute basic actions while running. These gestures are monitored with a smart watch, the Kinemic, that detect movements and can react accordingly.

1.2.2 Research question

The main objective of the thesis is reflected in the following research question:

What are the gestures that people agree on when running with a connected bracelet to perform specific actions?

1.2.3 Working hypotheses

Given the large number of possibilities while doing an elicitation, we imposed some restriction under the following hypotheses:

- We restricted the number of gestures considered by grouping them. At first, we had more than 70 gestures, this number was reduced to 32 to improve the analysis and to avoid considering two close gestures with the same meaning as two different actions.
- A set of 21 different actions were selected. We consider it sufficient to represent the majority of actions that people would be willing to do when running while remaining limited enough to allow participants to find clearly different gestures.
- The pool of participants is mainly composed of people between 20 and 26 years old. It can introduce some bias in the results, so we consider our work representative of the young generation of runner, more likely to use a smart watch while running.
- Two different examiners each separately administered half of the tests to the participants; we consider that no bias was introduced by them between the 2 subsets because they are two men of the same age and they both had the same instructions.

1.3 Outline of the thesis

This thesis is divided in five different chapters:

Chapter 1 is the introduction of the thesis. It has introduced the context and the objectives, in particular the mission statement, the research question and working hypotheses.

Chapter 2, related works, will present five articles from the same field and will discuss the good points and the bad points of each of them. This chapter will end with a comparison with our work and a final discussion.

The next chapter, Chapter 3, covers the method used in ours experiments and is divided into five sections. The first section is devoted to the presentation of the device used, the second to the set of actions. The third section presents the demographic form and the process of the experiment. The participants set is presented in the fourth section and the last section focuses on the final set of gestures. In summary, this chapter exposes ours choices and our methodology followed during the experiment process.

Chapter 4 analyses the results obtained from the experiments taking different approaches to cover all aspects of the work. These aspects are mainly the agreement rate, the final set of gestures for each actions, the characteristics of the gestures, the thinking time, the goodness of fit, and the ease to perform. Benefits and limits of our experiments are also addressed in the end of this chapter.

Finally, Chapter 5 summaries the main findings and concludes our work. Future developments of the work are also envisaged.

Chapter 2

Related works

2.1 Thumb-In-Motion: evaluating thumb-to-ring microgestures for athletic activity

This paper discusses the use and evaluation of a Thumb-to-ring in a context of athletic activity like running Boldu et al., 2018. It contains two different studies. The first one has the goal of comparing the performance of a thumb-to-index finger gestures at different levels of physical engagement. The second is about comparing their techniques (thumb-to-index finger gestures recognition) to two other techniques to see if theirs are more suitable for running or not. You can see a representation of the two different studies below 2.1.

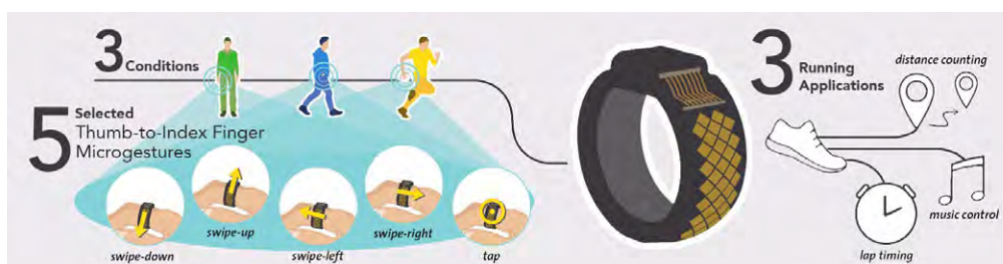


Figure 2.1: Image illustrating the various studies from Boldu et al., 2018

Before these comparisons, the authors did a pilot study to detect the more used gestures with their prototype. For that, they asked the five participants to creatively perform any kind of one-handed finger-gestures. With all the data collected, they choose five simple movements: *swipe-up/-down/-left/-right, and tap*.

For the first study, the participants were instructed to execute five specific gestures (swiping up, down, left, right, and tapping) on the ring-shaped touchpad upon hearing them through headphones. This research was conducted as a comparative study within subjects, examining the effectiveness of these gestures across three equally represented

conditions: standing, walking, and running.

The results have been grouped into three categories: ease of use, perceived precision, and task load. For the three categories, there is no large difference between standing, walking, and running. In addition, the time taken to complete the gestures remained consistent. The perceived level of precision reported subjectively did not vary as walking speed increased, except when performing the swipe-right gesture.

This study is interesting for us as we study movement during running. With small differences between standing, walking and running, it means that our work is also likely to apply for standing and walking positions.

The purpose of the second study is to contrast the thumb-to-index finger ring technique with interaction techniques that are frequently employed. Consequently, the authors assessed three proof-of-concept applications commonly utilized during running: (1) managing a music player, (2) operating a distance tracking application, and (3) controlling a stopwatch. The three interaction techniques are the following Boldu et al., 2018:

1. "Condition 1: bimanual interaction with an unmodified sports-watch using visual feedback on the screen (SO).
2. Condition 2: bimanual interaction with a modified sports-watch app using custom-added audio feedback (SA).
3. Condition 3: unimanual thumb-to-index interaction using our prototype with audio feedback (T)."

In terms of results, they show greater usability with condition 3 (T) than with the others. It proves that their solution is viable, but it works better with simple actions like switching the music than with complex interactions.

The interest of this study for our purposes is to be able to see different methods of controlling a device during physical activity.

2.2 Running Gestures: hands-free interaction during physical activity

The second paper is about a hand-free interaction system during physical activity Smus and Kostakos, 2010. The objective is to develop a system capable of interaction with a device for managing the music when running without using hands. The authors give examples for those situations as "soldiers wielding two handed rifles or athletes pumping with their arms during a run." Smus and Kostakos, 2010 The study mainly focuses on comparison of their method with two others: the touch screen of a smart phone and a button integrated into the headphone cable. To change music with their method one must

make two one footed jumps instead of one full stride.

To compare the different methods, they asked their seven participants "to run laps at a comfortable and steady pace around an oval path with approximate length of 30 meters. The experimental trials required participants to change music tracks on command." Smus and Kostakos, 2010.

For the results, they concentrated on the time for the participant to skip the music with different methods. It showed that the smart phone's touch screen was the slowest. However, there were no large difference between the button in the headphone cable and their method. Six of the seven participants prefer to use the hand free solution as it was funny and added variety to their running routine.

The interest in this paper is more limited than the first one. In fact, this work focuses on the interaction with the legs, not the arm. Moreover, this study was carried out on a small number of participants, and the device used to collect the data is a bit home-made, being a Wii remote control taped to the leg as presented below 2.2.



Figure 2.2: Prototype used for this study Smus and Kostakos, 2010

2.3 Designing concurrent full-body gestures for intense gameplay

This paper, Silpasuwanchai and Ren, 2015, addresses the challenge of designing effective and intuitive gestures for controlling game characters and actions in intense gameplay situations. With the increasing popularity of full-body gaming systems, there is a need for gestures that can be performed simultaneously to control multiple aspects of the game.

The objectives of the paper are to design a set of concurrent full-body gestures for intense gameplay, evaluate the usability and effectiveness of the designed gestures, and investigate the combination of gestures to control complex actions. To achieve these objectives, three user studies were conducted: first, to determine user preferences, a user-elicitation study was conducted where participants were asked to define gestures for common game actions/commands; second, to identify suitable and alternative body parts, participants were asked to rate the suitability of each body part (one and two hands,

one and two legs, head, eyes and torso) for common game actions/commands; third, to explore the consensus of suitable simultaneous gestures, they proposed a novel choice-based elicitation approach where participants were asked to mix and match gestures from a predefined list to produce their preferred simultaneous gestures.

The first study was conducted with 12 participants who have different gaming experiences. They derived events from various genres of Kinect games and a total of 32 actions of commands were selected. To identify the most preferred gesture and reduce any ordering effects, participants were allowed to choose the same gesture for multiple events. Each event was displayed along with the name of the event and a target scene on a large display. A total of 384 gestures were collected. One individual characteristic they found to affect gesture preference is gaming expertise. More specifically, gamers tend to define a more symbolic, efficient, unique gesture library, while less experienced gamers tend to define a more straightforward, physical gesture set.

In Experiment II, they seek to identify suitable and alternative body parts. They asked participants to rate the suitability of each of the body parts for each game event. Participants were asked to define possible game gestures for 40 game events using different body parts in randomized order. Comparing Experiments I and II, the largest group of defined gestures was consistent, i.e., 31 out of 32 events in both Experiment I and II have the same largest group of defined gestures. They analysed the most suitable body parts and alternatives based on the participants' subjective assessments of "The body part I used is suitable". The most suitable body part for each event was selected based on the highest mean score. The resulting set of suitable and alternative body parts posed a potentially useful, interesting design implication: the possible transferability between hand and leg gestures.

In the third experiment, they seek to develop a consensus set for simultaneous game gestures. They used a choice-based approach, the main difference with a user-elicitation approach is a predefined list of possible gestures. The predefined gesture list registers two data columns, one for possible gestures and another column for game events, with the relationship as many-to-one, respectively. Of all the gestures performed, 95.3% of gestures originated from the predefined list, in which 61.1% of gestures were changed after seeing the proposed set and 34.2% were part of the predefined list although the gesture may have been invented by the participant without the knowledge of the set. Only 4.6% were newly created gestures elicited by participants. Participants commented on the usefulness of the choice-based approach in two primary ways: first, it allows participants to discover more efficient, suitable gestures (better than they originally imagined/elicited); second, it provides participants with a reference point from which they can further develop their own gestures. The choice-based elicitation approach also allows the authors to achieve a high consensus with an agreement score of 0.27.

By developing a set of concurrent full-body gestures for intense gameplay, this paper contributes to the advancement of full-body gaming systems and human-computer interaction. The results demonstrate the effectiveness and usability of the designed gestures, but what is the most interesting for our own work is the methodology used in this paper. More specifically the first study where participants were asked to define gestures for game actions and the last one by showing an alternative to user-elicitation approach: the choice-based approach.

2.4 Design of an ergonomic gestural interface for professional road cycling

The paper Caona et al., 2020 is inspired by the need to improve the interaction between professional cyclists and their devices while cycling. Currently, cyclists need to take their hands off the handlebar to interact with their bike computer, which can be dangerous and disrupt their performance.

The objective of this research is to design an ergonomic gestural interface that allows professional cyclists to interact with their device while keeping their hands on the handlebar. The interface should be intuitive, efficient, and safe. Three different studies were conducted with seven professional cyclists adopting the gesture-elicitation technique. One study aimed at eliciting free micro-gestures; a second to evaluate gestures recognizable with a smart glove; the last focused on the gestures recognized through an interactive armband. The setup was composed of a road bike with drop-bars in front of a camera to record the performed movements at the Scott Sports SA headquarters. The participants were seven professional or semi-professional cyclists and had 8 possible actions.

In the first study, users were asked to elicit a gesture for every referent in complete freedom: cyclists could perform any gesture as symbol to control the application remotely without considering any technological constraints or references. During this study, it emerged that all the micro gestures can be classified by the type of movement into three categories: Press micro-gesture, Swipe micro-gesture and Extension micro-gestures. The spatial reference is not only important for the ergonomics of the posture and of the movements but also on a cognitive level. For instance, during the free gesture elicitation-study, it was also possible to note that “symmetric” referents implied symmetric symbols.

The second elicitation study was conducted with the GoGlove, which is a smart glove that allows users to control connected Bluetooth devices without touching them. The GoGlove allows recognizing only eight gestures based on the tap of the thumb with the other sensorized fingers. In this gesture elicitation study, the symbols (these eight

gestures) are already constrained by the technology, and the users are asked to associate them to the referents.

The last gesture-elicitation study was conducted with the Myo armband. This interactive armband is a portable gesture and motion control device that allows the user to take control of her phone, computer, and software via Bluetooth. The Myo armband can recognize five gestures by default. In this study, similarly to the one with the smart glove, the participants had to associate with the previously presented referents five symbols that were imposed by the technological choice.

The results of this work are particularly interesting for our thesis. The participants reasoned aloud while showing the chosen gestures, and they revealed that some micro-gestures were suggested just because they seemed more intuitive and convenient to perform. Therefore, the main criteria that guided the choice of cyclists were based on the ergonomics of the movements to be performed while holding the handlebar and the cognitive effort required to remember the gesture. A clear predominance of the index and thumb on the other three fingers has been observed. Using a set of gestures recognized by commercial devices such as the GoGlove and Myo while holding the handlebar was not ideal. As such, it presented some limitations: the sample size of participants was limited to seven, all of the athletes who took part in this study were working in the same company, all gesture elicitation sessions were conducted in a laboratory setting using a real road bike, but as a stationary bicycle, the shape of the handlebar can vary greatly and, for this reason, the results of this study can be applied only to a dropbar with a classic shape. Moreover, this study focused on the hoods position, therefore the final design recommendations are limited to this posture.

The interface was tested with professional cyclists, who reported improved safety, performance, and overall user experience. Overall, the paper presents a novel and innovative solution for professional cyclists to interact with their devices while prioritizing safety, ergonomics, and performance, but has also some limitations detailed above.

2.5 A hierarchical hand gesture recognition framework for sports referee training-based EMG and accelerometer sensors

The article Pan et al., 2020 presents a novel approach to hand gesture recognition for sports referee training using Electromyography (EMG) and accelerometer sensors. The authors propose a hierarchical framework for recognizing hand gestures, which enables referees to receive accurate and real-time feedback on their gesturing techniques. The context of the article is the importance of accurate and consistent hand gesturing in

sports refereeing, which is crucial for effective communication and fair decision-making. Existing methods for evaluating hand gestures rely on manual observation and video analysis, which can be time-consuming and subjective. The objectives of the article are as follows.

1. Develop a hierarchical hand gesture recognition framework using EMG and accelerometer sensors.
2. Evaluate the accuracy and robustness of the framework in recognizing
3. Investigate the applicability of the framework for sports referee training.

The methodology employed by the authors includes:

1. Inviting 11 subjects (seven males and four females) to participate in the signal recording process. Each participant was asked to perform nine types of quite different large motion gestures for basketball ORSs and 12 types of subtle motion gestures for system control. Each kind of gesture was performed ten times by each subject.
2. Development of a hierarchical framework consisting of feature extraction, gesture classification, and gesture recognition.
3. Evaluation of the framework using machine learning algorithms and performance metrics.

The results of the study show that the proposed framework achieves high accuracy and robustness in recognizing hand gestures, outperforming existing methods. The framework is also shown to be applicable for sports referee training, providing real-time feedback and improving gesturing techniques. By developing this hierarchical hand gesture recognition framework, the authors have created a novel solution for sports referee training, enabling accurate and real-time feedback on hand gesturing techniques. Unfortunately, the main challenge of this work concerns data processing and model training, which are very different from ours, the elicitation study.

2.6 Global comparison

To conclude the literature review, we can create a comparative table to analyse various articles alongside our own work and summarise the key aspects of each. Each article is evaluated based on several criteria. Firstly, we assessed the number of participants involved in each study. Next, we examined the number of actions participants were required to perform during the experiments. We also documented the specific devices used in each study. Additionally, we identified whether an elicitation procedure was employed, indicating if the study aimed to identify consensus gestures for specific actions.

Furthermore, we noted which parts of the body were used to perform the gestures in each study. Finally, we assigned a level of interest to each article in relation to our own work.

Articles	Thumb-In-Motion	Running Gestures	Full-Body	Road Cycling	Sport Referee	Our study
# participants	5	7	12	7	11	30
# actions	5	1	32	8	12	32
Device	ring-shaped touchpad	Wii remonte control	N.A.	glove/armband	EMG/accelerometer	Kinemic
Elicitation	No	No	Yes	Yes	No	Yes
Body part	arm	leg	full body	arms	arms	arm and hand
Interest	average	low	high	high	low	N.A.

Looking at the table above, we can observe that the second article, "Running Gestures" Smus and Kostakos, 2010, is of low interest due to its limited number of actions and lack of rigor. Similarly, the last article Pan et al., 2020 is also of little interest because it focuses mainly on data processing without conducting any elicitation study. The first article, "Thumb-In-Motion" Boldu et al., 2018, is somewhat more interesting; however, its touchpad limitations and relatively low number of participants and actions make it average in terms of overall impact. Lastly, the two most interesting articles are Caona et al., 2020 and Silpasuwanchai and Ren, 2015. These articles stand out for their extensive participant involvement and actions, along with their rigorous elicitation studies conducted in various contexts.

When comparing our work with other studies, we find that the ratio between the number of participants and the number of actions to be performed aligns with the average observed in similar projects. However, in terms of numbers, we have a higher count of participants and a greater number of actions compared to many of the other studies.

Chapter 3

Method

3.1 Device used

The device used in the experience is a Kinemic Band from the German firm "Kinemic GmbH". This bracelet contains an accelerometer that detects gestures made with the user's hand or arm. You can see a picture of the device below 3.1.



Figure 3.1: Device used in the experience Kinemic GMBH, 2024

This technology was developed to replace traditional input methods like keyboards, touchscreens, and mice, enabling control solely through hand gestures. Additionally, it's designed for interfacing with various digital devices such as drones, TVs, and robots. Their website outlines several use cases including maintenance, assembly, quality control, inspection, food technology, and remote assistance.

The system offers a range of pre-recorded gestures such as swipe (left/right/down/up), check mark, cross mark (X), clockwise and counterclockwise circles, and left/right rotations, along with left/right ear touches. Beyond these presets, users have the flexibility to encode their own custom movements to align with specific needs and tasks. The software

package includes integrated applications, for our project purposes, we didn't use it as we only did an elicitation study with the goals of finding gestures on which there is consensus.

We chose this device primarily for its lightweight and portable design, which is essential for running activities. Another key factor was our need to accurately capture a wide range of hand and arm movements, given the diverse possibilities involved. Additionally, the device allows us to augment the existing set of recorded gestures by adding new ones, offering flexibility and customization to adapt to different tasks and scenarios.

3.2 Set of actions

In this section we review the set of actions that we asked the participants to perform. Among these gestures, there are actions that are specific to racing and others that are more usual. Some acts require headphone to see the result like the actions concerning the music. Note that participants can make the same gesture several times for opposite gestures, for example, pausing the music and playing it again.

1. **Pick up the phone**
2. **Hang up the phone**
3. **Call a predefined contact:** performing this actions will result in calling a predefined contact. This was added with the idea to be performed for an emergency call. While running if something occurs like a fall, doing this gesture will call the rescue.
4. **Muting the microphone during a call**
5. **Put the microphone back on during a call**
6. **Pause the music**
7. **Starting the music**
8. **Skip to the next music**
9. **Return to the previous music**
10. **Increase sound**
11. **Decrease sound**
12. **Start a Strava's activity:** Strava is a largely used application among runners. It is used to record sports activities via GPS. It includes different sports like running, walking, cycling... This action will start the recording of the running activity.
13. **Stop the Strava's activity**
14. **Pause the Strava's activity**

15. **Resume the Strava's activity**
16. **Start the stopwatch**
17. **Stop the stopwatch**
18. **Reset the stopwatch**
19. **Give the pace in min/km:** this action is designed to give to the runners their speed. The unit is minutes per kilometer as it is the most commonly used unit in running. When performing this gesture, a voice will tell the pace of the runner in his headphone.
20. **Activate "do not disturb" mode:** The "do not disturb" mode is present in almost every smartphone. This mode allows you to mute the sound, deactivate the vibrator and block visual interference. For example, it could be used if you don't want to receive call during your run.
21. **Deactivate "do not disturb" mode**

3.3 Methodology

This section presents the methodology used to carry out the experiment with each participant. The sub-sections explain the different steps of the experiment starting with the description of the survey and explaining the process of the experiment.

3.3.1 Demographic form

The first thing we asked the participants to fill in after the consent form is the demographic one. This survey is used to better know what type of person the participant is. This form is presented in the appendix 5.2. In this form we asked the age, the profession, the field of activity and the school level.

Moreover, we asked several specific questions about running like the frequency of running, the use of a smartphone or a watch during running and if they know the device used. These questions are important because the answer of these will change how the participant will react. Indeed, one who runs and uses a smartwatch would feel more comfortable than a person who never runs.

3.3.2 Process of the experiment

In this section, we describe in detail the process followed during the experiment. This process was designed to meet the specific objectives of our study and to obtain meaningful

and reliable results.

To put the participants in context, the experiment was carried out in the open air and in sportswear. For each action, it works as the following description:

- First, we show referent of the action. It is a slide on which there is the result of the action but on the phone. You can find an example of such referent below 3.2. All the referents we created can be find in the appendix 5.2.

Pick up a call

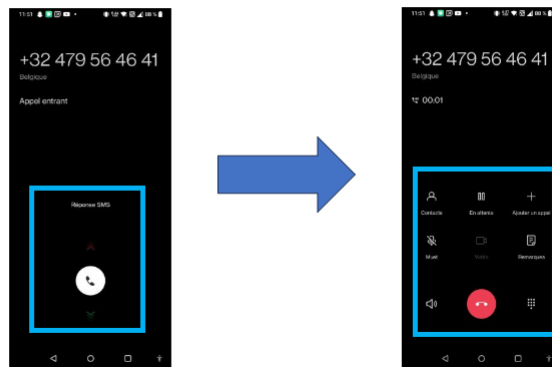


Figure 3.2: Example of referent

- After that we let the participant think of what gesture he is going to perform. When he is ready, he runs towards us and perform the gesture for a specific action. While he is running and performing the gesture, we film him so that afterwards we can analyse the movement he has made. Figure 5.4 from appendix show examples of participants doing gestures. A representation of the experiment can be found below on 3.3.

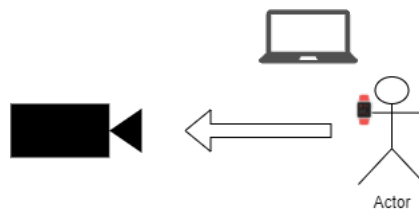


Figure 3.3: Representation of the experiment

- Finally, we ask him two questions to which he had to answer by giving a number between 1 and 10, with 10 very good and 1 very bad. The first question is called "*Goodness of fit*" which corresponds to knowing whether the gesture is logical for this action. Sometimes people do not have an idea for a specific gesture for a specific action and thus they perform random movement. The more logical the gesture, the

more interesting it is.

The second question is called "*Ease to perform*" and corresponds to how easy it is to do this while running. The more the movement is easy, the more it is interesting to keep.

This method is used for each action and is therefore repeated 21 times. After completed it, we asked participants to complete the **PSSUQ** questionnaire which means Post-Study System Usability Questionnaire "The PSSUQ (Post-Study System Usability Questionnaire)", n.d. It is a questionnaire designed to assess the usability of a computer system or software. It is used to gather user impressions on various aspects of the usage experience, including ease of learning, efficiency, overall satisfaction, and other usability-related dimensions. Some of the questions in this questionnaire are not relevant to our experiment and therefore removed. The PSSUQ used for the experiment is described in the appendix 5.2

3.4 Presentation of the participants set

In this section, we provide an overview of the participant group involved in the study, including their demographic characteristics and any relevant criteria used for selection. The set is composed by 30 people including 10 women and 20 men. All the information concerning the participants come from the demographic form they completed before the experience.

The demographic form provided participants with various options for profession, including student, executive, employee, self-employed, retired, unemployed, and other. As illustrated in the graph 3.4, a large proportion of participants are students, followed by employees and then we have one executive.

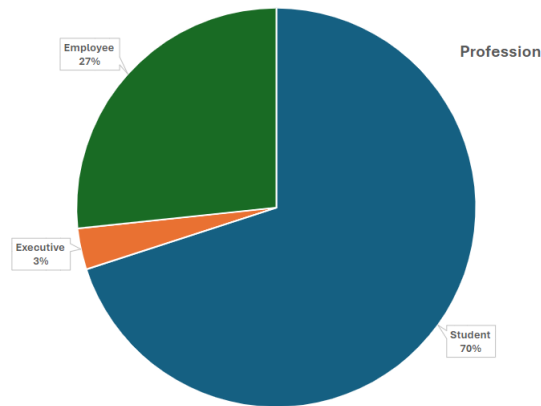


Figure 3.4: Graph showing the distribution of professions among participants

This is logical, because if we look at the graph 3.5 showing the different age groups,

we see a very large majority of 18-24 year old. In this group of 30 people, 4 are left-handed and 26 right-handed.

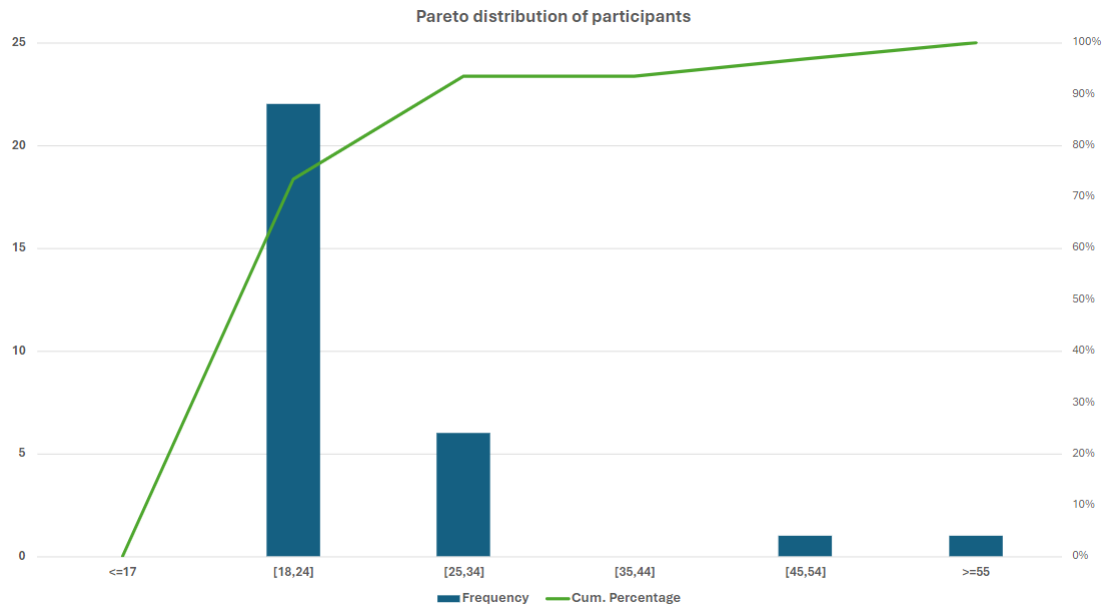


Figure 3.5: Pareto distribution of participants

As said before, we asked several questions to the participants in the demographic form that you can find in the appendix 5.2. We are interested in the questions about frequencies, all these are answered by giving a value between 1 and 7:

- I'm a frequent runner.
- I frequently use a smartphone when running.
- I frequently use a connected watch.
- I frequently use a connected watch when running.
- I frequently use a Kinemic.

The graph below 3.6 illustrates the distribution of results. We can see that the results for running frequency are well distributed. It is quite the same for the frequency of use for a smartphone during running. However, the pattern differs for using a connected watch during running, where responses are polarised between never and very often, with minimal middle-ground usage. Last thing to note is that nobody knows or use the device of the experience which is the Kinemic.

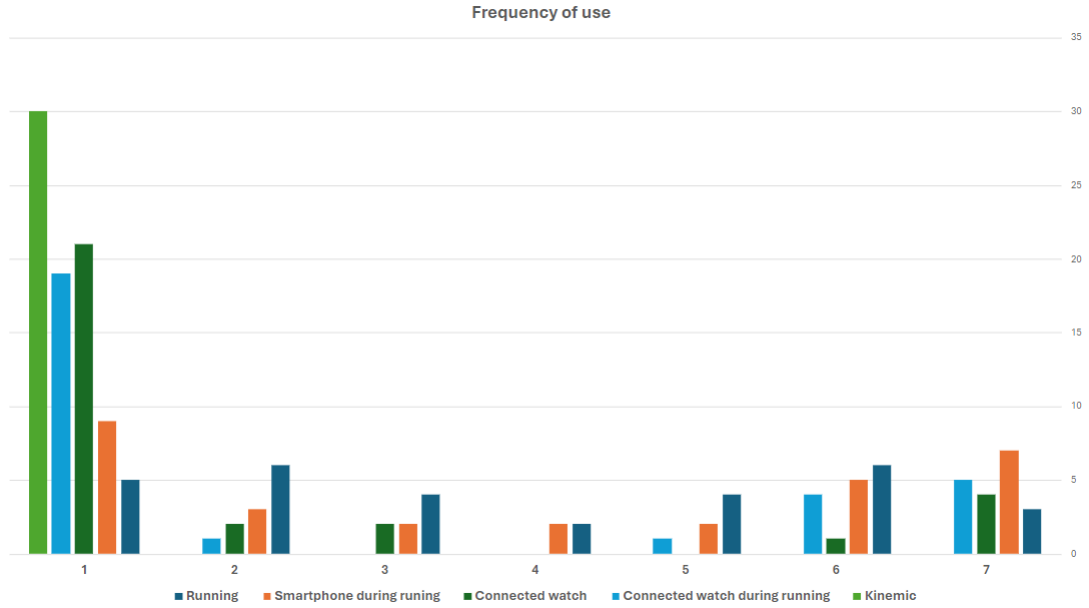


Figure 3.6: Graph of the results of the frequency questions

3.5 Set of gestures

As mentioned earlier, participants were instructed to perform what they perceived as the most logical gesture for specific actions. However, this method resulted in a wide variety of different gestures due to each participant creating their own movement. Therefore, although participants had similar ideas for specific actions, the actual gestures performed were slightly different for everyone.

To address this issue, we categorised all the gestures performed by participants into 32 distinct categories. Gestures were grouped together based on similarities in execution and intended meaning. For example, swiping left with the arm either bent or stretched was classified into the same category. We also grouped gestures that were essentially the same but varied in repetition. For instance, clapping once or twice was classified into one category, whereas swiping left and swiping right were categorised separately due to their distinct actions. We took care to not alter gestures that had been frequently performed by participants. This was done to preserve the authenticity of their responses as much as possible throughout the categorisation process.

This categorisation process helped to consolidate similar gestures and simplify the analysis of participant responses.

For each categories we give them characteristics:

- **Range of motion:** this is used to know if the gesture has a large amplitude and need space to be performed. There are 3 different ranges:
 - Small (S): concerns gestures made by moving nothing more than the wrist and

fingers of the hand.

- Medium (M): covers forearm movements in addition to optional wrist and hand movements.
- Large (L): involve movement of the whole arm, generally with full extension, as when raising the hand to the ceiling.
- **Nature:** this describes the meaning of a gesture using four categories from A. D. W. Jacob O. Wobbrock, 2009: symbolic (S), metaphorical (M), physical (P), and abstract (A).
 - Gestures belonging to the symbolic category depict commonly accepted symbols whose meaning is understood by everyone.
 - Metaphorical gestures are those that imitate real-life actions, indicates a metaphor.
 - Physical category concerns gestures that act physically on objects.
 - The category of abstract gestures brings together all gestures that do not fit into any of the previous categories.
- **Laterality:** this is used to characterize how the two hands are employed to produce gestures, with 4 categories : dominant unimanual (D), nondominant unimanual (N), symmetric bimanual (S), asymmetric bimanual (A).
- **Form:** specifies which form of gesture is elicited. Four categories have been distinguished, namely:
 - S: stroke when the gesture only consists of taps and flicks.
 - T: static when the gesture is performed in only one location, only the final position of the gesture matters.
 - M: static with motion (when the gesture is performed with a static pose while the rest is moving).
 - D: dynamic when the gesture does capture any change or motion, the movement matters.
- **Temporality:** distinguishes if the action is done after or during the gesture:
 - Discrete (D) after the gesture.
 - Continuous (C) during the gesture.

The graph below 3.7 illustrates the distribution of characteristics for all 32 gestures. Notably, for laterality, there is no category labelled "nondominant unimanual (N)" because the device only captures movement on the side where the bracelet is worn. This limitation

also applies to the "M" category from the form, this situation does not appear in our application.

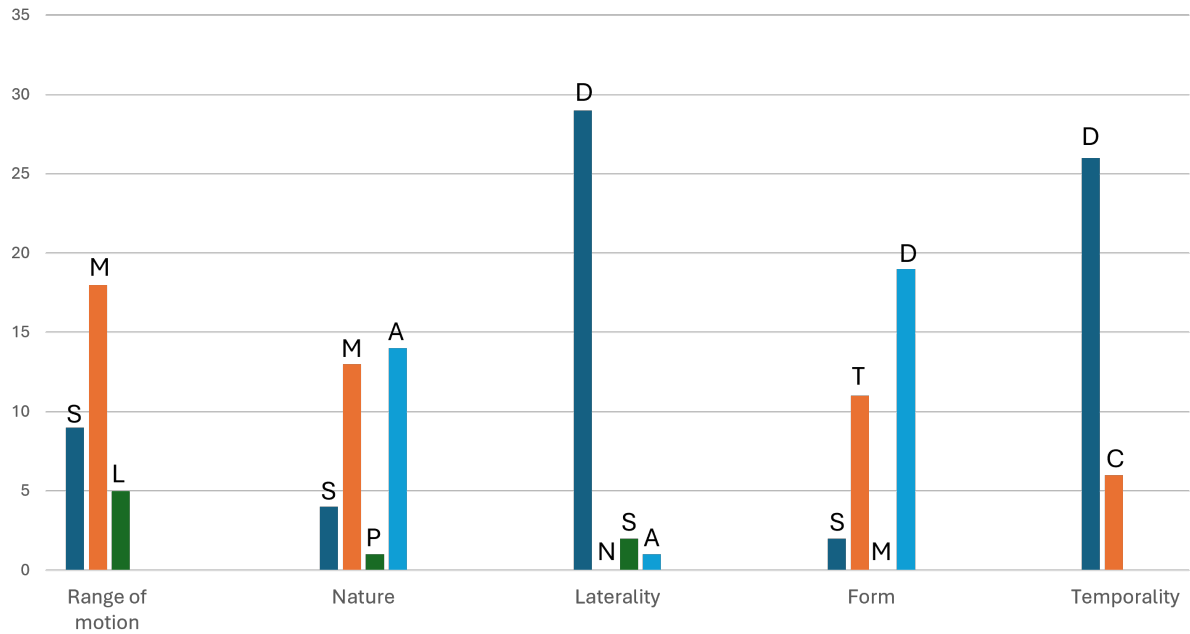


Figure 3.7: Distribution of categories for each characteristic

Chapter 4

Results and discussion

4.1 Categorisation

4.1.1 Agreement score and agreement rate

We are interested in learning how well the symbols that each participant suggested accord. Therefore, for a set P representing all proposals for referent r , we provide an agreement score $A(r)$ (B. R. Jacob O. Wobbrock and Myers, 2005).

$$A(r) = \sum_{P_i \subseteq P} \left(\frac{|P_i|}{|P|} \right)^2$$

According to intuition, agreement should be $\approx 0\%$ when suggested symbols are unique and 100% when they are identical.

Another work (Vatavu and Wobbrock, 2015) has shown that the agreement score needed two correcting factors, so they introduced the agreement rate.

$$\mathcal{AR}(r) = \frac{|P|}{|P| - 1} \sum_{P_i \subseteq P} \left(\frac{|P_i|}{|P|} \right)^2 - \frac{1}{|P| - 1}$$

We can now compare both scoring methods and see that the agreement rate 4.2 is less polarised than the agreement score 4.1, extreme values are closer to the mean. One obvious observation, especially on 4.1, is that the fourth largest value are much bigger than the others. It means that these four actions generally reached consensus. More specifically, managing sound was almost always done by moving the hand up and down, and managing current music by swiping the hand left or right. It also means that the other actions have received many different propositions and that none of them really stood out. Now if we look at the ordering, when we compare both methods the order is the

same for the biggest value but changes for other ones.

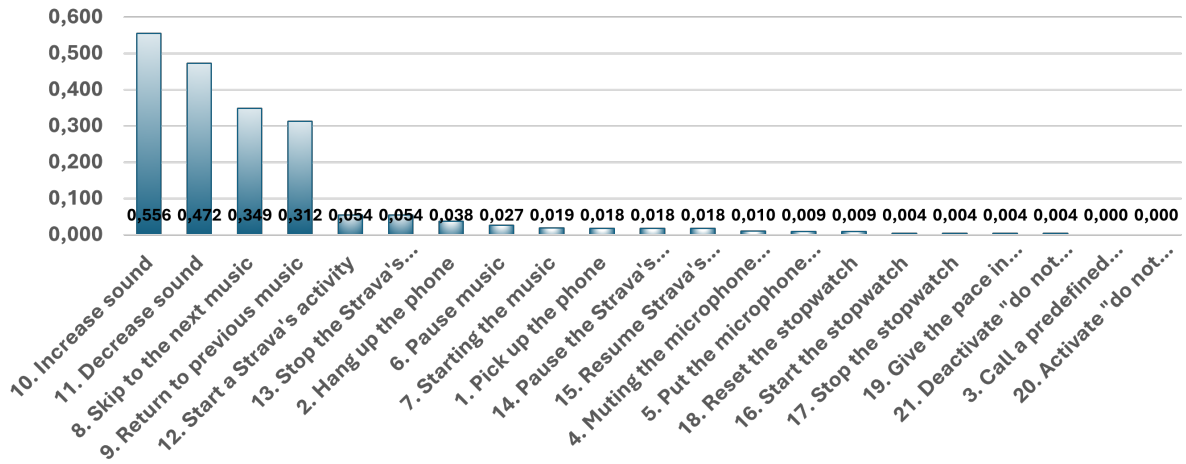


Figure 4.1: Referents in decreasing order of Agreement Score

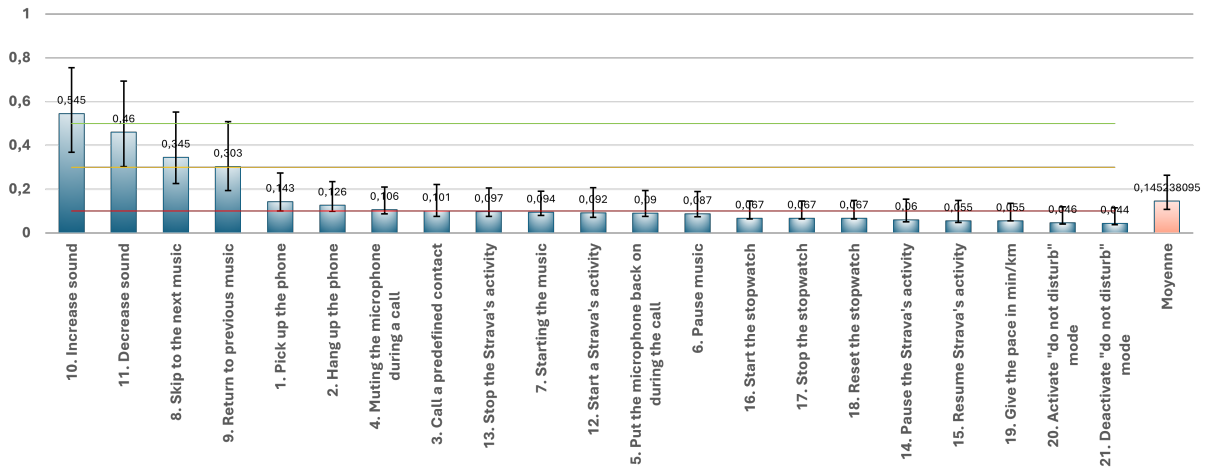


Figure 4.2: Referents in decreasing order of Agreement Rate

The Agreement Rate was computed thanks to AGATe, an AGreement Analysis Toolkit (Vatavu and Wobbrock, n.d.). This software also computes the Confidence Interval of 95% that is represented on the graph. The red, yellow, and green horizontal lines represent respectively values of 0.1, 0.3 and 0.5.

4.1.2 Most frequent gesture

On table 4.3 is represented the most frequent gesture for each referent sorted in descending order of its number of occurrences. We can therefore make a relation with the previous chapter, the agreement rate 4.2, and see that naturally it is the same referents which occupy the first four places with more than half of the participants making the same gesture. On the other end of the table, we found referents with 4 and 5 occurrences. They have less than 20% of frequency and a very low agreement rate, no consensus emerges

from these actions. Another conclusion that can be made is that referent with a similar action have often a close number of occurrences and the same most frequent gesture. It can be explained because many people tend to use the same gesture to start and to stop an action. In consequence, if every participant make a different gesture to start an action, they will make a different one to stop the same action.

Referent	Most frequent gesture	Number of occurrences
10. Increase sound	Swipe up	22
11. Decrease sound	Swipe down	20
8. Skip to the next music	Swipe right	17
9. Return to previous music	Swipe left	16
1. Pick up the phone	Tap your ear	9
3. Call a predefined contact	Shake wrist/hand	8
2. Hang up the phone	Tap your ear	7
4. Muting the microphone during a call	Touch the kinemic	7
5. Put the microphone back on during the call	Touch the kinemic	7
6. Pause music	Touch the kinemic	7
7. Starting the music	Touch the kinemic	7
12. Start a Strava's activity	Handclaps (any number), includes claping back of one hand vs palm of the other	7
13. Stop the Strava's activity	Handclaps (any number), includes claping back of one hand vs palm of the other	7
14. Pause the Strava's activity	Touch the kinemic	6
15. Resume Strava's activity	Touch the kinemic	6
18. Reset the stopwatch	Draw circle clockwise with index (forearm moving or reeling)	5
19. Give the pace in min/km	Tap your ear	5
16. Start the stopwatch	Tap your leg once	4
17. Stop the stopwatch	Tap your leg once	4
20. Activate "do not disturb" mode	Tap your ear	4
21. Deactivate "do not disturb" mode	Tap your ear	4

Figure 4.3: Most frequent gesture

If we compare our results with the study by Boldu et al., 2018, we can see that the most common gestures are relatively the same. Even though this study used a touchpad ring, actions such as swipe left/right, tap, or touch the device are present. This is quite interesting because it means that people tend to perform similar gestures with different devices. This consistency could stem from the frequent use of smartphones and other electronic devices in daily life, which often rely on sliding or touching gestures.

4.1.3 Characteristics of the gestures

In this subsection, we analyse the characteristics of the chosen gestures for specific actions. First, we examine the range of motion characteristics to determine whether participants prefer to make large movements or not. Following this, we explain the nature of the chosen movements. Next, we discuss the laterality characteristic to understand how the two hands are used. After that, we consider the form of the gestures, and finally, we examine their temporality.

Range of motion

When analysing the range of motion on 4.4, the first observation is that people tend to do more small and medium gestures than large gestures. It seems natural given our context,

in fact when we run, we already make large gestures so it seems more logical to order actions with small ones so that they are not mixed up.

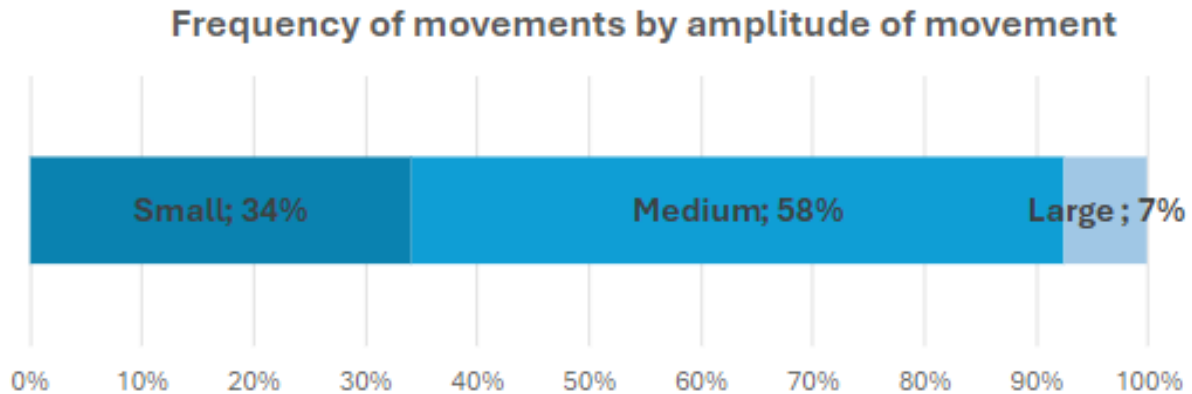


Figure 4.4: Frequency of movements by amplitude of movement

On the second figure 4.5, we can analyse the distribution for each action more precisely. So, we can see that actions 8 to 11 have a much bigger part of small movements than other actions. If we take into account the previous section about the agreement rate (4.2), we notice that these four actions are the four which have a very high rate. We can therefore conclude that the high percentage of small movements is due to a high number of people doing the same small movement. Beside that the range of motion is well distributed, there are only four actions which do not have the three range of motion. Moreover, opposite actions tend to have the same distribution. For example, "pick up the phone" has the same distribution as "hang up the phone" and "start an activity" has the same as "stop an activity".

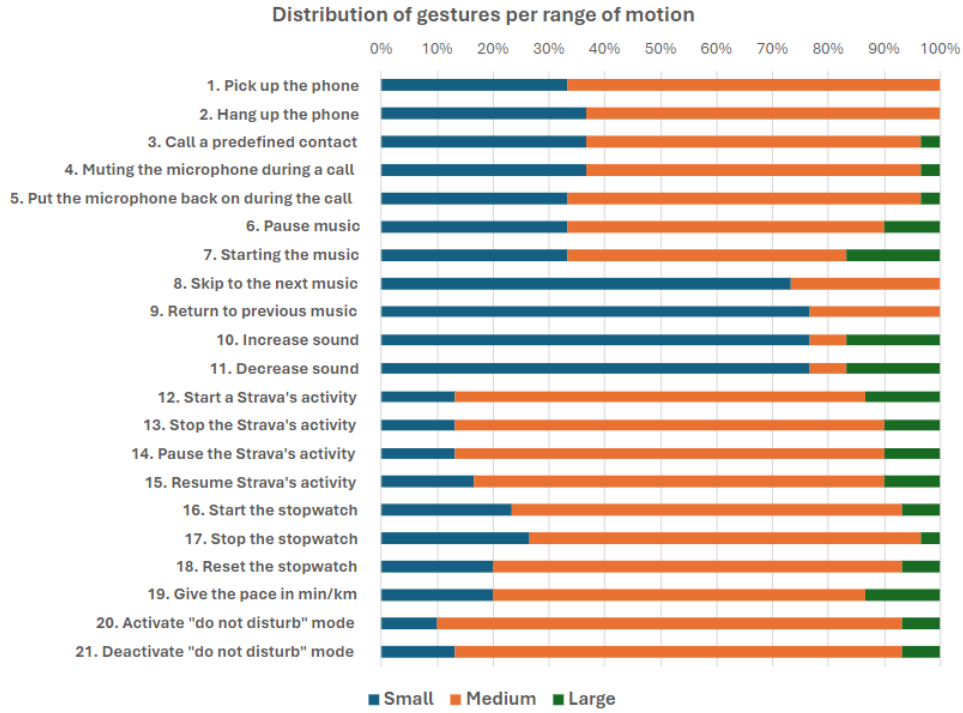


Figure 4.5: Distribution of gestures per range of motion

Nature

The graph below 4.6 represents the frequency of gestures by nature of movement for every action. Comparing this graph with the one from the previous chapter 3.7, it's interesting to note that even though the physical category is represented by only one movement, it still accounts for 15% of the gestures performed by participants. This movement is "Touch the Kinemic." It makes sense that this gesture is among the most used, as it is simple and quickly comes to mind. For the other three categories, the distribution remains similar to the previous graph 3.7, with each category slightly reduced to make room for the physical category.

We can also observe that people tend to perform more gestures that imitate the actions, as the metaphorical category has the highest frequency.

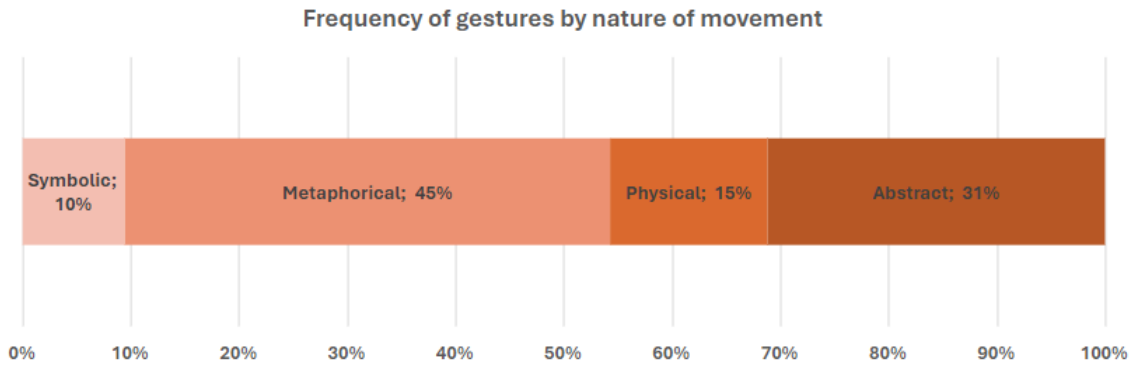


Figure 4.6: Frequency of gestures by nature of movement

For the second graph on the nature 4.7, it is interesting to see that actions with the highest agreement rates are those performed using metaphoric gestures. This means that people tend to agree more when making gestures that imitate the actions they represent. Another noteworthy observation is that the physical movement "touch the Kinemic" has been used for almost all actions. This is not necessarily good news, as it indicates that participants are using this movement for a variety of actions rather than for a specific gesture. In other words, there is a lack of consensus on when to use this movement, leading to a lower overall agreement rate.

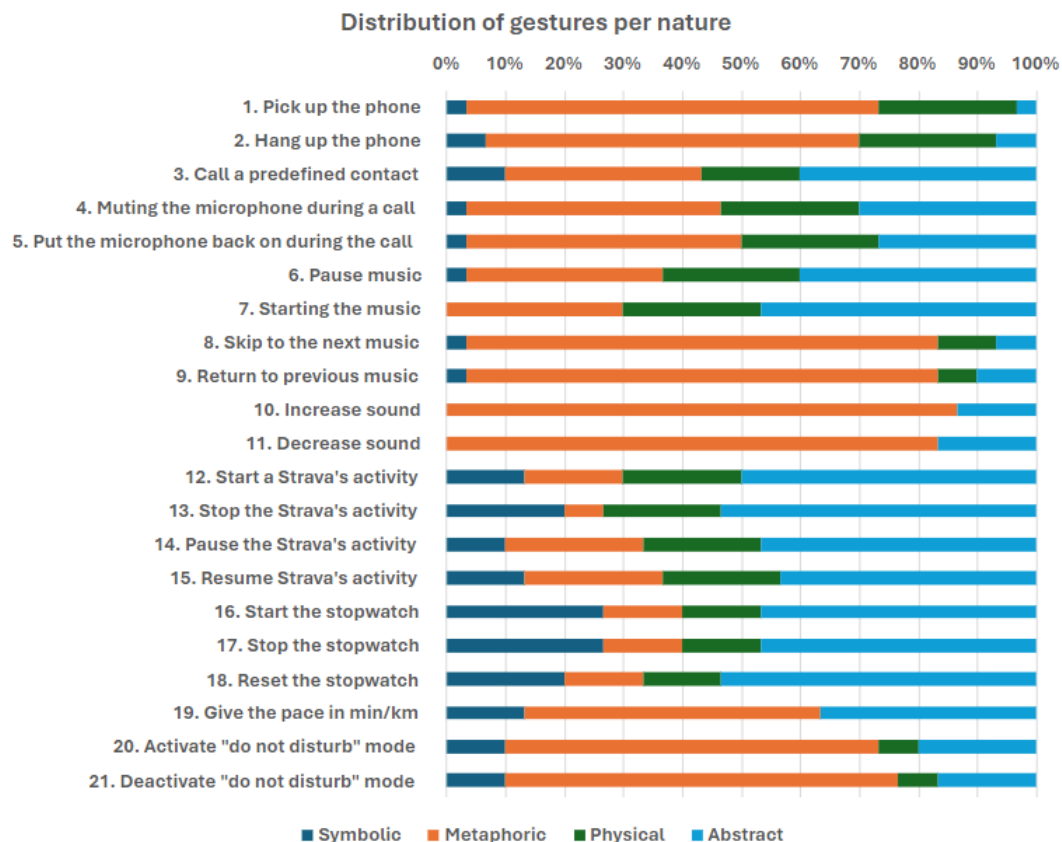


Figure 4.7: Distribution of gestures per nature

Laterality

On the graph 4.8 we see that one laterality type is very dominant: Dominant unimanual. It is a result already present on 3.7 because most of the different gestures are naturally done with one arm, the arm with the Kinemic. There are two symmetric bimanual and one asymmetric bimanual, we will analyse them in more detail with the second graph. The last type is nondominant unimanual and it is not used in our experiences, it is quite logical because any gesture done with the arm that does not wear the Kinemic is not captured.

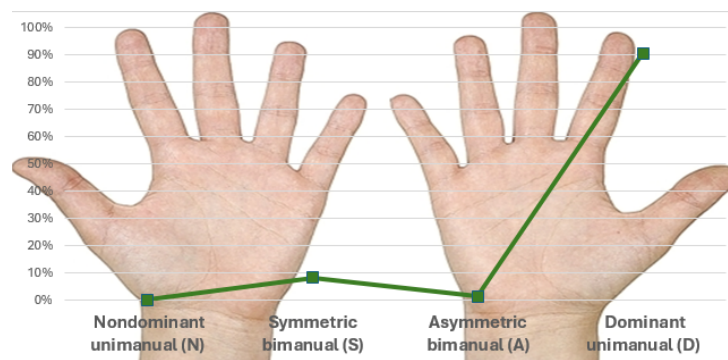


Figure 4.8: Frequency of gestures by laterality of movement

On the second graph about the laterality 4.9, we can analyse each action separately. The only asymmetric bimanual gesture is "touching the opposite wrist", it is often used to command a Strava activity or a stopwatch. There are two symmetric bimanual gestures, "making a cross with your hands" and "handclap". They are used mainly to control a Strava activity or to pause the music. These gestures are used up to 25% in some activities which show that they are still a non-negligible part of the elicitation.

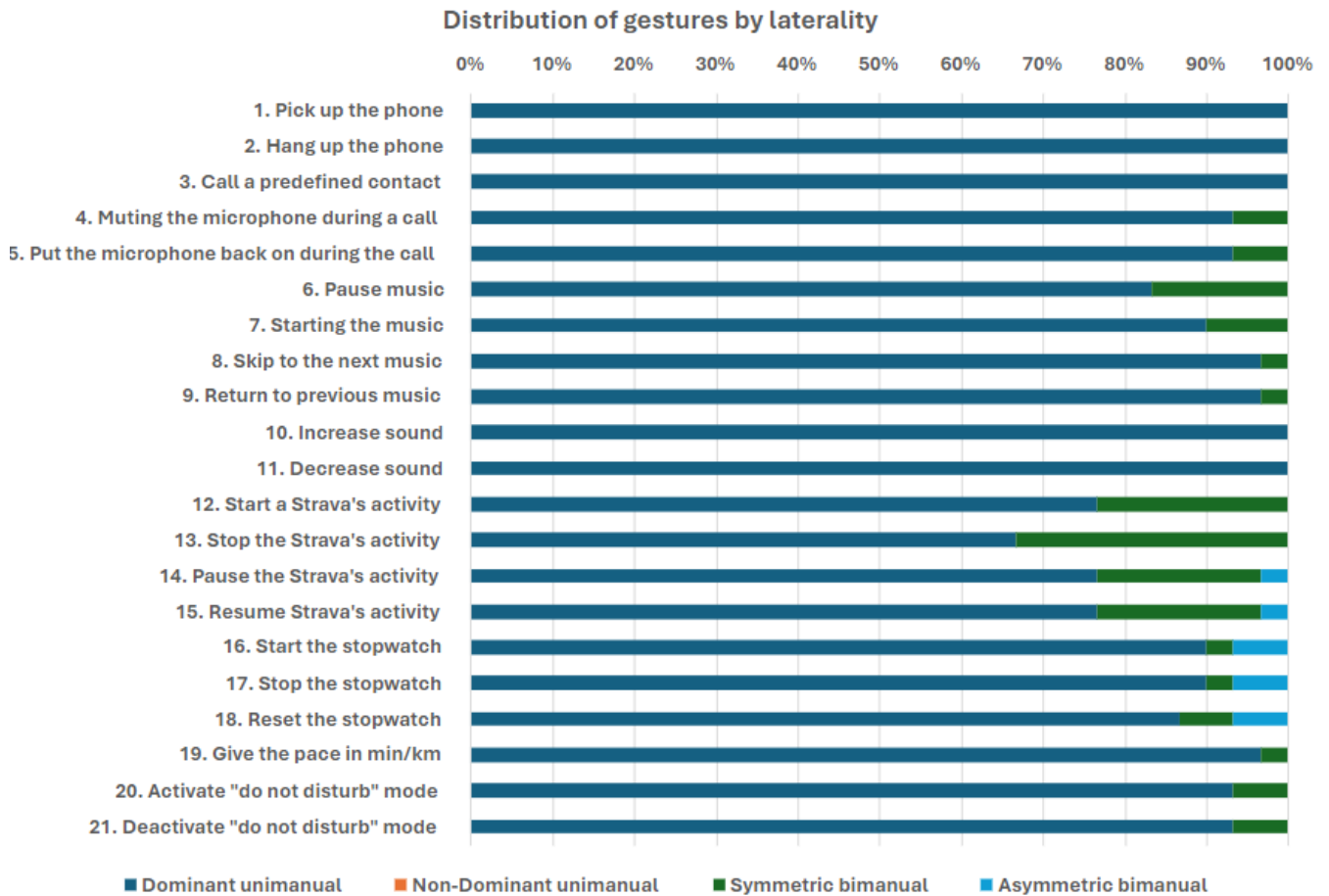


Figure 4.9: Distribution of gesture per laterality

Form

Among the four different types of form, only three are represented in our experiences (4.10): Stroke, Static, and Dynamic. Static with motion is not very suitable for running. Previously, we saw on graph 3.7 that only two gestures are in the Stroke category. These two are "Snap your fingers" and "Touch the Kinemic". However, we can see hereunder that it still represent 17% of the gestures so these two movements are frequently used.

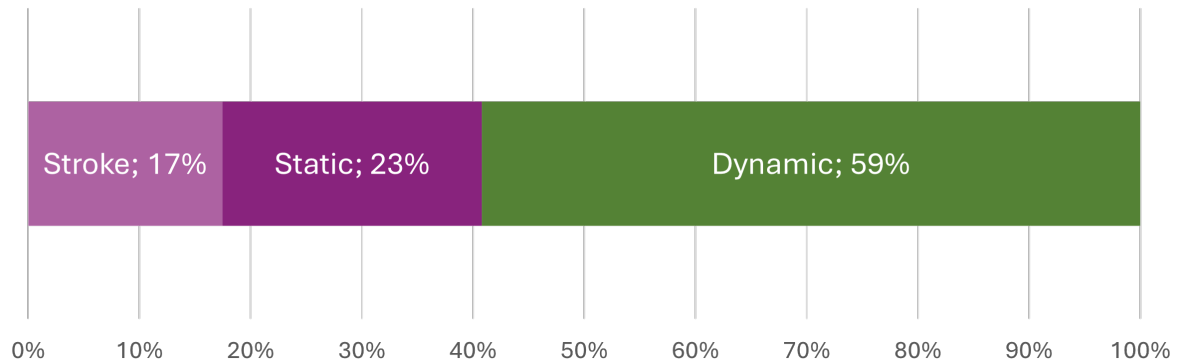


Figure 4.10: Frequency of gestures by form of movement

On the second graph 4.11, the distribution of form is quite balanced except for actions 8 to 11. Once again they are gestures with the biggest agreement rate 4.2 and the agreement of the participants over one gesture ensure that the distribution of form is unbalanced. So, the dynamic represent 80 to 95% of the movements for these actions.

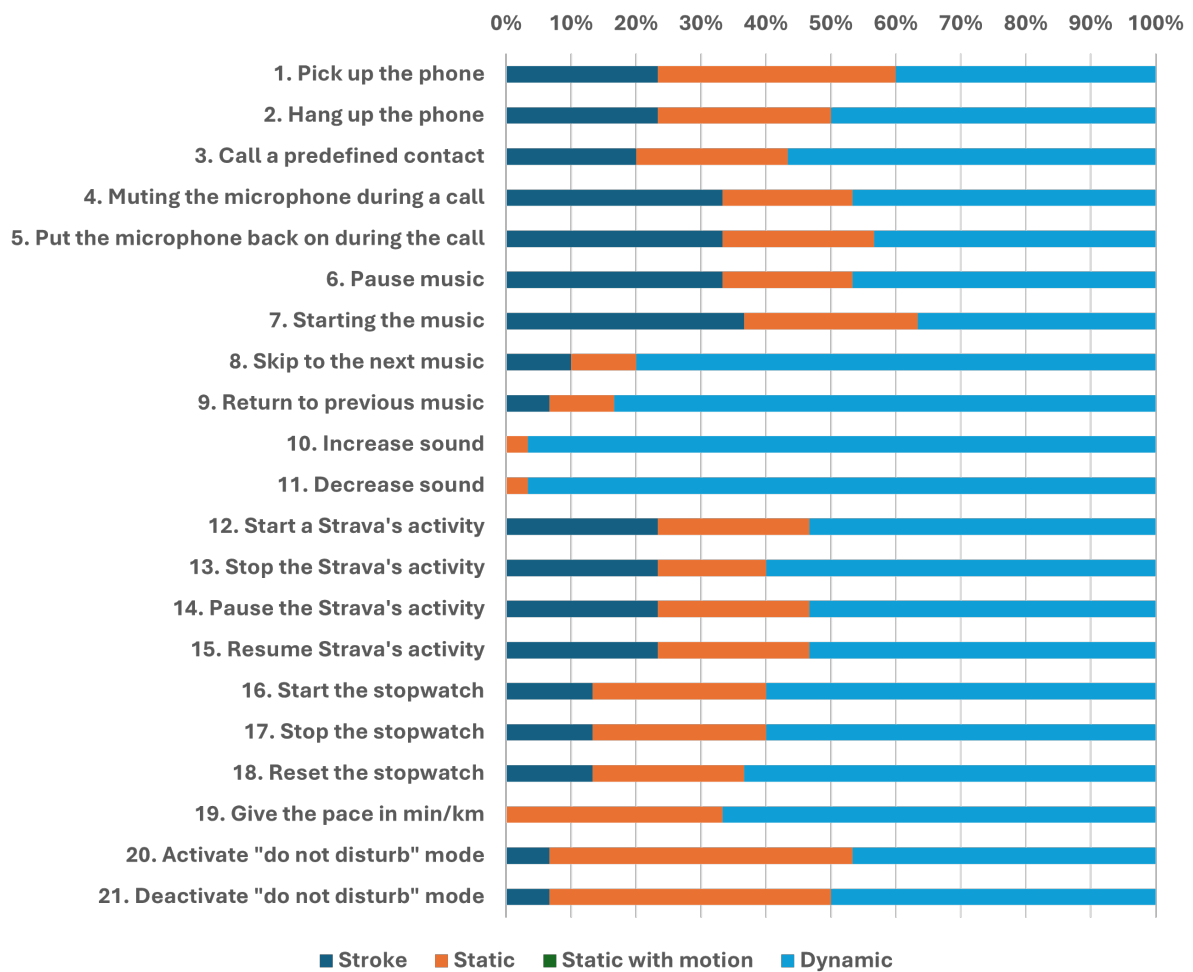


Figure 4.11: Distribution of form per laterality

Temporality

By looking at the graph below 4.12, we can see that people are more likely to perform discrete gestures, meaning the action is completed after the movement. This aligns with the graph from the previous chapter 3.7, which shows more discrete gestures than continuous ones. Thus, it can be concluded that participants prefer gestures that result in the action being executed following the gesture.

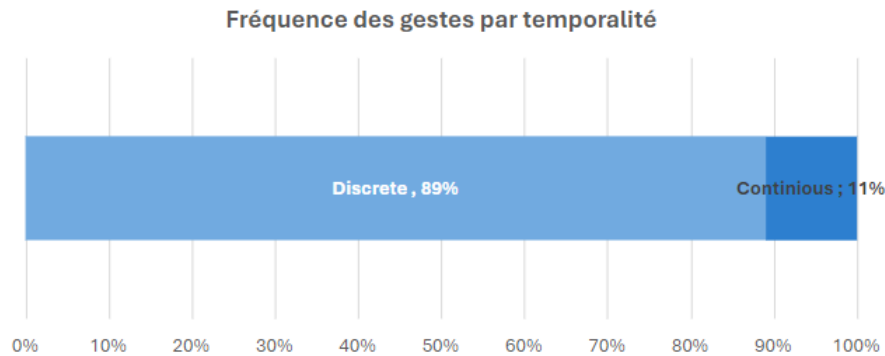


Figure 4.12: Frequency of gestures by temporality of movement

4.2 Thinking time

In this section, we examine the time each participant takes before performing a gesture and discuss the findings. First, we analyse the average time for each participant to see if there are significant differences between them. Following that, we look at the average time across all actions. Finally, we see if there is a relation between the agreement rate and the thinking time.

The graph below 4.13 displays the average thinking time for each participant. The overall average thinking time is 9.03 seconds. While there are a few outliers, the majority of participants exhibit relatively similar response times. This similarity is logical, considering that most of the participants share common characteristics. For participants with longer thinking times, there are no distinct characteristics that set them apart from the others. The similarities in their attributes suggest that factors other than demographic differences might be influencing their response times.

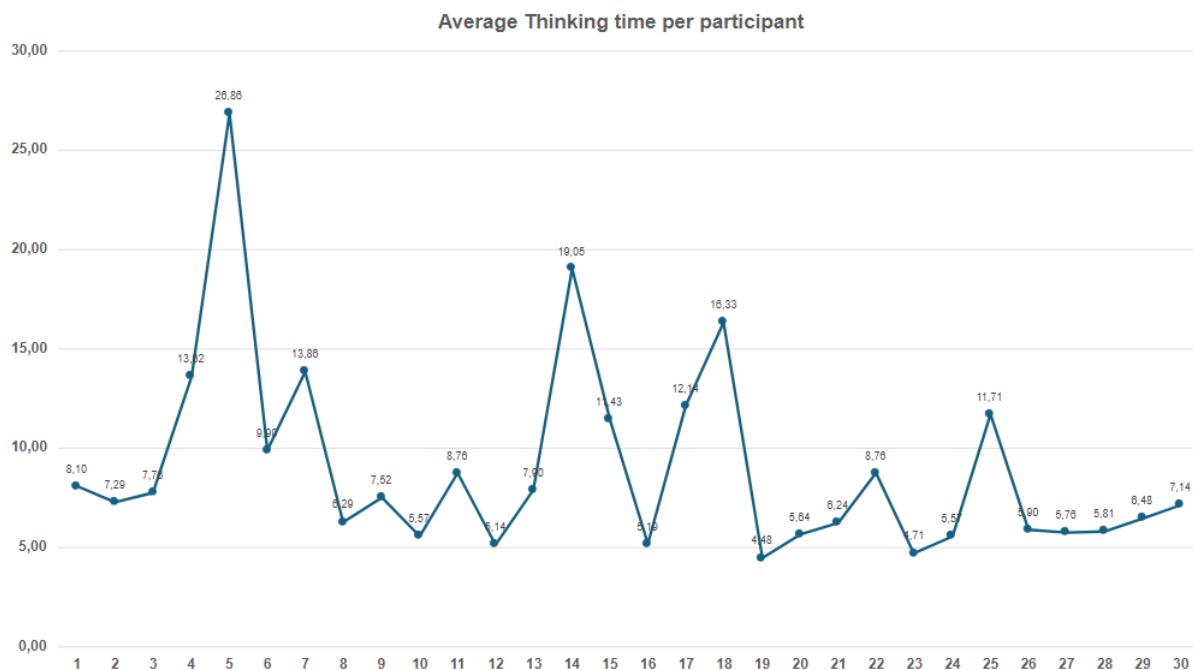


Figure 4.13: Average thinking time per participants in second

The second graph 4.14 is more intriguing than the first one. It represents the average thinking times of participants for each action. We observe that for some basic actions, the thinking time is extremely short, such as for decreasing the sound or hanging up the phone. This can be partly explained by the fact that these actions are often the reverse of the actions they had just performed, leading many to simply repeat the same gesture. For instance, the action "Start the stopwatch" has a much longer reflection time compared to "Stop the stopwatch." This suggests that people tend to use the same gesture for opposite actions rather than creating a new movement. This behaviour indicates a preference for familiar gestures over inventing new ones, highlighting the participants' tendency to stick with what they already know.

This graph also highlights the variations in thinking times between different actions. For some actions, the reflection time is relatively short, while for others, it is significantly longer. Typically, the longer thinking times are associated with more complex or unfamiliar actions that participants are not used to perform without a mobile phone. For example, "starting a Strava activity" requires more thought and time because it is a more intricate task that participants are accustomed to handling directly on their phone. In contrast, simpler actions like increasing the volume can be performed quickly and easily using headphones. This difference illustrates how familiarity and complexity influence the time participants take to decide on a gesture.

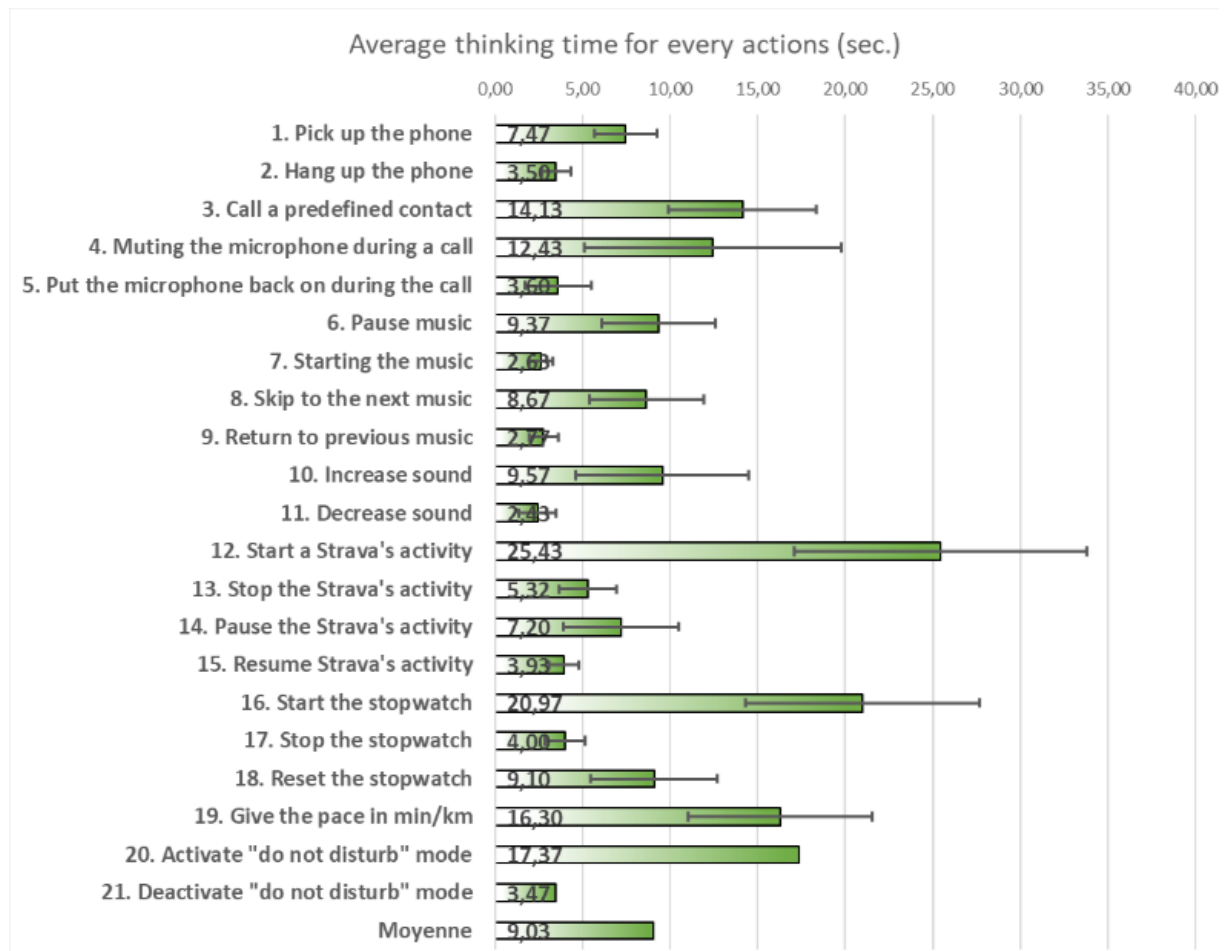


Figure 4.14: Average thinking time for every actions in second

The final graph in this section 4.15 compares the thinking time with the level of approval for each gesture. The graph reveals a slight correlation between these two variables. Specifically, when the level of approval for a gesture is high, the thinking time tends to decrease. This trend makes sense, as gestures with higher consensus are generally more intuitive and logical for the participants. As a result, they require less time to decide on and perform these movements.

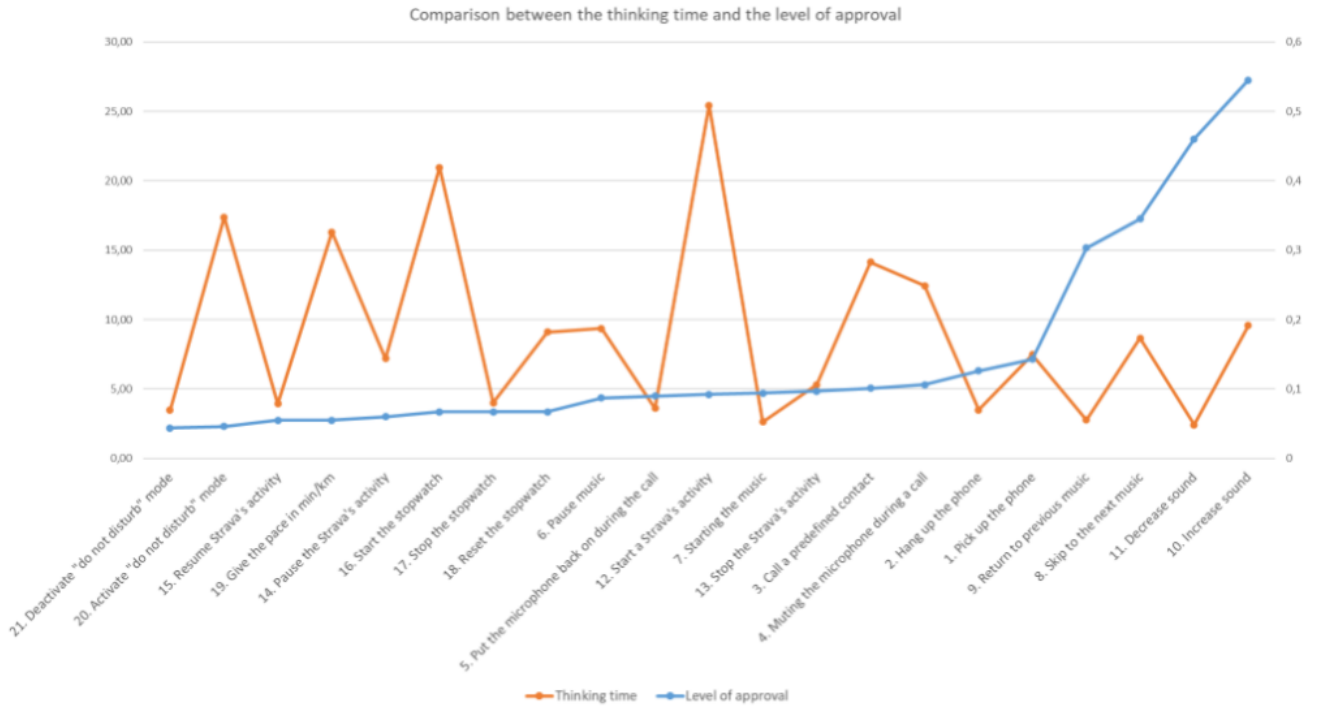


Figure 4.15: Comparison between the thinking time and the level of approval

4.3 Goodness of fit

In this section, we examine the goodness of fit, which represents how logical the gesture is in relation to the action. Like the previous section, we first review the average goodness of fit for each participant, followed by an analysis of the average goodness of fit for each action. Finally, we check if there is a relation between the agreement rate and the goodness of fit.

Let's begin with the average per participant, as shown in the graph below 4.16. We observe that nearly all participants have a high score. Except for one participant, all scores are above average, with the majority being rated as good or excellent. This suggests that the gestures performed by the participants were generally perceived as logical and natural. High scores across most participants reflects the intuitive nature of the gestures chosen by the majority of participants.

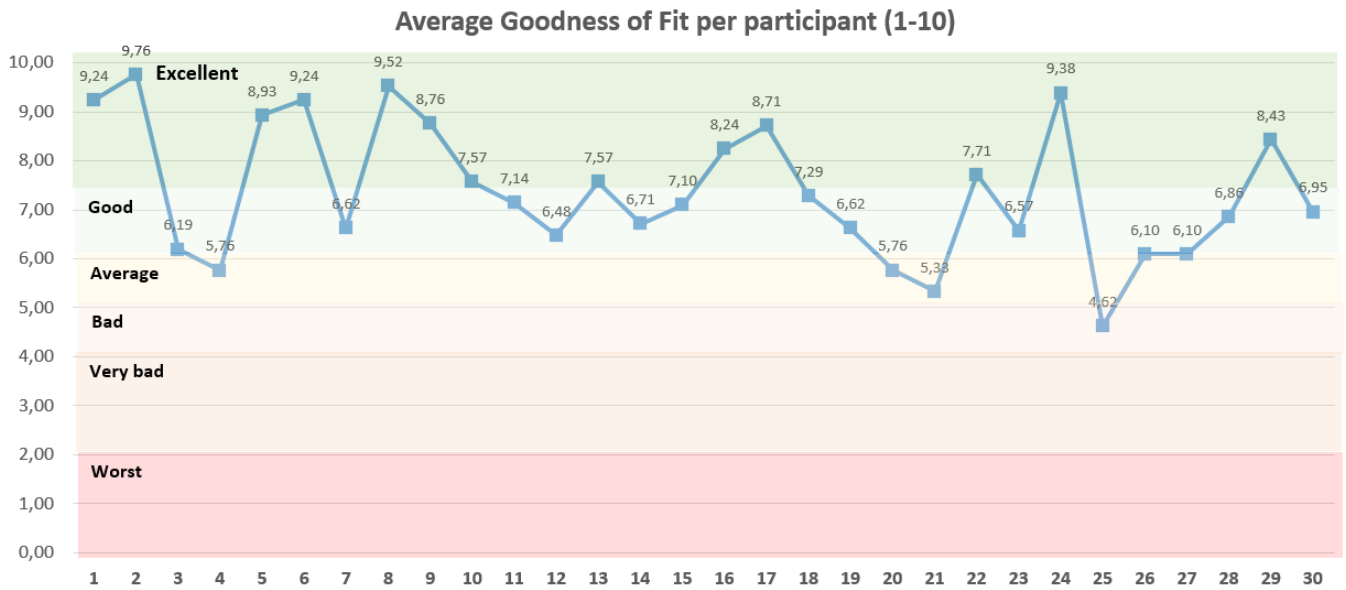


Figure 4.16: Average goodness of fit per participant

The second graph shows the goodness of fit for each action. We observe that for opposite actions, the goodness of fit scores are very close. For instance, "Starting the music" and "Pausing the music" have a difference of only 0.30. Like the thinking time analysis, we see that more complex or less common actions have lower goodness of fit scores. This indicates that participants performed gestures that made less sense for these actions, suggesting a greater difficulty in creating logical and intuitive gestures for more complicated tasks.

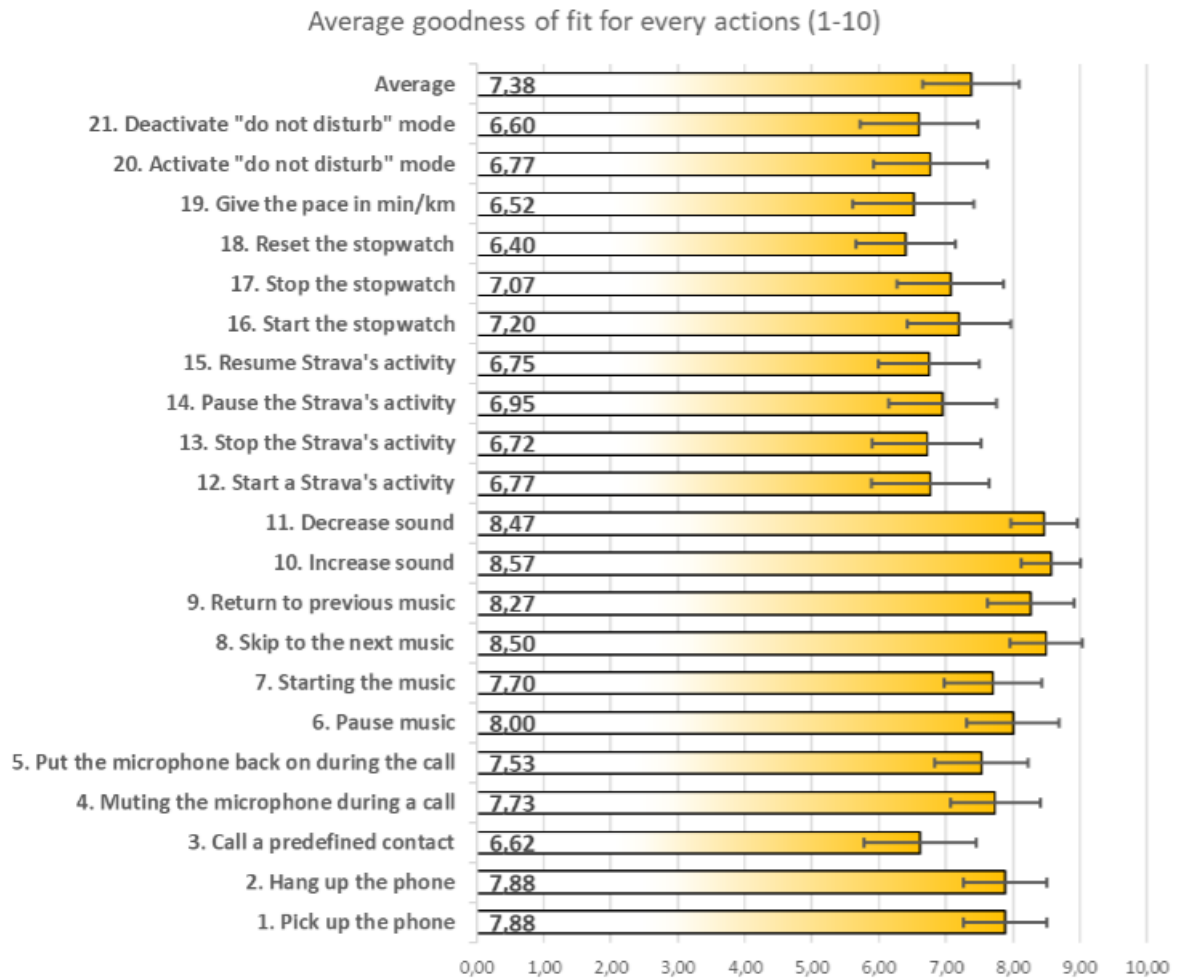


Figure 4.17: Average goodness of fit per actions

Finally, the last graph of this section 4.18 illustrates the relationship between the goodness of fit and the agreement rate. We observe a slight increase in the goodness of fit score as the agreement rate rises, although this trend is not highly significant. Nonetheless, it is fair to conclude that as the goodness of fit improves, the agreement rate tends to increase as well. This suggests that gestures perceived as more logical and natural are more likely to achieve higher consensus among participants.

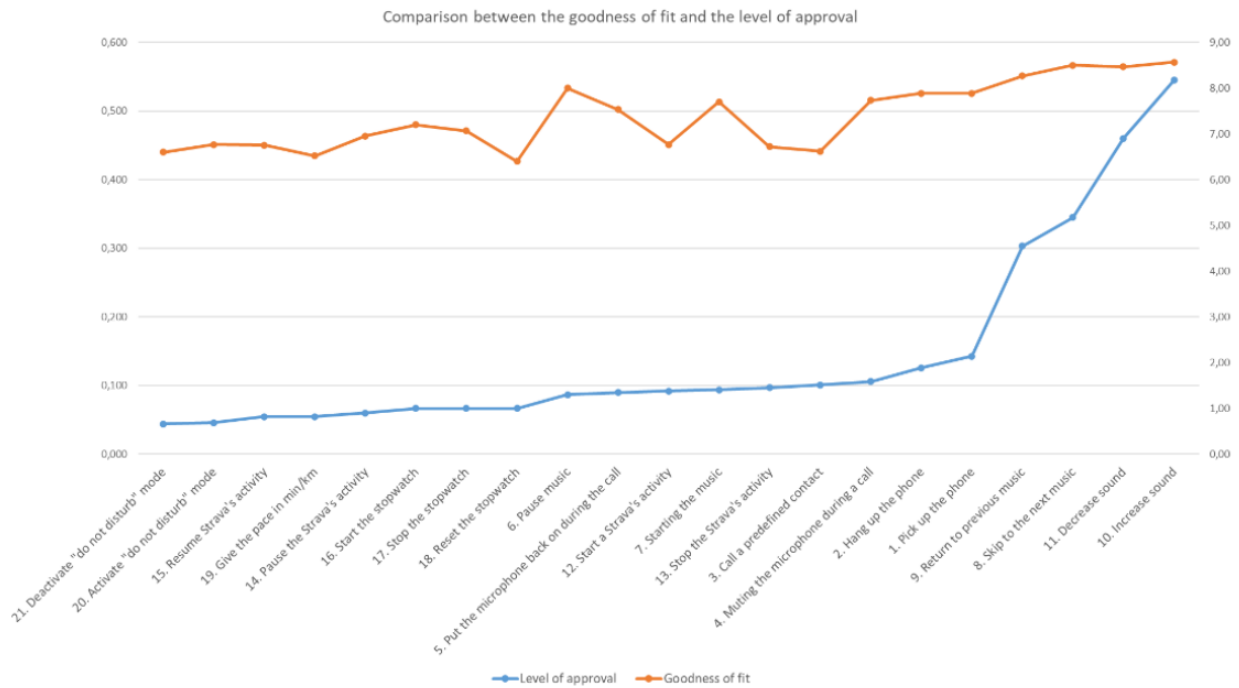


Figure 4.18: Comparison between the goodness of fit and the level of approval

4.4 Ease to perform

In this section, we examine the ease to perform, which represents how easily a participant can perform a certain gesture. Unlike the previous sections, we don't review the ease to perform for each participant individually, as the graph does not provide significant information. Instead, we first present the graph showing the average ease to perform for each action. Following that, we explore whether there is a correlation between the ease to perform and the agreement rate.

The first graph 4.19 shows the average ease of performance for each action. As noted previously, opposite actions tend to have similar ease of performance scores, often because they use the same gesture. Interestingly, there is no significant difference between more complex actions and simpler ones. This is because we are evaluating the difficulty of performing the gesture itself, not the complexity of the action. Therefore, it is logical that there are no substantial differences in ease to perform scores. This finding suggests that participants do not necessarily choose more complex gestures for more complex actions; instead, they prefer gestures that are straightforward and easy to perform, regardless of the action's complexity. This highlights the importance of intuitive and simple gestures in creating an effective interaction system.

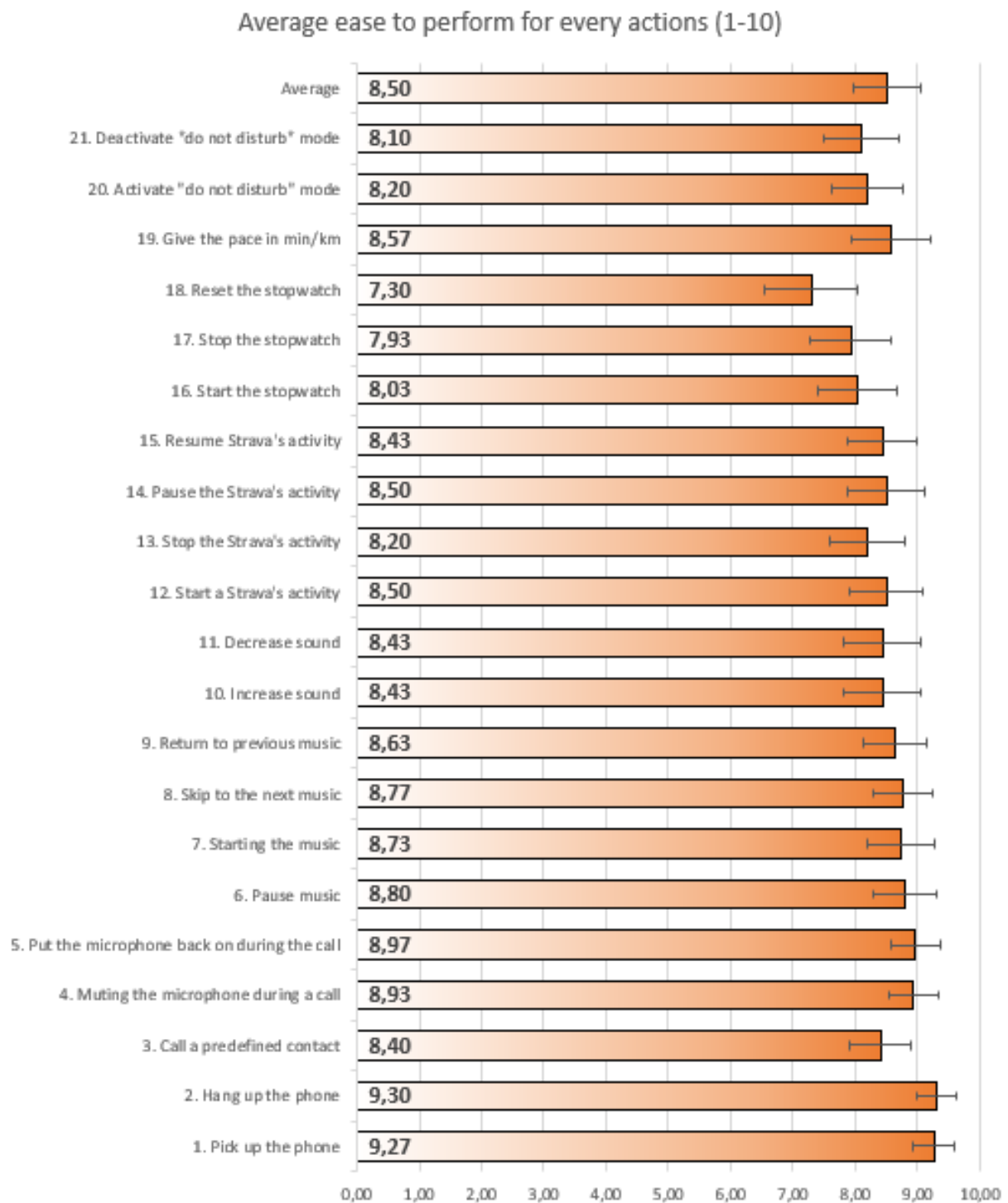


Figure 4.19: Average ease to perform per actions

The second graph 4.20 shows a comparison between the ease to perform score and the agreement rate. As we can see, there is no clear correlation between the two curves. The ease to perform curve appears to oscillate around a certain score independently of the agreement rate. This indicates that the ease with which participants can perform a gesture does not necessarily influence how much they agree on using that gesture for a particular action. Even if a gesture is easy to perform, it does not guarantee a high

level of agreement among participants, suggesting that factors other than ease to perform might play a significant role in determining consensus.

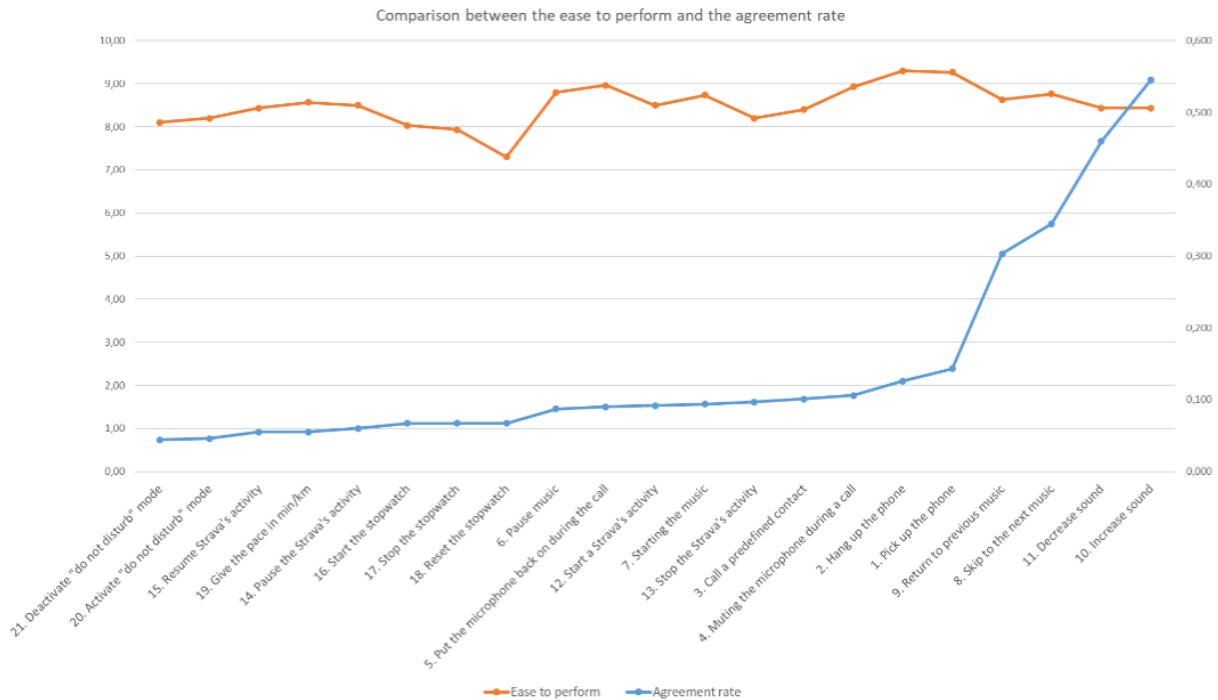


Figure 4.20: Comparison between the ease to perform and the agreement rate

4.5 Benefits and limits

This section presents the benefits and limitations of our work. We begin by discussing the benefits and then move on to the limitations.

The first benefit we observe is illustrated in the graph below 4.21, which represents the average IBM PSSUQ score per participant. Apart from two individuals, the scores are relatively high. This indicates that participants generally found the system easy to use and felt productive while using it. High scores on the PSSUQ suggest that our system meets usability standards effectively and is well-received by users. This positive feedback shows the relevance and the potential impact of our work as our approach is user-friendly and efficient for the intended tasks.

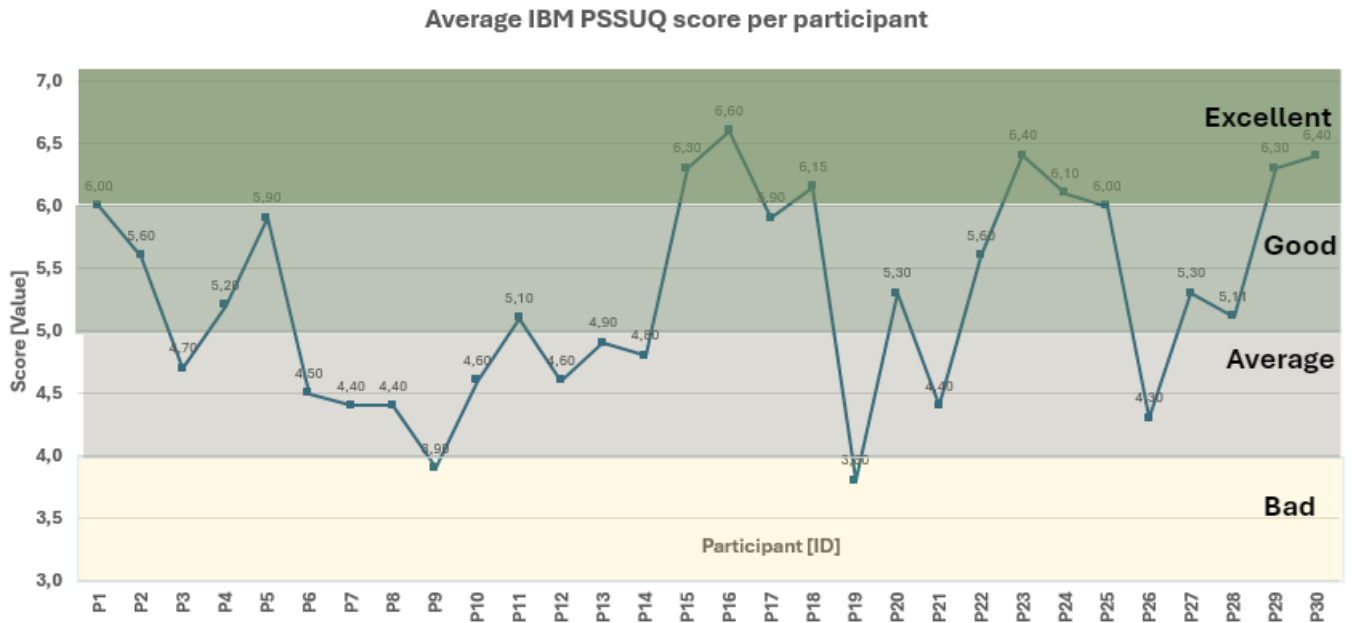


Figure 4.21: Average IBM PSSUQ score per participant

On the second graph below 4.22, we can see the average responses from all participants to two different questions:

1. I like the system's design.
2. I would be ready to use this system on a daily basis.

The results show that a large majority of the participants like our system's design, indicating they are comfortable with it. Moreover, about half of the participants are willing to use it on a daily basis, suggesting they are open to replacing their current systems (such as headphones or phones) with ours. This positive reception highlights the potential of our system to be adopted as a regular tool by users, reflecting both its aesthetic appeal and functional viability.

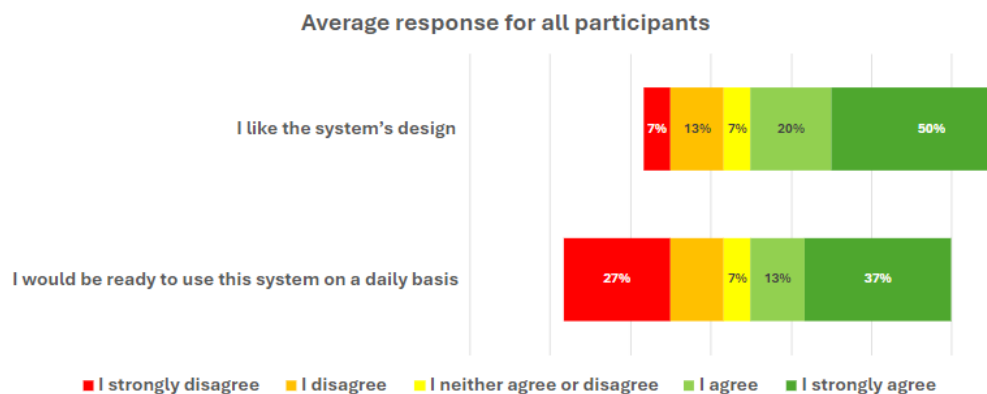


Figure 4.22: Average response for all participants

However, there are a few limitations with our implementation. First, some participants mentioned feeling uncomfortable making grand gestures in public. This is evident from the number of small and medium gestures performed compared to the large ones 4.4. This issue could be mitigated if the use of motion to control computer systems becomes more widespread and socially accepted.

Additionally, while running, people naturally make various gestures, such as swinging their arms. This can pose a challenge during the implementation phase, as the algorithm must accurately identify intentional gestures made while running. Moreover, the speed of running and varying road conditions can introduce unintended movements, complicating gesture recognition. One potential solution could be requiring users to make a specific gesture to initiate the capture process before performing the intended gesture, thereby reducing the likelihood of misinterpretation.

Chapter 5

Conclusion and perspectives

5.1 Summary of the contributions

In this work we sought to answer the following research question: **What are the gestures that people agree on when running with a connected bracelet to perform specific actions?**

We opted to utilise a connected bracelet called Kinemic, which is equipped with sensors capable of detecting the wearer’s movements. This decision was made after reviewing literature on motion capture in sports. We conducted a comparative analysis of several studies to assess the potential benefits it could offer to our research.

To address the research question outlined above, we conducted an elicitation study involving 30 participants to identify consensus gestures for 21 specific actions. However, before this, we developed a methodology to guide the interrogation of each participant.

Subsequently, we analysed the results from various perspectives. Below is a graph showing all our results 5.1. Initially, we examined which actions had the highest agreement rates and identified the most frequently encountered gestures. Following this, we analysed the gestures based on their characteristics, including range of motion, nature, laterality, form, and temporality. We then discussed the findings related to the participants’ thinking time, the goodness of fit of the gestures, and their ease to perform. Finally, we reviewed the benefits and limitations of our work.

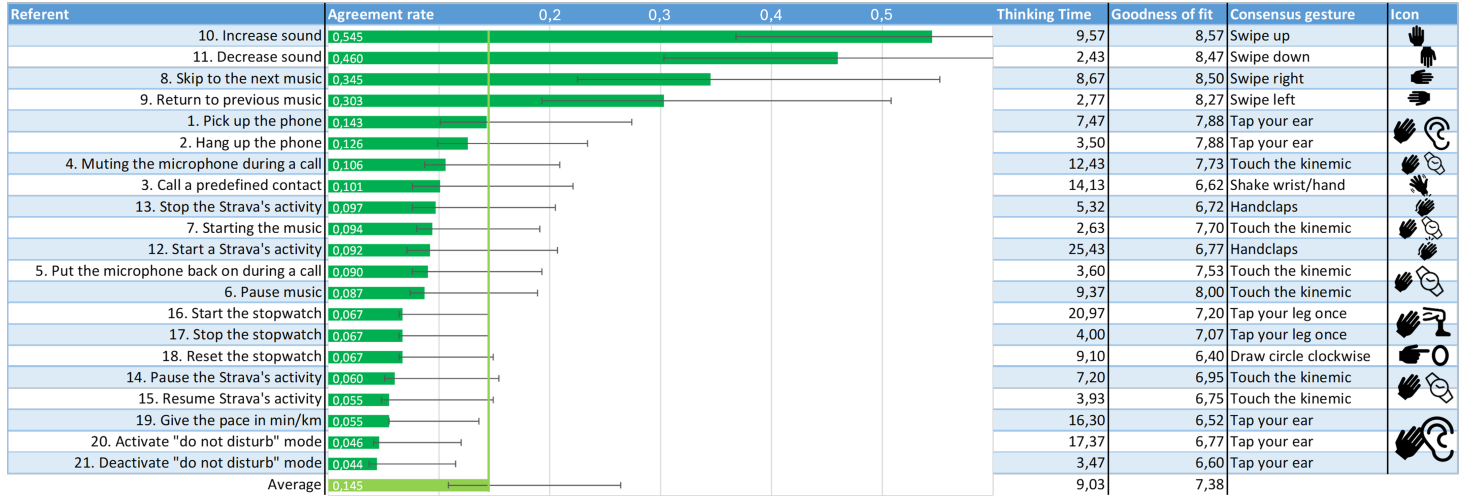


Figure 5.1: Summary graph

5.2 Future works

Finally, we can end this work by giving some leads that could be completed in future works.

A first idea could be to redo our experiments with a more diverse set of participants. As previously said, our sample is composed of a majority of young people so it could be a factor that introduces bias, and our results may not be suitable for older people.

To continue the work, the logical step is to test with the Kinemic which gesture is best captured. So that means taking a new sample of participants, asking them to do the 32 selected gestures and analysing which gesture is the best detected. Then the selection of gestures could be modified by considering both the number of occurrences and the ability of the Kinemic to detect this gesture.

A last idea can be to use a choice-based approach just as in the article Silpasuwanchai and Ren, 2015. Instead of redoing an elicitation starting from scratch, this approach could use some our 32 selected gestures and ask participants to choose between them. This way, results would be less scattered, and this work would reach more consensus.

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Appendix

Participants doing gestures



Figure 5.2: Before touching the Kinemic



Figure 5.3: Swiping left

Figure 5.4: Participant doing different gestures

Demographic form



QUESTIONNAIRE POUR PARTICIPER A L'EXPERIENCE

Titre de l'étude: Elicitation de gestes
 Professeur: Prof. Jean Vanderdonckt, UCLouvain
 Expérimentateurs: Nathan Flamend et Lucien Remacle
 Email de contact: jean.vanderdonckt@uclouvain.be

Données personnelles (qui seront anonymisées)

Code anonyme: (à attribuer par l'expérimentateur)
 Prénom : (anonymisés dans la base de données)
 Nom de famille :
 Genre : ☐ Femme ☐ Homme
 Age : (années)
 Profession : ☐ Etudiant ☐ Cadre ☐ Employé
 ☐ Indépendant ☐ Pensionné ☐ Chômeur
 ☐ Autre : (préciser s.v.p.)
 Domaine d'activité: (p. ex., administration, enseignement)
 Etudes : (domaine de votre dernier diplôme)

Je fais de la course à pied fréquemment :	Pas d'accord	1	2	3	4	5	6	7	D'accord
J'utilise un smartphone en course fréquen ^t :	Pas d'accord	1	2	3	4	5	6	7	D'accord
J'utilise une montre connectée fréquen ^t :	Pas d'accord	1	2	3	4	5	6	7	D'accord
J'utilise une montre connectée en course fréquen ^t :	Pas d'accord	1	2	3	4	5	6	7	D'accord
J'utilise une Kinect fréquemment :	Pas d'accord	1	2	3	4	5	6	7	D'accord

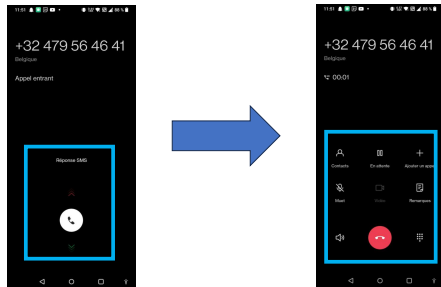
Données expérimentales

Connaissez-vous l'appareil utilisé dans l'expérience ☐ Oui ☐ Non
 Combien de fois l'utilisez-vous? Rarement 1 2 3 4 5 6 7 Fréquemment

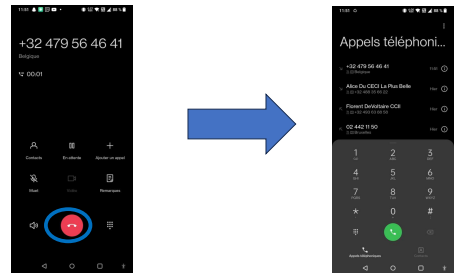


Referents

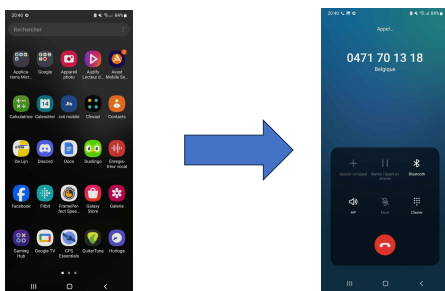
Pick up the phone



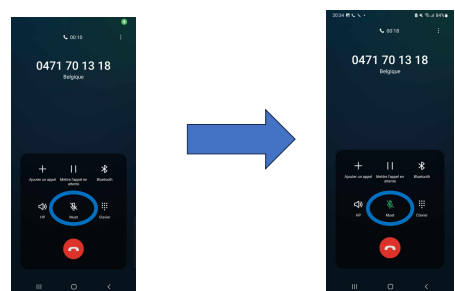
Hang up the phone



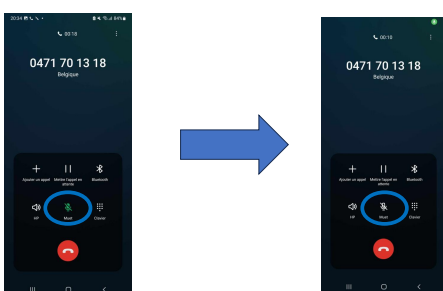
Call a predefined contact



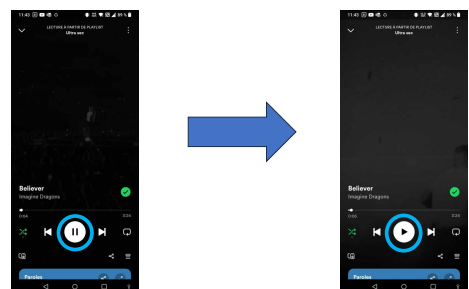
Muting the microphone during a call



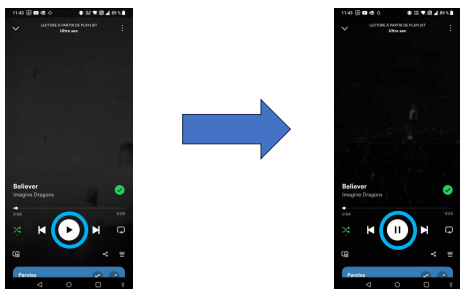
Put the microphone back on during a call



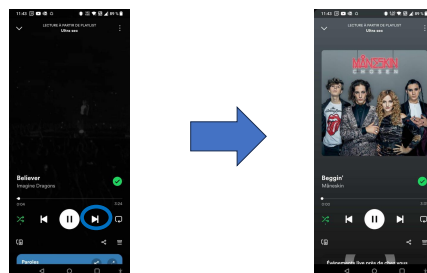
Pause the music



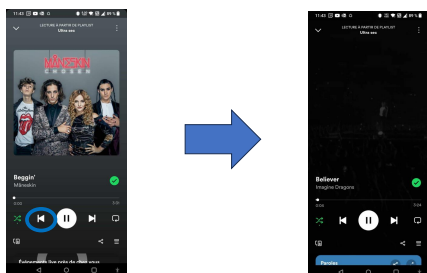
Starting the music



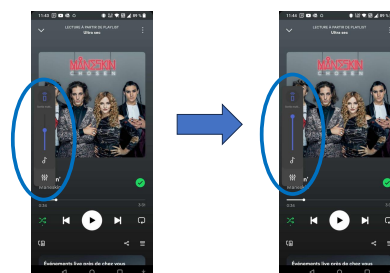
Skip to the next music



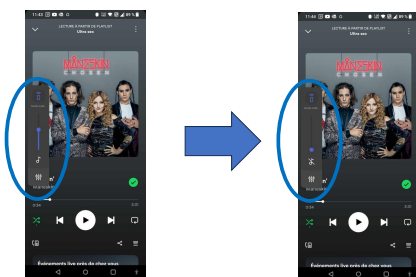
Return to the previous music



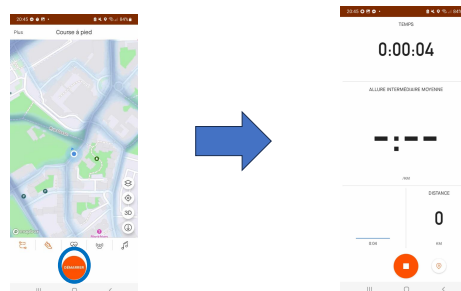
Increase sound



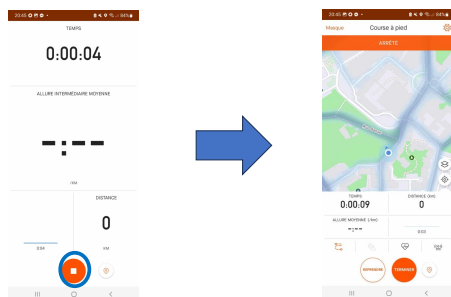
Decrease sound



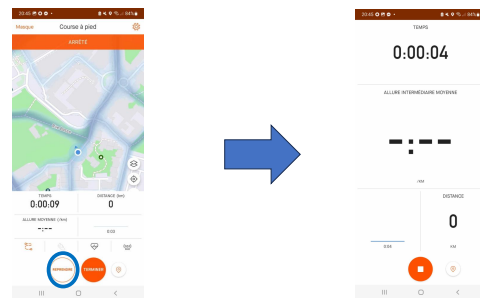
Start a Strava's activity



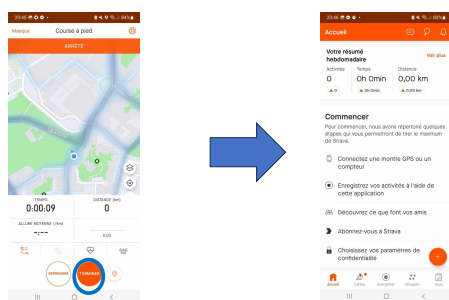
Pause the Strava's activity



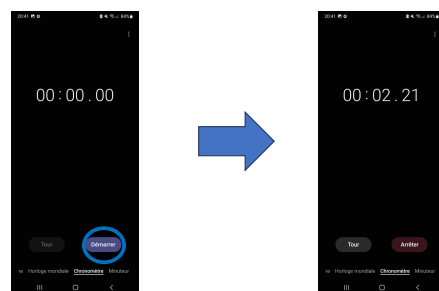
Resume the Strava's activity



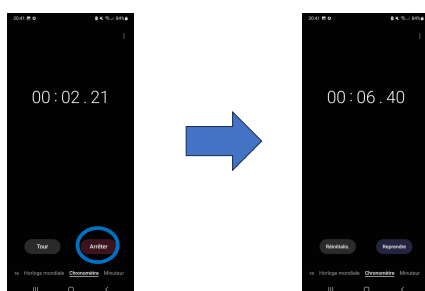
Stop the Strava's activity



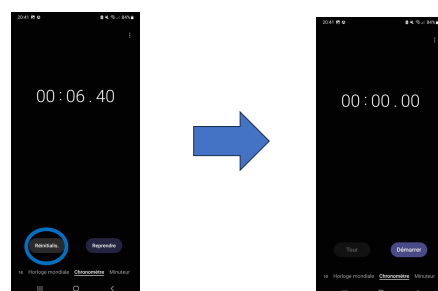
Start the stopwatch



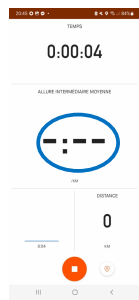
Stop the stopwatch



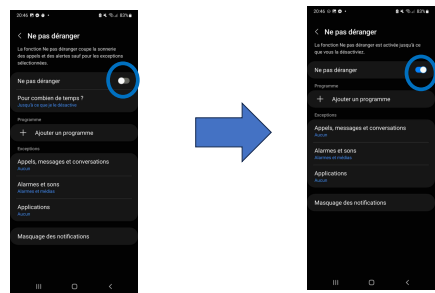
Reset the stopwatch



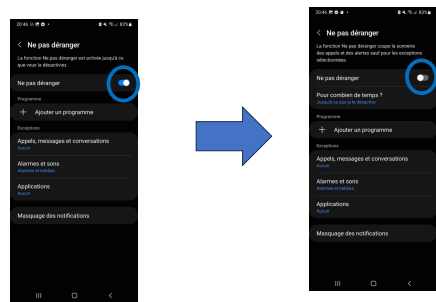
Give the pace in min/km



Activate "do not disturb" mode



Deactivate "do not disturb" mode



PSSUQ (value 1-7)

1. Overall, I'm satisfied with the ease of use of this system.
2. The system was simple to use.
3. I was able to complete the tasks and scenarios quickly with this system
4. I felt comfortable with the system
5. The system was easy to learn
6. I think I'll quickly become productive using this system
7. The system interface was pleasant
8. I enjoyed using the system interface
9. The system had all the functions I wanted
10. Overall, I'm satisfied with the system
11. I would be ready to use this system on a daily basis

Categories of gesture

Gestures	Range of motion	Nature	Laterality	Form	Temporality
1. Handclaps (any number), includes clapping back of one hand vs palm of the other	M	A	S	D	D
2. Swipe up	S	M	D	D	D
3. Swipe right	S	M	D	D	D
4. Swipe left	S	M	D	D	D
5. Swipe down	S	M	D	D	D
6. Rotate wrist left (counterclockwise) (can be for turning a button)	S	M	D	D	C
7. Rotate wrist right (clockwise)	S	M	D	D	C
8. Lift hand up palm up slowly (or fast, repeatedly or not)	L	A	D	D	C
9. Move hand down palm down slowly (or fast, repeatedly or not)	A	L	D	D	C
10. Draw circle clockwise with index (forearm moving) or reeling)	M	S	D	D	D
11. Draw circle counterclockwise with index (forearm moving) or reeling	M	S	D	D	D
12. Stretch out your arm with the palm of your hand raised	L	A	D	T	D
13. Bend your arm 90 degrees upwards in front of you	L	A	D	T	D
14. Tap your ear	M	M	D	T	D
15. Making cross with your hands	M	S	S	D	D
16. Touching your chest	M	A	D	T	D
17. Tap your head	M	M	D	T	D
18. Draw letters or shape	M	S	D	D	D
19. Wipers (left) to right (rainbow) or (right) to left.	M	M	D	D	D
20. Snap fingers	S	A	D	S	D
21. Shake wrist/hand	S	A	D	D	D

Gestures	Range of motion	Nature	Laterality	Form	Temporality
22. Open hand (one or two hands) (hand can be lifted to the ceiling)	S	A	D	T	D
23. Swipe left to right multiple times	M	M	D	D	C
24. Touching shoulders	M	A	D	T	D
25. Tap your mouth	M	M	D	T	D
26. Move hand to ceiling	L	M	D	D	D
27. Touch the Kinemic	M	P	D	S	D
28. Tap your leg once	M	A	D	T	D
29. Swing your forearm with your arm against the person's side	M	A	D	D	C
30. Look at your watch	M	M	D	D	D
31. Touching the opposite wrist	M	A	A	T	D
32. Touch your stomach	M	A	D	T	D

Wrist-based Gesture Interaction for Sports: Elicitation and Application

Resume

When you're running, it's not always very practical to take out your phone to change music, to answer a call or to monitor your pace. In this thesis, we work on a solution to this problem, Kinemic. This connected bracelet allows you to detect the gestures made by your arm to transform them into actions. The objective of this work is to carry out an elicitation study to determine the most intuitive and natural gestures that should be made for each action. To do so, we chose the 21 most useful actions while running and asked 30 participants which gesture they would do for each action. After that we put together their movements to make a group of 32 gestures, we analysed their characteristics and identified those with the most consensus. Finally we discussed the results obtained and we provided guidelines for the use of these gestures in other applications.

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