GEStory: An Atlas for User-Defined Gestures as an Interactive Design Space

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Abstract

How can we provide designers and developers with some support to identify the most appropriate gestures for gestural user interfaces depending on their context of use? To address this research question, GEStory was developed to address this research questions. It is an on-line atlas of gestures resulting from gesture elicitation studies with four main functionalities: (1) search for user-defined gestures identified in such studies by querying its features in an interactive design space, (2) show the preferred gestures and their characteristics for a given action (represented through a referent) with a given device in an environment and/or carried out with various body parts, (3) compare the existing studies and (4) suggest adding new studies. To feed GEStory, two Systematic Literature Reviews (SLR) were performed: a macroscopic analysis of 216 papers on their metadata, such as authors, definitions, year of publication, type of publication, participants, referents, parts of the body (finger, hand, wrist, arm, head, leg, foot, and whole body), number of proposed gestures; a microscopic analysis of 267 papers analyzing and classifying the referents, the final gestures coming out the consensus set, their representation and characterization. It also proposed an assessment of credibility of these studies as a measure for categorizing their strength of impact. GEStory acts as an interactive design space for gestural interaction to inform researchers and practitioners on existing preferred gestures in different contexts of use, and enable the identification of gaps and opportunities for new studies.

Keywords

Human–computer interaction, Gesture interaction, Gesture Elicitation Study, Gesture Preferences.

1. Context of the problem

Gesture-based interaction has acquired its letters of nobility, *e.g.*,in terms of user-defined gestures [1] made available through numerous Gesture Elicitation Studies (GES) [2], but also in terms of algorithms for gesture recognition [3]. Yet, identifying which gestures would be the most appropriate for a given task in a given context of use remains a challenging task for researchers and practitioners, such as designers and developers. Determining these most appropriate gestures brings us back to the question of identifying the gestures according to the end user, the interactive task, the gesture capture device, and the physical environment. Fortunately, several GES address this question, but too often for a context of use that is specified either too fuzzily or too specifically. These GES are heterogeneous, sometimes inconsistent or

EICS'22: The 14th ACM SIGCHI PhD Workshop on Engineering Interactive Computing Systems, June 21–24, 2022, EICS, Sophia Antipolis, France
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overlapping, rarely incremental and complementary.

Let us consider an example showing how a GES is conducted: Suppose the case that a designer wants to develop a gesture user interface for a new smartwatch prototype that allows users to control 5 actions (materialized as *referents*) in the environment of a smart car: (t1) turn on the radio, (t2) turn on air conditioning, (t3) answer a call, (t4) turn off the radio, and (t5) turn off the air conditioning. For the study a group of potential users P is brought together, perhaps 20 in number, *i.e.*,$|P| = 20$. Each participant is shown the context existing before and after performing each action: *e.g.*,The radio is off (before) and the radio is on for the referent t1 (after). The participant is asked to propose a gesture command using the smart watch to execute the referred action. At the end of the GES, the designer, who compiled a set of 100 gesture proposals = 5 (referents) × 20 (proposals), now looks at the set of gestures elicited for each function to understand which gestures are in agreement among participants. If the agreement is substantial and the sample of participants is representative enough of the target population that the gesture-based interface is targeting, then the designer is expecting that the prompts are intuitive and that other users, who were not part of the GES, are likely to guess, to learn easily, and hopefully to prefer the same types of gestures. Although these GES are numerous [2], they do not answer all design questions as they do not cover many contexts of use. Consequently, the following research question emerges from this paradoxical situation:

RQ=*how can we provide designers and developers with some support to identify the most appropriate gestures for gesture-based user interfaces depending on their context of use?*

The expected contributions of our doctoral thesis are as follows:

1. Two SLRs related to gestural interaction: one on GES metadata and one on gestures characteristics, along with a classification and discussion. An on-line Zotero collection of relevant papers and classification.
2. New methodological aspects for conducting a GES and new GES [4, 5, 6, 7, 8, 9].
3. GESTORY, an on-line web application serving as a repository for gesture elicitation studies and their results.
4. A validation of GESTORY based on multiple queries answering the initial research question.
5. A transition between GESTORY and GESistant. If the result of a search in GESTORY is zero gestures, the researcher could export these criteria to GESistant to conduct a new GES distributed in time and space.

2. Related Work

Regarding GES surveys and reviews, there are only three such studies: Vuletic *et al.* [10] conducted a systematic literature review (SLR) on hand gestures for user interfaces, but without having GES as the focus of their investigation; Vogiatzidakis and Koutsabasis first performed a GES review [11] for mid-air interaction, then a SLR [12] with a corpus of N=47 papers. These two studies are limited in scope in terms of gestures covered and in terms of investigation methods.

Regarding software tools, there are several software pursuing different goals than ours. GestMan [13] support practitioners in creating and managing 2D stroke gesture datasets, but do not exploit them in GES. GECKo [14], and more extensively, Omnis Praedictio [15]) support designers in evaluating important characteristics of stroke gestures, their consistency and their features such as time production respectively. GestureMap [16] provides visual analytics of Kinect-based full body gestures to analyze their similarities and differences. GestuRING [17] compiles an inventory of all ring gestures [18] found in the literature. These software tools do not address the above research question directly: they are not aimed at covering the whole body of gestural knowledge contained in the available GES and they are aimed supporting some specific design questions other than finding the gestures for a given context of use.

3. Research Methodology

Since our research question is not fully addressed, our initial idea consists of compiling and consolidating the results of all existing GES into a single gesture repository that can be queried to address the research question. This repository becomes a gesture atlas where each gesture is characterized according to several dimensions: user, task, device, environment, human limbs, etc. For this purpose, our research method is structured in five connected stages (Fig. 1):

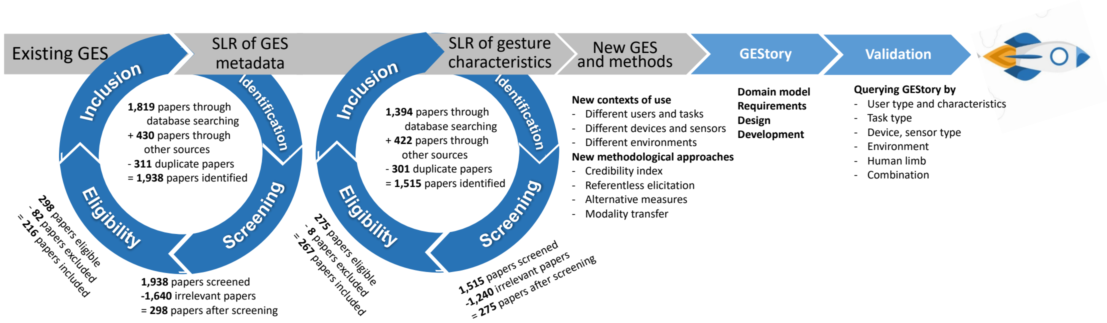


Figure 1: Research Methodology of GEStory.

SLR of GES metadata: conduct a first SLR based on the metadata describing each GES [2], such as the year of publication, venue, number of participants, number of referents, experimental setup, number of proposed gestures and number of consensus gestures. Our approach was inspired by the four-phase SLR method (Identification, Screening, Eligibility and Inclusion) proposed by Liberati *et al.* in [19] and the flow was represented in a PRISMA diagram. For *identification*, the query Q = ("Gesture" AND "Elicitation" AND "Study") was performed on five major Computer Science digital libraries (*i.e.*,ACM DL, IEEE Xplore, Elsevier ScienceDirect, Elsevier Ei Compendex, and SpringerLink) and other sources (*i.e.*,DBLP CompleteSearch and Google Scholar) to identify 2,249 candidates, from which 311 duplicates were eliminated. For *screening*, we retained only those papers that explicitly introduced a GES for UI design, discussed a GES, or explicitly used a method to examine a GES, thereby leaving 298 papers. For *eligibility*, 82 papers were excluded that did not match 3 conditions, leaving a final corpus of N=216 studies for our examination. For *inclusion*, we verifyied quantitative and qualitative aspects of our corpus of papers, stored and maintain as an on-line collection with Zotero, a multi-platform bibliography management.

SLR of gesture characteristics. Since the first SLR focused on GES metadata only, we ran a second SLR to provide an in-depth analysis of gestures elicited and agreed upon in GES after updating the collection, stopped at the beginning of 2021. We follow the same methodology with the Q = ("Gesture" AND (guess* OR elicit*) AND (study OR experience)): 1,816 papers were firstly identified, 1,515 papers were screened after duplicates removed, 275 papers became eligible, and 267 papers were finally included. Based on these SLRs, we have obtained concepts and terminologies that are part of the GES studies, we discussed some examples of representative GES, and we provided data and calculations such as the average, the mean, maximum, and minimum of the number of participants, references, collected gestures, final gestures, etc. Moreover, consensus gestures are classified according to several dimensions: a taxonomy of referents based on task classification [20], a classification of 3D gestures [21], a classification of gestures in Augmented Reality [22] and another one for the whole body to control a humanoid robot [23]. Bernsen's theory of multimodality will be used to classify the modalities and McAweeney*et al.* [24] criteria will be expanded to classify gesture representations (*e.g.,*images, animations, videos).

New GES and methods. To complement our repository, our search conditions focus in new contexts such as different users and tasks, different devices and sensors and different environments, we identified some areas uncovered by existing GES and subsequently conducted some of them, such as for head and shoulders gestures [9], for zenithal gestures [5], for radar-based gestures [6, 7], for facial gestures [4] and Squeeze Gestures [8]. We are exploring new methodological approaches, such as GES without any explicit referent to discover more proposed gestures than with legacy bias [25] or by transformation [26].

Development of GEStory [27]. Based on the results of the two aforementioned SLRs, a domain model has been defined (Fig. 2) to create the database of GEStory, an on-line gesture atlas for querying GES on multiple criteria. GEStory is presented as an interactive design space, such as the one for wearable devices [28], where various design dimensions can be explored. In particular, selecting any particular human limb should result in selecting GES satisfying this criterium (see a prototype in Fig. 3). GEStory, beyond making gestures accessible, should also provide some guidelines in selecting and designing gestures based on its atlas [29] and, possibly, automate its evaluation based on guidelines [30].

The framework used is Vue.js. The Vue file format is divided into 3 parts:

1. The HTML structure of the page or element that you want to display,
2. The JavaScript methods and state variables used by the component. This part also allows use the Listener design pattern to push changes to other components,
3. The CSS part that corresponds to the style of the component.

GEStory has a total of 3902 gestures from 267 gesture elicitation studies (GESs) obtained in the 2 SRLs, the information of these gestures are public and available in the data.json file

The architecture of the main page is divided into 3 parts (See Fig. 3) which communicate with each other. These 3 components all inherit from the Vue.component class:

- The bodyMap component which takes care, based on data extracted from the *data.json* file, of displaying points representing gestures on the body map. It has different attributes such as the list of body regions (bodyRegions). As for its methods, it mainly has methods

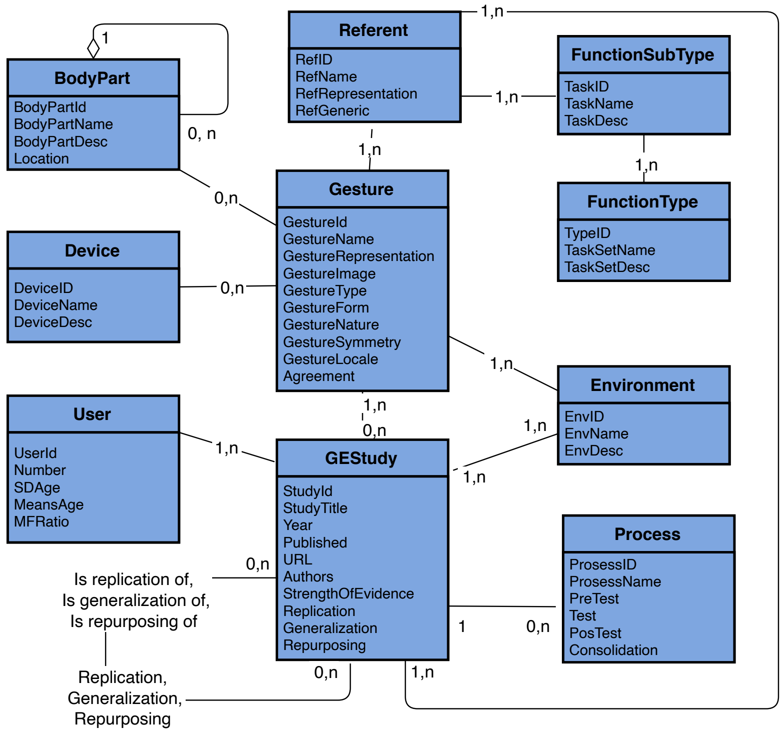


Figure 2: UML diagram class of the domain model.

related to the display of points on the body map (getPositionForTypeAndItem, drawLineR, changeBodySelection for example).

- The DataFilter component takes care of displaying filters as well as displaying the list of gestures extracted from the same *data.json* file. Each gesture in the list has the name of the gesture, the name of the study and the *credibility* percentage. This component communicates to bodyMap the list of gestures to be displayed according to the filters. It has all the attributes related to the filters (those active, the total list of filters). As far as methods are concerned, these are mainly methods aimed at adapting its display according to the display of the other two components (if these are closed, you can increase the size of DataFilter, which is achieved with returnClass, mainClass).
- The last component, ItemDisplay, takes care of displaying the gesture that has been selected on the bodyMap or in the list of gestures. It therefore depends on these 2 components in order to obtain the gesture selected by the user. This element is used to display the advanced details of the chosen gesture. The main attribute of this element is the user selected gesture (item). Shows gesture information such as its name, name of origin GES, authors, URL of study, year of publication, *credibility*, etc. (see Fig. 3).

To provide quantified, peer-reviewed gestures to inform the design of gesture-based user interfaces, it is important that each stored gestures includes relevant information to become effective. In some other references, recommended gestures could be based on the personal

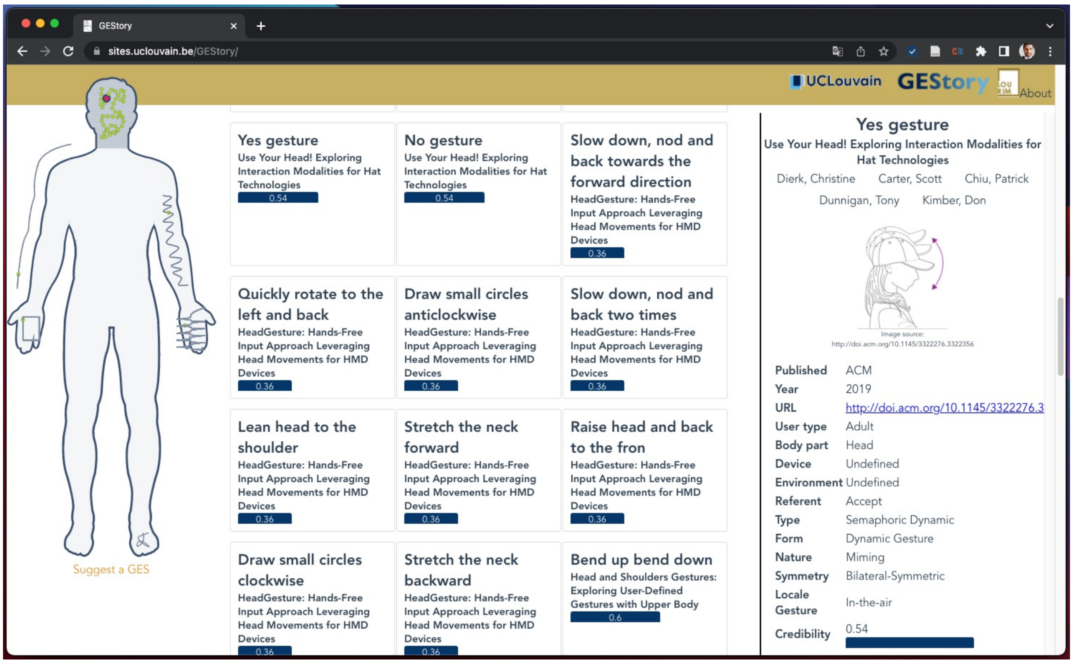


Figure 3: GESTORY screenshot.

opinions of a few experts, do not provide any reference to support them or any empirical evidence to backup their application, do not provide any indication as to whether a particular gesture represents a consensus of researchers or a large agreement among participants, do not give any information about the relative importance of individual GES. To this end, a numerical measure was proposed to quantify the *credibility* of consensus gestures offered by a GES. It has reflected the essential criteria for a GES considering: (a) the length of the study (the number of pages, *e.g.*,a poster of 4 pages is different from a paper of 25 pages), (b) the expertise of the authors in gesture research (*e.g.*,, how many papers they published on topics related to gestures, *e.g.*,7 for an author based on Google Scholar entries, (c) the venue where the GES was published (for which we use Scimago's journal ranking in terms of Q1/Q2/Q3/Q4/none categories and CORE Rankings Portal for conferences in terms of A * / A / B / C / D), (d) the number of participants involved in the study (*e.g.*,, a GES with 5 participants is assumed to have a lower validity than a GES with >30 participants), and (e) their diversity in age, we use the standard deviation of participants' ages (*e.g.*,, SD ages = 5 when reported in the GES. It combines (a), (b), (c), (d) and (e) in one single *Strength of evidence* measure, defined as follows:

$$SE(\text{GES}) = \frac{(\frac{a}{A})^2 + (\frac{b}{B})^2 + (\frac{c}{C})^2 + (\frac{d}{D})^2 + (\frac{e}{E})^2}{5} \qquad (1)$$

where:

- A = the typical limit of page numbers for a full paper at the major HCI conferences (*e.g.*,10 pages), so A=10. If A >= 10, then a/A is bounded to 1, so that each component of the sum above is between 0 and 1.

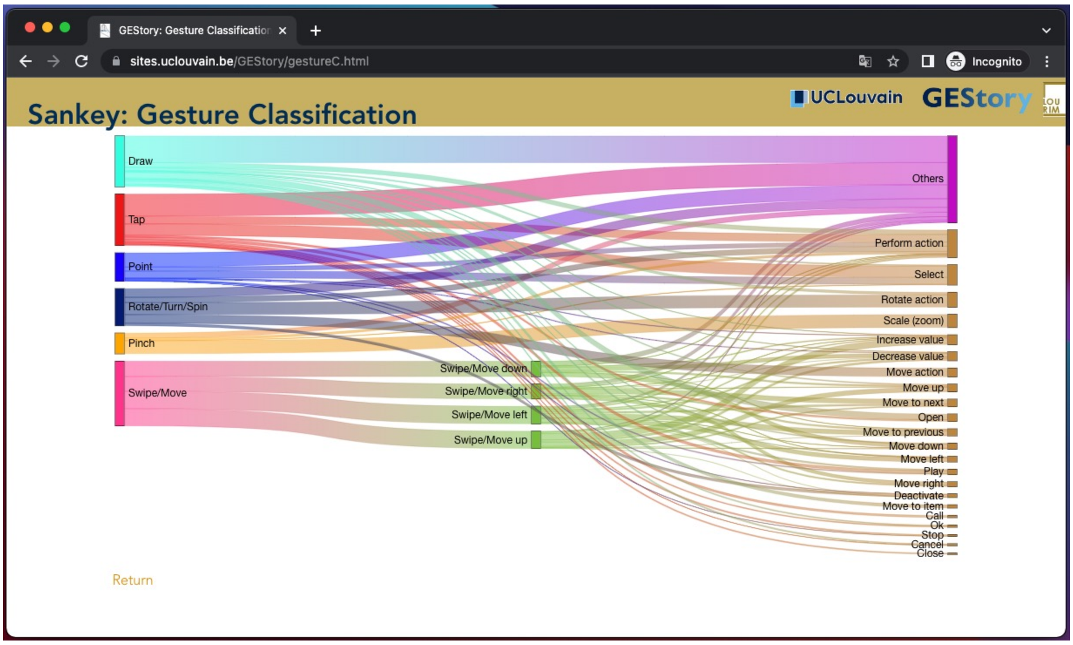


Figure 4: GEStory, Sankey diagram of the relationship between gestures and referents

- B = the total number of articles published by all authors of the GES study, and b is the total number of gesture articles published by all authors of the GES study.
- C = 5 and we encode Q1 = 5, Q2 = 4, Q3 = 3, Q4 = 2, and other = 1 (low strength of evidence based on the estimated quality of peer review).
- D = 20 (the typical number of participants in GES studies; this value should result from the analysis of the appendix where the number of participants is discussed). If d >= 20, then d/D is limited to 1, so that each component of the sum above is between 0 and 1.
- E = the standard deviation of participants' ages extracted or computed, *e.g.*,, E=4.15.

For example, Fig. 3 displays a list of gestures coming from different GES, "Yes gesture" has a strength of evidence of *SE*=0.54, and Bend up bed down has a strength of evidence of *SE*=0.6.

Through my participation in the Doctoral Consortium at EICS22, we were recommended to foster qualitative data, to propose a legacy classification of gesture names that are the same but differ across studies. Inspired by this, we incorporate a Sankey diagram using the "chartjs-chart-sankey" library to show the different relationships that exist between gestures and referents (See Fig. 4).

Validation of GEStory. To validate GEStory we carry out tests with a group of twelve volunteer participants (7 Males, 4 Females, 1 not specify, aged from 17 to 79 years). Recordings of these interviews were made to allow calculation of success/failure rates per task and completion of the UEQ+ questionnaire.

In order to perform our tests, I have drawn up a list of 4 actions that the "testers" are required to perform. I decided on them based on the changes made to the platform. This allows me to see how the user behaves in front of the different navigation tools (the selection menu, the navigation bar, the "suggest a GES" button, etc), Below is the list of actions:

1. Look for an iconic dynamic type gesture of 2018
2. Submit new gesture data
3. Look for the "Move hand UP" from 2015, to be performed with the arm.
4. Find the information containing the name of the tool on which the prototype was built

Following the UEQ+ analysis, figure 5 shows that the two most important parameters for test participants are dependability (2.42/3) and efficiency (2.33/3). Looking at the "ratings" assigned by the testers to the organization of the GESTORY platform, we can see in figure 6 that these two parameters are among the top five rated (with ours of 0.63 and 0.58 respectively).

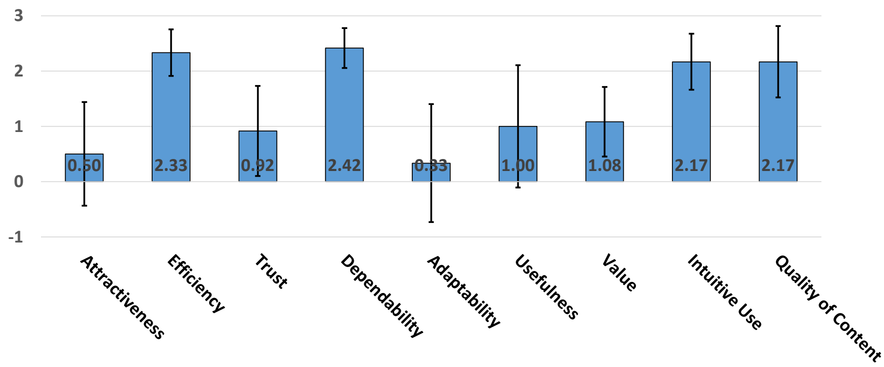


Figure 5: importance by parameters in UEQ+

In Fig. 6, The best ranked parameter of the participants is that relating to the intuitive use of the GESTORY platform (1.04/3). This allows us to link this last criterion with the hypotheses we have developed above. Indeed, we can quite easily say that we have succeeded in sufficiently reducing the workload of the platform (which seemed very high to us on the initial version of the project) so that the user can handle this tool without needing a very extensive training. We can also highlight the fact that the accounting of the interface is quite suitable for it to allow users to carry out their various tasks. This allows us to draw a parallel with the success rate of the tasks we asked them to perform which is, for each task, at least, greater than 75% success.The utility is a parameter of the UEQ+ analysis that had the most negative result (-0.98). If we rely on the given definition, this parameter represents the fact that the use of the product brings benefits to the user.

Fig. 7 shows the result of task success/failure rate. In general, the participants were able to perform the various tasks that were asked of them. The least successful task being number 1 (9 successes, 2 successes with our help, and 1 failure, see Fig. 7a). During our tests, we were able to observe that the failure of the task was often explained by a phase, on the part of the user, of "taking control of the platform". Most of the participants took the time to discover the different search tools (the search engine and the search criteria system) and sometimes did not understand how they work directly (despite a platform presentation phase). performed before the various tests).

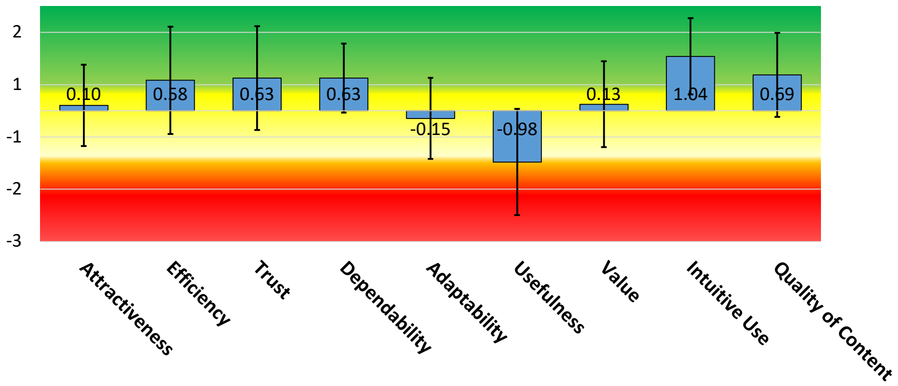
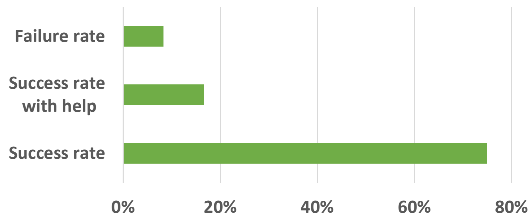
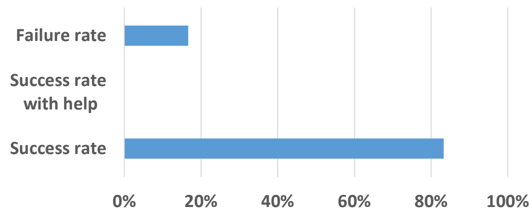


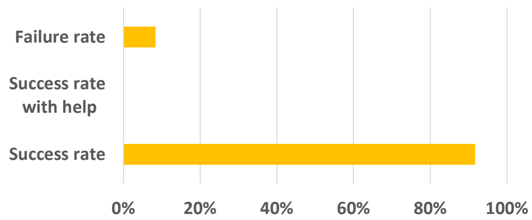
Figure 6: UEQ+ results



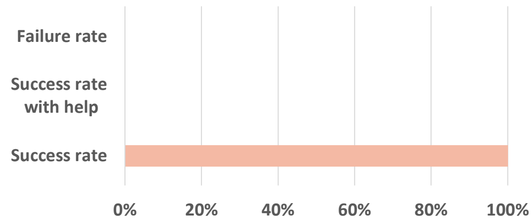
(a) Task 1



(b) Task 2



(c) Task 3



(d) Task 4

Figure 7: Task success/failure rate

By looking at the average resolution time of each task, we can also notice that task No. 1 is the one that took the longest to complete (which could also be justified by this phase of ”getting started with the tool”). The average resolution times being for task No. 1: 73 seconds, task No. 2: 27 seconds, task No. 3: 61 seconds, task No. 4: 24 seconds.

These task resolution times also allow us to observe the fact that the tasks requiring the use of the search tools present on the site (task No. 1 and No. 3) required longer resolution times than the two others. As a reminder, the first task being: Look for an iconic dynamic type gesture from 2018, and the third: Look for the ‘Move hand UP’ from 2015, to be performed with the arm.

Transition to GESistant. A transition should be ensured between GEStory and GESistant, a software aimed at assisting the experimenter to conduct a GES in a way that is distributed in time (stages are asynchronous) and space (participants are contributing remotely, self-assisted and without any constraint) structured into 6 stages: define a study, conduct a study, classify gestures, measure gestures, discuss gestures, and export gestures. When a query in GEStory does not lead to a compelling set of appropriate gestures, the parameters of the query should be transferred to the "define a study" stage in GESistant in order to match the suggested GES criteria.

4. Conclusions

Based on the research methodology (Fig. 1), the first SLR has been completed and its results are published [2]. The second SLR of gesture characteristics has been completed in terms of research and are momentarily stored as on-line spreadsheets. Their results are under analysis. Other GES have been conducted and published. Several others have been conducted, but not yet analyzed, such as a GES for a haptic device *vs.*without it.

The GEStory prototype was created based on its domain model (Fig. 2) whose classes include Body part, Device, Gesture, Environment, Participant, Study, Referent Classification (FunctionSubType and FunctionType). The relationships between device and gesture, body part and gesture, gesture and referent, participant and study, study and gesture, gesture and environment are also considered. Currently, GEStory [27] is considered an interactive design space [28], whose classes are dimensions of investigation. Checking or unchecking the values of each dimension will automatically result in the display of GES satisfying these criteria and their consensus gestures (Fig. 3). Each gesture is displayed according to a textual representation, a textual description, a picture, JSON-based formal definition based on an Extended Backus-Naur Form (EBNF) grammar with transformations between [26]. By means of a Sankey diagram (Fig. 4) the relationship between the classified gestures and the classified referents is shown; this diagram shows the distribution of the preference of the users of a gesture to perform a referent.

A validation of the current version of GEStory was carried out in which 12 participants evaluated "Attractiveness", "Efficiency", "Trust", "Dependability", "Adaptability", "Usefulness", "Value", "Intuitive use" and "Quality of content" with the UEQ+ questionnaire (Fig. 5 and Fig. 6) and performed 4 tasks for which the time to perform and the success/failure rate were calculated (Fig. 7).

It is developing the transition from GEStory to GESistant, this will allow the user to export the GEStory information (*e.g.*,GES result for replication, configuration parameters for a new GES, etc.), This will allow experimenters to have a preload for a new GES. GESistant will allow the study to be carried out remotely and asynchronously.

Acknowledgments

The author of this paper acknowledges the support of SIGCHI Gary Marsden Travel Awards 2022 for the support given for the trip and AFIHM for the invitation of Doctoral Consortium EICS2022.

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