

# Exploring gesture generation for smartwatches: is user elicitation enough?

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## Abstract

Gestures are a preferred mode of interaction for smartwatches and these are commonly elicited either by expert/designers or by users. This paper aims to understand the most promising approach for generating and assessing gestures by employing two empirical studies to validate a set of expert/designer-generated gestures. It further gains insights into the users' mental models, their role as co-creators, and their considerations for one-handed gestures in smartwatches, and discusses the virtue of incorporating both approaches of gesture elicitation.

**Keywords:** *gesture elicitation, conceptual design, design evaluation, smartwatch, usability*

## 1. Introduction

Smartwatches, conceived as a natural progression from traditional timepieces, represent a convergence of technological innovation and the evolving needs of modern lifestyles. Today, smartwatches have 216.43 million global users, as of 2022 (Ruby, 2023), and its market share has been growing the fastest since the last decade due to the rising inclination of consumers towards wearables, with a forecasted CAGR of 14.6% between 2023-30 (Wearable Technology Market Share & Trends Report, 2030). Touch-screen interaction has been the primary interaction method for smartwatches since their introduction, however, this interaction method has multiple limitations owing to the small screen size of the watch, usually only about 1.5 to 2.5 inches (Kerber, et al., 2016). Users are limited to providing input to the device by tapping and swiping the touchscreen which is often slow and prone to errors owing to; fat finger, the issue of input errors caused by the relatively large size of a users' finger in contrast to the size of a target on the touchscreen, and occlusion problem, the occlusion of a large portion of the viewable screen because of the relatively wide finger surface (Arefin Shimon, 2016). These problems become more acute when the user is on the move. Such challenges have inspired research in non-touch, i.e., gesture-based interaction for smartwatches, particularly through the use of one-handed gestures (Gong, et al., 2016; Chan, et al., 2016). In 2021, Apple devised 'Assistive Touch' which had 4 universal functions under one-handed gesture interaction: previous/next/confirm/open action menu. This allowed users to navigate and operate all applications via several simple gestures. Currently, the 'confirm' gesture is a default, further establishing the need for design and research of dedicated gestures to enhance usability in smartwatches.

This paper presents the design of a set of one-handed gestures for smartwatches by expert/designers through a systematic design process considering key parameters identified, and further validates the same through two sets of user studies, to glean insights on the most promising approach to generate and evaluate gestures. This explorative research stems from a larger body of work on gaining insight into

users' mental model, their role as co-creators and their considerations while creating and evaluating one-handed gestures in smartwatches.

## 2. Literature

Gestures play a pivotal role in the tapestry of human communication, serving as a fundamental component of our daily linguistic life. From conveying emotions to expressing nuanced meanings, gestures have been an integral part of human expression and a natural mode of interaction with the physical world and objects in it (Zimmerman et al., 1987; Buchmann et al., 2004).

Hand gestures, including the use of fingers and arms, are widely explored as a natural and intuitive interaction modality for a variety of applications (Vuletic et al., 2021). While touch interaction is generally bimanual (one hand to hold the device and another to interact), one-handed gestures allow users with upper limb disabilities to use electronics without having to touch the display or watch the crown (Ye et al., 2023). This also aids the average user with the option to operate their smartwatch via gestures, especially in situations where the opposite hand may be preoccupied. Though gestures can only be designed to match a specific system and not be used universally (Cassell, 1998), design considerations and parameters emerging from past research can be used to identify principles that guide designers in their generation of gestures for smartwatches, as in (Table 1) below:

**Table 1. Design considerations for gestures: A literature review**

Consideration	Description	References
Effort	Easy to perform	Nielsen et al., 2004
Fatigue	Not to be physically stressing when used often	Nielsen et al., 2004
Memorable	Easier to remember and less likely to be confused with other functions	Nielsen et al., 2004
Intuitive	Mapped to an user's instinctive actions	Nielsen et al., 2004
	Metaphorically and Iconically logical towards functionality	McNeil, 1985; McNeil, 1987
	Similar gestures for similar actions	McNeil, 1985
	Opposing gestures for opposing actions	Kerber, 2016
	Continuous gestures for continuous actions	Kerber, 2016
Socially Acceptable*	Be acceptable in a social environment	Chan et al., 2016
Line of sight*	Screen visibility is not compromised	
Gesture Delimiters*	Not be accidentally triggered	Zhao et al., 2016

\*Refers to considerations that were specific to a smartwatch

Ever since gestures were first considered for human-computer interaction in the early 1980's, multiple methodologies of gesture generation and evaluation have been introduced. The two widely accepted methods include: Expert generation, and Gesture Elicitation or Guessability Study Methodology (Wobbrock et al., 2005), commonly referred to as User elicitation. Expert generation involves experts (designers, engineers, ergonomists, etc.) to generate and evaluate gestures for interfaces as in Cannanure, et al. (2016), and Zhao, et al. (2022). Where as, during Gesture Elicitation participants are typically shown the effect of a certain action, and are then prompted to perform the gesture that would

cause this action. Emerging from the field of participatory design, user elicitation studies have extensively been applied in gesture design as they are considered a bottom-up approach to identifying and designing “good gestures” (Wu, et al., 2022). In user elicitation, end users are involved in generating gestures for selected actions (Vuletic, et al., 2021; Ye, et al., 2023; Chan, et al., 2016).

Traditional Gesture Elicitation may often face issues of gesture disagreement where participants face a lack of consensus when generating gestures for a particular action, due to their varying understandings or perceptions of a specific gesture. Participants may also face a legacy bias which refers to the end users’ tendency to transfer gestures they have learned from existing input devices, interfaces and techniques to new designs. Moreover, participants may often get confused when facing many choices and newly introduced complex conditions. This is exemplified in complex cases such as smartwatches, where the system itself is attached to the user’s arm introducing additional design considerations. Therefore, there is a need for a methodological update of how gestures are designed, and how elicitation studies are currently conducted (Wu, et al., 2022).

### 3. Methodology

A two-phase approach was adopted to Design gestures and Validate the same with potential users, as elaborated below. To remove the bias and attachment of users/participants with their own gestures during self-evaluation, two studies of validation was conducted.

#### 3.1. Design

The designers followed a 3-step systematic design process, akin to other domains of design, that entailed; problem discovery by identifying smartwatch actions and selecting a final set of actions to design for, generation of gestures for the selected actions by analyzing design considerations, and finally, evaluation of the gestures to select a final set of gestures.

##### Identifying smartwatch actions

The designers started out by systematically listing and examining the available actions, i.e., 7 physical and 4 on-screen actions, across various smartwatches. These were then grouped, combined, and evaluated to identify the most crucial actions for smartwatch functionality. Adhering to Miller’s Law of 7±2 actions (Miller, 1956), this resulted in a set of 7 distinct actions to make it easy for users to remember all gesture-based commands.

The actions were chosen such that they would enhance the user’s ability to navigate and operate a smartwatch when using a Gyroscopic Pointer with maximum coverage. The Gyroscopic Pointer controls a cursor for navigating the device based on the tilt of the wrist. The resulting 7 actions include Gesture Mode Activation (A1), Home Screen (A2), Button Press (A3), Continuous Scroll (A4), High- pressure situations, such as answering and rejecting phone call, -positive (A5) and negative (A6), and Shortcut menu (A7).

##### Generating gestures

Before developing gestures, a set of constraints were established to guide the design process. The designers further identified design parameters and considerations, from (Table 1), that each potential gesture should possess, as follows:

- Gestures for a particular action should be easily distinguished from all other gestures within the final gesture set.
- The gesture should ideally be metaphorically and iconically logical towards functionality.
- The gesture should be easy to perform, i.e., that it should be such that it cannot usually be performed unknowingly by the user.
- Similar actions can use similar gestures and it should be noted that, users would find opposing gestures for opposing actions cognitively optimal.
- Continuous gesture, referring to a continuous range, should be designed to operate differently from the other gestures.

Gestures were then collected from various gesture repositories, previous studies, existing gesture command systems of which some were previously elicited from users. A total of 65 gestures for the 7 target actions were generated via brainstorming.

### **Evaluating and selecting gestures**

The 65 gestures were then evaluated based on the following criteria: Fatigue, Effort, Time required, Cognitive mapping, Social acceptability, Technological feasibility, and whether the User's screen visibility would be compromised. Multiple iterations were conducted to ensure that gestures not only suited their intended actions but also formed a distinct and seamlessly integrated gesture set. This resulted in a final set of 6 unique gestures (1 common to 2 actions) for the corresponding 7 actions.

## **3.2. Validation**

For validation, empirical studies were conducted in two studies, 1 and 2.

Participants from study 1 'User Elicitation' generated multiple gestures before deciding on a final gesture for a specified action to reduce legacy bias. This process may have led to a bias in the participants resulted in them preferring and rating their self-generated gestures highly. In order to eliminate this bias, study 2 was conducted with a separate set of participants who were asked to choose between the user elicited gestures from study 1 and the expert generated gestures for each action.

In study 2 'Gesture Evaluation', another group of 32 participants were asked to evaluate the set of user generated gestures against designer generated gestures for each of the 7 actions. Evaluation was done using 5-point Likert scales.

### **Participants**

Study 1 of the study had 16 participants with 10 male and 6 female, with an average age of the participant being 21.1 years ( $sd = 3.17$ ). 10 of them had previous experience using a smartwatch and 6 of them had used gestures to control devices previously.

Study 2 had 32 participants out of which 12 were female and the rest male. The average age of the participants was 20.6 years ( $sd = 2.71$ ). 20 of the participants had previous experience with a smartwatch and 16 of them had used gestures previously to control devices.

Participants in study 1 (user elicitation followed by gesture evaluation) and study 2 (gesture evaluation) did not overlap, and all participation was voluntary.

### **Study 1 methodology**

To understand user's preferences for one-handed gesture in smartwatches and investigate the efficiency of user elicitation study techniques in such complex scenarios, 16 participants were asked to; (i) elicit gestures for each of the 7 actions, (ii) self-evaluate their gestures and select the 'best', (iii) further evaluate their selected gesture against the gestures designed by the designers, and (iv) state their preferred gesture.

This resulted in a total of 112 gestures, with 16 gestures for each of the 7 gestures. 59 of them were distinct across all actions. Study 1 had 3 sub-stages, Introduction, Elicitation and Evaluation.

*Introduction:* At the start of each session, the participants were asked to fill out a questionnaire regarding their experience with smart-wearables and gestures. They were then introduced to the project and the goals of gesture elicitation. The participants were asked to wear an Apple Watch Series 6 on the hand their preferred hand and only use that hand for gesture generation. They were then shown a simple animation explaining the action on a laptop and the Apple Watch was set to show the initial state of the action.

*Elicitation:* Once the participants sufficiently understood the action, they were asked to generate gestures they thought were natural and suited for each function without a time limit or concern for technical feasibility. Participants were asked to generate multiple gestures and select one to reduce any legacy bias, based on the 'Production Principle' (Morris et al., 2014).

*Evaluation:* The final gesture and time taken was recorded and the participants then filled in a survey rating the usefulness of the action and self-evaluated their gesture on a 5-point Likert scale for satisfaction, ease of use and ease of understanding. This process was repeated for all 7 actions. Once all

7 gestures were elicited, the participants were shown a video-clip of the expert designed gestures for each action and asked to rate them on the same scales of satisfaction, ease of use and ease of understanding along with stating their preference between the self-generated and expert generated gesture. Participants also selected the parameters they considered while generating and evaluating gestures.

## Study 2 methodology

In this study, 84 user elicited gestures and 7 expert generated gestures were presented to the participants. Study 2 had 2 sub-stages, Introduction and Evaluation.

*Introduction:* The participants started out by filling in a questionnaire regarding their experience with smart-wearables and gestures. They were introduced to the project and one-handed gestures for smartwatches were defined. The actions were explained using a simple animation on a laptop (same as Study 1). Participants were then presented with two sets of gestures for each of the 7 actions, “Set A” contained all the unique gestures elicited by participants of study 1 for that particular action, and “Set B” contained the expert-generated gesture for the same. In case the expert generated gesture was also elicited by users, it was removed from “Set A” and only presented “Set B”. “Set A” contained 9-14 distinct gestures depending on the action. The gestures were performed one by one, and the participants were asked shadow the hand movement to get a better understanding. Participants were asked not to be concerned about technical feasibility.

*Evaluation:* Once the participants were well acquainted with all the gestures for an action, they were asked to fill out a survey stating their preferred set and the preferred gesture within the set. This was repeated for all 7 actions. Once the poll was complete, the participants were asked to select the parameters they considered when evaluating the gestures.

## 4. Analysis of results

Three analysis tasks were performed, i.e., assignment of nomenclature; identification of 'discrete' or 'continuous' classification, and calculation of agreement score. For both Study 1 and Study 2, the total number and percentage of preference and votes were calculated per Action for both user elicited and designer generated gestures.

- The 112 user elicited gestures, 16 for each of the 7 Actions, from Study 1 were analysed as follows; first, nomenclature is assigned to each according to the involved body parts, fingers (including thumb), wrist, elbow and the movement of the parts involved, in a similar manner to the designer generated gestures. On doing so, the total number of gestures were resolved into 59 distinct gestures across all actions by combining the identical gestures, as different users elicited the same gesture for different actions.
- In addition, gestures were further classified as being 'discrete' and 'continuous'. Due to the nature of the Action, all elicited gestures for Action 4 (9 gestures) were continuous and for all other actions were discrete (50 gestures).
- Analysing the gestures within the action they were elicited for, an Agreement score (Ar) was computed as proposed by Wobbrock, et al. (2005) and refined by Vatavu and Wobbrock (2015). It ranges between [0,1] and is defined as (in Equation 1):

$$Ar = \frac{\sum_{t \in T} \left( \frac{|P_t|}{|P_t|-1} \sum_{P_i \subseteq P_t} \left( \frac{|P_i|}{|P_t|} \right)^2 - \frac{1}{|P_t|-1} \right)}{|T|} \quad (1)$$

't' refers to an action in the set of all Actions 'T', Pt is the set of gestures executed for task t, and Pi is a subset of Pt consisting of identical gestures.

- A higher agreement score refers to a higher agreement among the participants, i.e. a larger number of people that consistently chose an identical gesture. Agreement score of the set of Actions 'A' was found to be 0.046.
- 9 - 14 (median = 14) unique gesture was elicited per Action. Across the different actions, the most commonly elicited gesture ranged was repeated 4 - 2 times.



Table 1: Study 1

*Agreement Score: The score that measures the tendency of participants to elicit similar gestures to other participants.*

*Perceived Usefulness: The degree to which a participant believes that using a particular action would enhance his/her job performance.*

*Satisfaction: The degree to which a participant's needs, expectations, and preferences are met by a particular gesture for an action.*

*Ease of Use: The degree to which the participant believes that using a particular gesture for an action would be free from effort.*

*Ease of Understanding: The degree to which the participant believed that the particular gesture for the action would be simple to understand.*

*User Preference: The % of users that preferred the designer's gesture more than the participant's self-elicited gesture.*

**Table 2. Validation study 2, exemplars**

Table 2(a): Poll for Gesture Mode Activation(A1)

Gesture	Set	Votes	%
1. Forearm Twist ×2	B	13	40.62
2. Wrist Shake	A	4	12.50
3. Arm Inward Twist	A	3	9.37
4. Finger Snap	A	3	9.37
5. Four Finger Twist	A	2	6.25
6. Raise Watch	A	2	6.25
7. Double Clench	A	2	6.25
8. Clench	A	2	6.25
9. Finger Spread	A	1	3.10

Table 2(b): Poll for Button Press (A3)

Gesture	Set	Votes	%
1. Finger Pinch	B	16	50.00
2. Index Air Tap	A	8	25.00
3. Fist Clench	A	2	6.25
4. Index Surface Tap	A	2	6.25
5. Thumb Up	A	1	3.10
6. Wrist Down	A	1	3.10
7. Wrist Up	A	1	3.10
8. Clenching Fist	A	1	3.10

Table 2(c): Poll for High Pressure - Positive (A5)

Gesture	Set	Votes	%
1. Thumb Up	A	5	15.60
2. Wrist Up	A	5	15.60
3. Watch to Ear	A	5	15.60
4. Finger Pinch	B	4	12.50
5. Index Air Tap	A	3	9.37
6. Finger Spread ×2	A	3	9.37
7. Clench Extended...	A	3	9.37
8. Finger Spread	A	1	3.10
9. Watch on Body	A	1	3.10
10. Watch to Face	A	1	3.10
11. Watch to Face, Pinch	A	1	3.10

Table 2(d): Poll for Continuous Scroll (A4)

Gesture	Set	Votes	%
1. Index Slider	A	10	31.25
2. Index and Finger	B	8	25.00
3. Thumb Index Spread	A	6	18.75
4. Wrist Up and Down	A	4	12.50
5. Open and Close Fist	A	3	9.37
6. Arm Up and Down	A	1	3.10

**Table 3. Parameters considered by participants across both studies**

Parameters	Study 1 Votes	Votes Percentage	Study 2 Votes	Votes Percentage
1. Effort	14	87.50%	32	100%
2. Fatigue	2	12.50%	11	34.40%
3. Time	13	81.30%	20	62.50%
4. Intuitivity	8	50.00%	22	68.75%
6. Social Acceptance	5	31.30%	15	46.90%
7. Technological Feasibility	8	50%	8	25%
8. Losing Sight of Screen	4	25%	-	-
9. More optimal for other actions	4	25%	9	28.0%
10. Memorability			1	3.12%
11. Consistency within set			1	3.12%
12. Purpose of Activity			1	3.12%

*Highlighted Parameters are those which were not provided by the expert*

## 5. Findings and inferences

### Strong cognitive mapping (A3, A4)

A3 and A4 (Button Press and Continuous Scroll) received high agreement scores in Study 1, 0.083 and 0.066 respectively. For A3, 4 of the elicited gestures were identical to the designers' gesture as well and it was highly preferred as well (93.75%). This was further supported by Study 2 where the gesture was preferred by 50% of the participants and the next three most voted gestures were all variants of the designer's gesture. In A4, while Study 1 showed clear preference for the designers' gesture at 75%, it only received 25% of the votes in Study 2 and was overtaken by a user elicited gesture at 31.25%. The winning gesture (Index Slider) was a close variant of the designers' gesture (Index Thumb Rub).

A3 and A4 present a clear consensus among the participants in both studies, wherein the majority was able to easily generate and prefer a singular gesture (or variants) in both studies. This could stem from a strong cognitive mapping ability of the actions themselves, allowing users to draw from their past physical or digital experiences (pressing physical buttons or scrolling on the phone).

### Poor cognitive mapping (A2, A5, A7)

In Study 1, compared to the other actions, A2, A5, and A7 (Home Screen, High Pressure Positive and Shortcut Menu) demonstrated notably low agreement scores of 0.033, 0.016, and 0.024, respectively, with 13, 14, and 14 unique gestures elicited. On average, gestures designed by researchers scored higher on satisfaction, ease of use and ease of understanding. In all 3 cases, majority of the participants preferred designer generated gestures at 71.88%, 75.00%, and 62.50% respectively.

However, in the subsequent study, the performance of designer-designed gestures for these actions was less impressive. For A2 and A7, while the designers' gesture was most preferred (25%), user elicited gestures were also more evenly preferred (15.60% - 18.75%). In the context of A5, the top three gestures were equally preferred (15.60%), followed by designer's gesture (12.50%). This even distribution of votes and absence of a clear winner shows a lack of coherence among the participants. This may be due to the inherently abstract nature of the actions, making it difficult to cognitively map a single gesture to it making users fall back to their personal preferences while voting.

*Note: Although the designers' gesture was not most preferred in A5, it was chosen to be identical to A3 due to the similarity and overlapping use cases of the actions. This adherence to Miller's Law, advocates reducing the total number of gestures for memorisation that may enhance the overall recall of the gesture set.*

### High pressure negative (A6)

In study 1, A6 (High Pressure Negative) had a low agreement score of 0.016, with 78.13% of participants preferring the designer's gesture. However, contrary to the actions mentioned above, the designer's gesture received 37.5% preference in study 2. The second most preferred gesture only received 12.50% of the votes.

While A6, may be a difficult action for participants to cognitively map a coherent gesture to, designer assigned gesture (Wrist Shake) outperformed user elicited gestures in both studies by a clear margin. It was also found to be more satisfying and easier to use.

### Activation action (A1)

In study 1, the activation action (A1) received the highest agreement score (0.083) with 16 participants eliciting 9 unique gestures. The designer's gesture was only preferred by 43.75% of participants. However, the designer's gesture scored higher in all 3 metrics of satisfaction, ease of use and ease of understanding compared to the user elicited gestures. While A1 initially seems to be more suitable for user elicitation, the discrepancies between user ratings and preference in Study 1 highlights the bias of participants evaluating and comparing their self-generated to designers' gestures. This is further supported in study 2, where the designer's gesture was preferred by a majority of the participants (40.62%), followed by the Wrist Shake (12.5%).

### General insights

- Participants' **perceived usefulness of the Actions** were relatively high across all designer chosen Actions (A1-A7), ie., set A, with an average rating of 4.705 out of 5



- In study 1, the overall **set of designer generated gestures** was preferred majorly at 71.87% (sd = +- 15.52%). In study 2, participants preferred the designer's gesture set at 30.80% (sd = +- 12.55%). While it is higher than any user elicited set, this decrease in preference could be the result of participants in study 2 comparing 9-14 user elicited gestures against a single designer gesture, whereas in study 1, participants only compared the designer's gesture against their own elicited gesture.
- In study 1, **participants with prior experience with smartwatches preferred the designer's gestures** 87.14% of the time opposed to the participants with no such experience, who preferred the designer's gestures only 64.28% of the time. This may indicate that participants who have used a smartwatch prior have an implicit understanding of suitable one-handed gestures.
- In study 1, 16 participants elicited a total of 9-14 gestures per action, resulting in low agreement scores ranging from 0.01-0.08. In comparison to a study conducted to generate gestures for surface computing, the elicited gestures there had agreement scores ranging from 0.1, all the way up to 1. This may imply that **participants may struggle to generate agreeable gestures for one-handed gestures for specialised context, such as smartwatches.**
- On an average, participants from study 1 considered 3.625 parameters when designing gestures. In study 2, participants considered an average of 3.125 parameters for each action (Table 3). Most participants were likely to consider more generalised parameters like, Effort, Time and Intuitivity, leaving a gap in considering essential, specific parameters for smartwatches, such as, Social Acceptance, Losing sight of the Screen, Fatigue. Participants also lacked a structured design process. In contrast, the designers considered at least 9 parameters when designing and evaluating gestures for each action and followed a structured design process. This is **indicative of the designers' gesture set being more satisfying, easier to use, as well as easier to understand** across all gestures, were also highly preferred in both studies.
- Although participants were asked not to concern themselves with technological feasibility of the gesture, 50% of participants in study 1 and 25% in Study 2 considered it as a parameter while eliciting and evaluating. Some participants also **added their own parameters** of memorability, and consistency within a set, in study 2.

## 6. Discussions and conclusions

While there was wide acceptance on the Actions identified by the expert/designers, the lack of consideration of design parameters by the user participants may be the primary cause of high preference for the designers' set of gestures. Since designers follow a structured design process, they consider a vast set of general and specific parameters when designing and this is observable in the design of gestures as well. Users, in contrast, missed out on multiple parameters, especially those individual to that specific system, the smartwatch in this case.

Actions which had a strong cognitive mapping resulted in the same or similar gestures being elicited by both users and designers, with a clear preference for a singular gesture. In such cases, both user elicitation and expert generation of gestures may be used to arrive at a suitable gesture. However, for actions with poor cognitive mapping, neither user elicited nor expert generated gestures were able to garner a strong majority vote. In such scenarios, design considerations as mentioned in (Table 1) have potential to help generate and evaluate gestures better, further improving the overall usability of the gesture set.

Though gestures have been used in human computer interaction since the 1980's, the field of gesture generation and evaluation is still in its adolescence, with most gesture-based systems lacking ease of use and satisfaction, despite their novelty of interaction. This may be attributed to the Gesture Elicitation approaches which, while being widely adopted and accepted in theory, have failed to generate usable gestures for complex scenarios. A hybrid methodology allowing for co-creation of gestures from both users and experts may result in more suitable gesture, especially in complex systems like a smartwatch.

## References

- Arefin Shimon, S. S., Lutton, C., Xu, Z., Morrison-Smith, S., Boucher, C., & Ruiz, J., (2016), Exploring Non-touchscreen Gestures for Smartwatches. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. <https://doi.org/10.1145/2858036.2858385>
- Buchmann, V., Violich, S., Billingham, M., and Cockburn, A., (2004), FingARtips: Gesture Based Direct Manipulation in Augmented Reality. In *Proceedings of the 2nd International Conference on Computer Graphics and Interactive Techniques in Australasia and South East Asia* (New York, NY, USA) (GRAPHITE '04). Association for Computing Machinery, 212–221. <https://doi.org/10.1145/988834.988871>
- Cassell, J., (1998), *zz*
- Chan, E., Seyed, T., Stuerzlinger, W., Yang, X. D., & Maurer, F., (2016), User Elicitation on Single-hand Microgestures. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. <https://doi.org/10.1145/2858036.2858589>
- Gong, J., Yang, X. D., & Irani, P., (2016), WristWhirl. *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*. <https://doi.org/10.1145/2984511.2984563>
- Kerber, F., Löchtefeld, M., Krüger, A., McIntosh, J., McNeill, C., & Fraser, M., (2016), Understanding Same-Side Interactions with Wrist-Worn Devices. *Proceedings of the 9th Nordic Conference on Human-Computer Interaction*. <https://doi.org/10.1145/2971485.2971519>
- McNeill, D. (1985). So you think gestures are nonverbal? *Psychological Review*, 92(3), 350– 371. <https://doi.org/10.1037/0033-295X.92.3.350>
- McNeill, D., (1987), *Psycholinguistics: A new approach*. Harper & Row Publishers.
- Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, 63(2), 81–97. <https://doi.org/10.1037/h0043158>
- Morris, M.R., Danielescu, A., Drucker, S., Fisher, D., Lee, B., Schraefel, M.C., and Jacob O. Wobbrock, (2014), Reducing Legacy Bias in Gesture Elicitation Studies. *interactions* 21, 3 (May 2014), 40–45. <http://dx.doi.org/10.1145/2591689>
- Nielsen, M., Störing, M., Moeslund, T. B., & Granum, E., (2004), A procedure for developing intuitive and ergonomic gesture interfaces for HCI. In *Gesture-Based Communication in Human-Computer Interaction: 5th International Gesture Workshop, GW 2003, Genova, Italy, April 15-17, 2003, Selected Revised Papers 5* (pp. 409-420). [https://doi.org/10.1007/978-3-540-24598-8\\_38](https://doi.org/10.1007/978-3-540-24598-8_38)
- Ruby, D., (2023), Smartwatch Statistics 2023: How Many People Use Smartwatches? <https://www.demandsage.com/smartwatch-statistics/>
- Vikram Cannanure, Xiang Chen, and Jennifer Mankoff. 2016. Twist & Knock: A One-handed Gesture for Smart Watches. In *Proceedings of the 42Nd Graphics Interface Conference (GI '16)*. Canadian Human-Computer Communications Society, School of Computer Science, University of Waterloo, Waterloo, Ontario, Canada, 189–193. <http://dx.doi.org/10.20380/GI2016.24>
- Vuletic, T., Duffy, A., McTeague, C., Hay, L., Brisco, R., Campbell, G., & Greal, M. (2021). A novel user-based gesture vocabulary for conceptual design. *International Journal of Human-Computer Studies*, 150, 102609. <https://doi.org/10.1016/j.ijhcs.2021.102609>
- Vatavu, R. D., & Wobbrock, J. O. (2015, April 18). Formalizing Agreement Analysis for Elicitation Studies. <https://doi.org/10.1145/2702123.2702223>
- Wearable Technology Market Share & Trends Report, (2030). *Wearable Technology Market Share & Trends Report, 2030*. <https://www.grandviewresearch.com/industry-analysis/wearable-technology-market>
- Wobbrock, J.O., Brandon Rothrock, H., and Myers, B.A., (2005), Maximizing the Guessability of Symbolic Input. In *CHI '05 Extended Abstracts on Human Factors in Computing Systems (CHI EA '05)*. ACM, New York, NY, USA, 1869–1872. <https://doi.org/10.1145/1056808.1057043>
- Wu, H., Fu, S., Yang, L., & Zhang, X., (2022), Exploring frame-based gesture design for immersive VR shopping environments. *Behaviour & Information Technology*, 41:1, 96-117, <https://doi.org/10.1080/0144929X.2020.1795261>
- Ye, L., Yue, J., Wei, Y., Liang, S., & Chang, D., (2023), “Just Like Blooming Fireworks, And Match With Function Perfectly”: Explore and Evaluate User-Defined One-Handed Gestures of Smartwatch. *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*. <https://doi.org/10.1145/3544549.3585914>
- Zhao, Y., Zhao, Y., Tu, H., Huang, Q., Zhao, W., & Jiang, W., (2022), Motion Gesture Delimiters for Smartwatch Interaction. *Wireless Communications and Mobile Computing*, 2022, 1– 11. <https://doi.org/10.1155/2022/6879206>
- Zimmerman, T. G., Lanier, J., Blanchard, C., Bryson, S., & Harvill, Y. (1986). A hand gesture interface device. *ACM SIGCHI Bulletin*, 18(4), 189–192. <https://doi.org/10.1145/1165387.275628>