

Article

GCI: Efficient Design of Gesture Based Human Computer Interaction Targeting Visually Impaired People

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Abstract

Human-computer interaction (HCI) exploits various input methods to improve user experience, but those without visual access suffer more than the mainstream. In this context, this paper proposes a novel Gesture-based Human-Computer Interaction (GCI) system for visually impaired people (VIP). However, a large set of gestures introduces complexity, which poses challenges for VIP to interact with computers. Therefore, an accessible assistive application with a minimal set of gestures is designed here. Nineteen (19) participants engaged, and several dimensions were evaluated, including skin conductance, NASA-TLX, and performance indicators. The gesture response time revealed that the proposed GCI technique is 39% faster than the existing technique. In addition, the skin conductance revealed a modest reduction, which means GCI caused a more relaxed reaction than the existing technique. GCI demonstrated significant statistical advantages in gesture response time, skin conductance, and forgot word count, while other measures showed comparable performance between the two techniques. GCI provides a more efficient and cognitively favorable interaction experience which opens a new era in the design and development of assistive technologies for VIP.

Keywords: human-computer interaction; HCI; gesture-based human-computer interaction; GCI; visually impaired people; cognitive load; galvanic skin response

1. Introduction

Human-computer interaction (HCI) is an interdisciplinary field dedicated to the design, evaluation, and implementation of interactive computing systems intended for human use [1]. In addition, it involves designing interfaces that can be used by people with visual, auditory, motor, or cognitive limitations [2]. However, those who cannot access visual interfaces suffer more than others [3]. Therefore, interfaces that cannot be accessed by visually impaired people (VIP) must be made accessible. Some software and applications have not been designed with accessibility features for blind candidates [4]. Currently, HCI explores different ways for users to interact with computers, including traditional input methods such as keyboards and mice, as well as newer techniques such as touchscreens [5], voice commands, gesture, and virtual reality [6]. Hand gestures are a form of non-verbal communication that involves the movement or positioning of the hands to convey meaning, express emotions, or interact with the environment [7]. In the context of HCI, hand gestures have gained importance in interactions with computers



Academic Editors: Mariofanna Milanova and Friedhelm Schwenker

Received: 20 May 2026

Revised: 15 June 2026

Accepted: 22 June 2026

Published: 26 June 2026

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and other devices [8]. Surprisingly, very few studies have considered VIP as users of hand gesture-based technologies [7,9,10]. Moreover, understanding how humans perceive and process information helps design interfaces that align with human capabilities and limitations [11]. In this context, cognitive load (CL) is an essential parameter because it directly impacts the effectiveness and efficiency of HCI [12].

CL refers to the total amount of mental resources required to perform and process any task or piece of information [13]. CL should be considered while working with a new technology or a new HCI for a particular group of users [14]. An individual's cognitive system represents a multidimensional construct of CL involved in the execution of tasks [15]. The amount of CL applied affects one's mental state, and if the load reaches a certain threshold [16], learning can suffer significantly. Therefore, maintaining an ideal amount of CL is necessary to increase productivity [17]. It is widely recognised that no single measure can adequately estimate CL on its own [18,19], as each has its advantages and limitations. In contrast, while HCI performance metrics are less invasive, they are not as effective in identifying low CL levels [20]. However, physiological measures, such as the galvanic skin response (GSR), offer the ability to continuously assess CL.

At present, hand gestures are used in different applications for VIP, including gaming, entertainment [21], and computer interactions [22]. Researchers have used different types of hand gestures for computer interaction [22,23]. It has been observed that as the number of gestures increases, the difficulty of retrieving them also increases [24]. Hence, a large variation in the pose of the hand gesture creates complexity for the user when interacting with computers [7]. Therefore, there is a need to develop simple and productive hand gestures capable of producing all essential symbols for VIP to interact with the computer. In this direction, a study of the performance evaluation of the existing method and the proposed gesture-based human-computer interaction (GCI) technique has been done from the CL perspective. To the best of our knowledge, none of the studies has performed a CL-based performance evaluation between the proposed GCI input technique and the existing Dactylology for VIP. The salient features of the proposed method are as follows:

- This work introduces a minimal gesture framework that aims to reduce cognitive load (CL) through a hand gesture-based interaction system for VIP.
- Identification of the relationship between physiological parameters, performance parameters, and subjective measurement is performed with all CL levels.
- The impact of hand gesture-based computer interaction on VIP's cognitive states is analysed, and the significance of the proposed mechanism is established.
- The superiority of the suggested method over traditional approaches highlights its importance in crafting HCIs for VIP.

The sections are organised as follows. Section 2 offers an in-depth overview of the pertinent literature regarding the evaluation of the CL of VIP and the current hand gesture methods. Section 4 outlines the proposed methodology. Section 4 presents a detailed examination of the results and discussion. Finally, Section 5 concludes the study with directions for future research.

2. Related Works

Recent studies have combined the hand gesture and cognitive load (CL) to enhance human-computer interaction for visually impaired people (VIP). Rodrigues et al. investigated the challenges faced by VIP in their daily use of mobile phones [25]. In [26], knowledge-based techniques were used for customisation, taking into account user abilities and preferences. In addition, Mellissa [27] and William et al. [28] stated that VIP use more gestures in daily interactions. Meenakshi [23] explored a hand gesture-based application area for VIP with 18 gestures. Furthermore, Saransh et al. [29] identified a framework based

on facial and hand gestures to act as virtual assistants for VIP. Avni et al. [9] confirmed that gestures can lighten CL if the relationship between the use of hand gestures is semantically related. Samer et al. [10] explored the use of hand gestures for VIP in the object detection field using six different hand gestures. In essence, none of the studies focus on a dedicated framework for VIP with alternate access to computer input. Gourav et al. [14] presented a full-fledged alphabet and number input method for VIP using hand gestures. However, because of the large set of different hand gestures, there is a need for further investigation into real-time applications. Together, these findings suggest that it is necessary to develop a simple and effective hand gesture set for VIP compared to existing methods.

Furthermore, physiological measurements have been observed to have been used for real-time CL assessment of VIP. Kalimeri et al. [30] explored a charted route designed to incorporate many mobility challenges facing VIP. Saitis et al. [31] designed a multimodal framework for CL assessment. This model is used to design the technological aids for VIP in an indoor environment. However, some authors have discussed the impact of CL in the design of assistive technologies [32]. Saitis et al. [33] identified indoor and outdoor activities to assess CL under various CL conditions (low, medium, and high). Saitis et al. [34] designed mobility aids for VIP while navigating unknown indoor and outdoor environments. Afroz et al. [35] used the data taken by previous authors in [31] to improve the precision of CL assessment for different environmental factors. Pigeon et al. [36] investigated the cognitive load (CL) associated with walking in visually impaired individuals using gait analysis and subjective evaluations. Subjective cognitive workload is commonly assessed using the NASA Task Load Index (NASA-TLX), a widely adopted questionnaire that measures perceived workload. Modanwal et al. [14] discussed computer interaction for VIPs using a hand gesture-based technique, Dactylology. Dactylology- enables computer interaction through predefined hand and finger configurations representing specific commands. Overall, the review of the literature on GSR and VIP highlights a significant research gap in using GSR to detect cognitive load during VIP interactions with computers. However, it is important to note that, while these studies align with our interest in hand gesture-controlled applications, their task paradigms focused predominantly on navigational tasks, differing from our approach. Consequently, our results may diverge or exhibit less relevance than their findings.

3. Proposed Methodology

To address the constraints of the current mechanism, a portable leap motion device [37] was introduced to perform gestures (refer to Table 1). The setup incorporated a leap motion device to record the symbols displayed within its range. The captured symbols are then processed by a dedicated unit, enabling the recognition and interpretation of user commands. In our previous work [21], we conducted a user satisfaction study to develop and evaluate hand-gesture-based accessible games for VIPs. The study demonstrated that hand-gesture-based interaction provided an intuitive, interactive, and easy-to-use experience, achieving a System Usability Scale (SUS) score of 91. Motivated by these findings, we adopted and extended the validated hand gestures from the previous study to develop the proposed GCI for text input. Furthermore, the gesture set was intentionally designed to remain small, simple, and easy to perform, as a large number of gestures can increase learning effort, memory demands, and cognitive load [12]. By reusing a limited set of distinct gestures across multiple input operations, the proposed design minimizes memorization requirements while enabling efficient interaction. An experiment with a keyboard application was conducted under three cognitive load conditions in a within-subject framework: (1) low, (2) medium, and (3) high-load tasks (refer to Table 2). Each

condition was executed through a distinct access application, with the sequence of the three rounds varied among the participants.

Table 1. Proposed Hand Gestures with meaning.

Set Number	Gesture	Front Side of Left Hand					Front Side of Right Hand				
											
Set One (Left Hand)		1	2	3	4	5	6	7	8	9	0
Set Two (Left Hand)		A	B	C	D	E	F	G	H	I	J
Set Three (Right Hand)		K	L	M	N	O	P	Q	R	S	T
Set Four (Right Hand)		U	V	W	X	Y	Z	-	-	-	-

Table 2. Task Description.

Sr. No.	Load Conditions	Task Descriptions
1	Low Load	Randomly generated alphabet (A-Z) or Numbers (0–9)
2	Medium Load	Randomly generated 3 letter words or numbers (e.g., CAR, 431)
3	High Load	Randomly generated 6 letter words or numbers (e.g., FASTED, 564390)

3.1. Experiment Setup

The experimental setup configuration is shown in Figure 1 designed in such a way that a tabletop setup incorporates a Leap device close to the user and a computer. The post-experiment evaluation was performed by the domain experts by utilising the responses. In addition, the Shimmer GSR solid gel foam electrode sensor, commonly employed in prior studies, collected data at 256 Hz. Two GSR sensors were attached to the uncovered left foot, one positioned centrally and the other close to the heel [38].

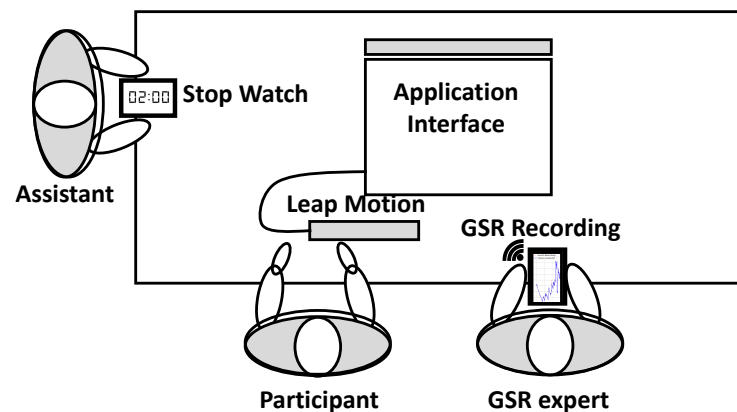


Figure 1. Experimental test bench (Setup).

3.2. Participants

We called 19 participants (visually impaired (5), blind folded (14)) for the experiment, with 7 female and 12 male participants. The participants voluntarily came from the Institute and the necessary permission and consent were obtained for the legalities. Among the 19 participants, 17 were right-handed and 2 left-handed, but none of them had prior knowledge of the existing and proposed hand gesture methods. They have a basic understanding of keyboard access while interacting with the computers. We intentionally selected this early learning participant to avoid the prejudice effect. All participants underwent a training session using the proposed hand gestures and the existing hand gesture techniques. The average age of the 19 participants was 22 years (standard deviation (SD) = 3.31), with 12 males (average age = 22, SD = 3.47) and seven females (average age = 21, SD = 2.91). All participants successfully completed this experiment. Our sample size of participants exceeded the number compared to the majority of other similar studies that identified the impacts of external cognitive task load on VIP performance, subjective measurement, and physiology (e.g., [39,40]).

3.3. Experiment Procedure

The eligibility of the participants was confirmed and consent was obtained upon arrival. To finalise the inclusion process, we administered a verbal survey to verify that the participants were not taking any medication. Initially, the participants completed a training session with a brief overview of the location and hand gestures used to complete the experiment. The participants practiced different hand gestures and the location of the device to create gestures in time and experience prior to the experiment (shown in Figure 2). Subsequently, physiological sensors were attached to the participants, and the experiment lasted up to 2 min to identify the maximum rest point of the participants. This was done to obtain a baseline for the GSR signals of the participants in a non-experimental context. After receiving the rest point, the participants were notified by voice instructions about starting the experiment (the methods were randomly selected). In addition, in each session, participants were given a group of three (1-length, 3-length, and 6-length) words. The participants waited 2 min to complete each task load session. The procedure was similarly applied to the other hand gesture techniques. Participants were advised to remain relaxed throughout the experiment and perform the task with maximum speed and precision. The design of tasks in relation to various CL conditions influences the accuracy and speed of the users. Ultimately, upon completion of the experiment, the participants completed the NASA-TLX questionnaire [41].

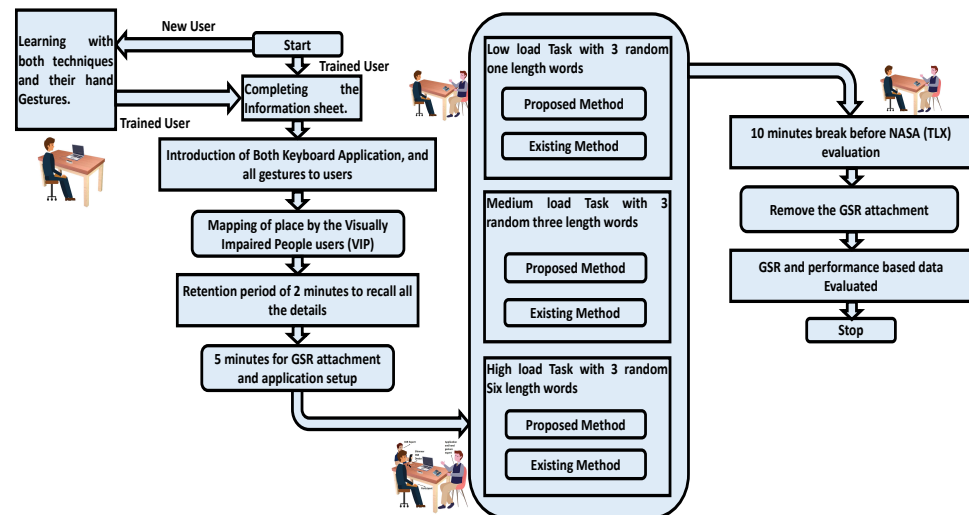


Figure 2. Flowchart of experimental procedure.

4. Results and Discussion

Among all, physiological measurement, GSR differentiates the different task loads and identifies the difference between Dactylology and the proposed gesture-based human-computer interaction (GCI) technique. Performance was measured using four parameters: response time, gesture response time, false responses, and forgotten word count. Response time refers to the total duration (in seconds) from the beginning of the task in each cognitive load scenario until the hands were correctly positioned according to the task requirements for both methods. The Gesture response time was determined as each hand pose creation time (in seconds) with respect to each letter as per the tasks. Incorrect answers were addressed by counting the frequency of the participants' mistakes. During task execution, participants pose the wrong hand gesture counted as mistake for the alphabet presented in the respective task. Finally, yet importantly, forgot word count settled as the number of times the participants forgot the respective word in medium and high load tasks. In addition, the subjective results were measured using the NASA-TLX score to assess the effects of both GCI and Dactylology technique. To calculate the overall NASA-TLX score, we followed the method mentioned in [42].

Figure 3a–p shows the minimum, first quartile, median, third quartile, and maximum values, with circles indicating individual data points and mean values shown as hollow diamonds. The distribution of skin conductance showed very little difference between the two techniques shown in Figure 3a. Subsequently, medium- and high-level skin conductance data are presented in Figure 3b,c also have minor differences in comparison of both techniques. The mean measured skin conductance data clearly states that skin conductance has a marginal difference between both techniques under all task load conditions. At low loads response time has a marginal difference, but the gesture response time has a significant difference in both techniques shown in Figure 3e,h. Under low load conditions, the gesture response time of GCI outperformed Dactylology by a significant margin. Subsequently, medium- and high-level gesture response time data are presented in Figure 3f,g,i,j, which also show significant differences in the comparison of both techniques. The mean shows that gesture response time has a significant difference between both techniques, rather than response time in all task load conditions shown in Figure 3e–j. At low loads, the distribution of false responses and forgot word counts has a marginal difference and very little difference between the two techniques shown in Figure 3k,n. Subsequently, medium and high-level false response and forgot word count data are presented in Figure 3l,m,o,p shows the significant difference between the two techniques.

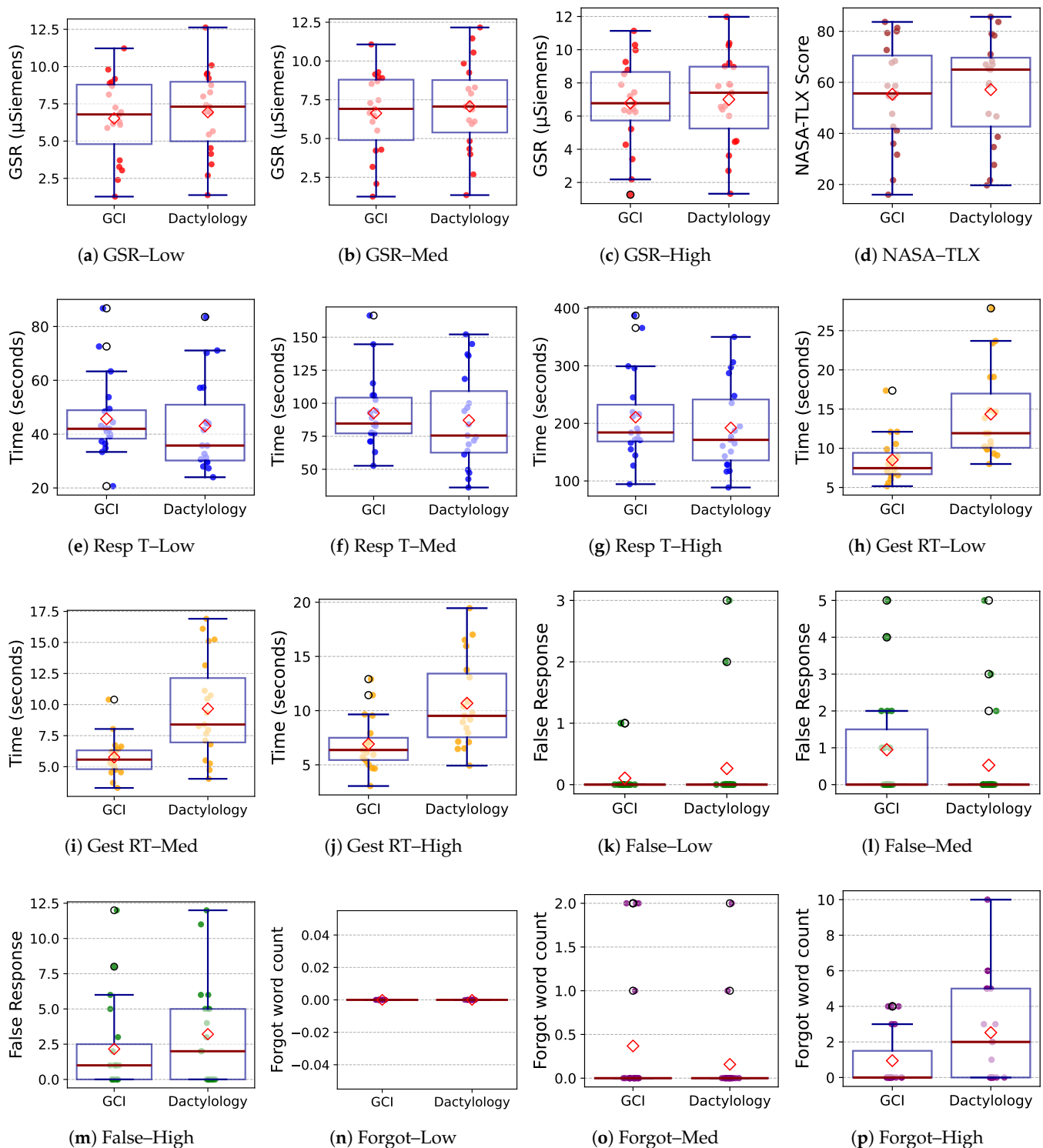


Figure 3. Unified comparison of all measured parameters across low, medium, and high cognitive load conditions using GCI and Dactylogy techniques. (a–c) Skin Conductance (GSR); (d) NASA–TLX subjective workload; (e–g) Response Time; (h–j) Gesture Response Time; (k–m) False Responses; (n–p) Forgot Word Count. Each box plot represents results for 19 participants, showing minimum, first quartile, median, third quartile, and maximum values, with mean values indicated by hollow diamonds and individual data shown as circles.

In addition to this, the mean false responses and forgot word count data clearly state that false responses and forgot word counts have a significant difference between both techniques under high load task shown in Figure 3k–p. The distribution of the NASA–

TLX score was similar for both techniques. The mean NASA-TLX scores (represented by a hollow diamond) showed very little marginal difference between the two techniques shown in Figure 3d. Along with, we analysed the analysis of variance (ANOVA) test to determine if there were significant differences between 2 input techniques and 3 levels of task load (shown in Table 3).

Table 3. Summary of ANOVA results for different dependent variables across techniques and cognitive load conditions.

Measure	Overall GCI–Dactylography (M/SD)	Low (GCI/Dactylography)		Medium (GCI/Dactylography)		High (GCI/Dactylography)	
		M	SD	M	SD	M	SD
(A) Skin Conductance (GSR)							
Techniques	6.65/2.65–7.00/2.79	–	–	–	–	–	–
$F_{(1,18)}$	11.42 **						
Cognitive Load	–	6.73	2.77	6.85	2.75	6.89	2.69
$F_{(1,40,25,22)}$	0.97						
Techniques × Load	–	6.52/6.94	2.74/2.85	6.63/7.07	2.66/2.89	6.79/7.00	2.68/2.78
$F_{(1,76,31,73)}$	0.80						
(B) Response Time							
Techniques	116.31/84.54–107.48/79.26	–	–	–	–	–	–
$F_{(1,18)}$	1.51						
Cognitive Load	–	44.38	15.91	89.80	31.68	201.50	75.50
$F_{(1,16,20,89)}$	132.08 **						
Techniques × Load	–	45.69/43.06	14.96/17.12	92.52/87.09	27.35/36.04	210.71/192.28	77.42/74.45
$F_{(1,1,19,8)}$	0.54						
(C) Gesture Response Time							
Techniques	7.06/2.60–11.57/5.02	–	–	–	–	–	–
$F_{(1,18)}$	44.56 **						
Cognitive Load	–	11.43	5.36	7.71	3.60	8.80	3.85
$F_{(1,61,29,06)}$	21.66 **						
Techniques × Load	–	8.51/14.35	2.91/5.70	5.75/9.67	1.58/4.00	6.91/10.68	2.45/4.13
$F_{(1,33,24,10)}$	2.48						
(D) False Responses							
Techniques	1.33/2.65–1.07/2.23	–	–	–	–	–	–
$F_{(1,18)}$	1.41						
Cognitive Load	–	0.18	0.60	0.73	1.40	2.68	3.51
$F_{(1,08,19,45)}$	12.42 **						
Techniques × Load	–	0.10/0.26	0.31/0.80	0.94/0.52	1.47/1.34	2.15/3.21	3.32/3.72
$F_{(1,29,23,23)}$	2.55						
(E) Forgot Word Count							
Techniques	0.43/0.89 - 0.89/2.04	–	–	–	–	–	–
$F_{(1,18)}$	5.31 **						
Cognitive Load	–	0.00	0.00	0.26	0.64	1.73	2.46
$F_{(1,05,18,93)}$	12.56 **						
Techniques × Load	–	0.00/0.00	0.00/0.00	0.36/0.15	0.76/0.50	0.94/2.52	1.64/2.91
$F_{(1,26,22,74)}$	9.13 **						
(F) NASA-TLX Score							
Techniques	55.33/20.20–57.14/20.64	–	–	–	–	–	–
$F_{(1,18)}$	0.54						

** Significant at 0.005 level.

The assumptions necessary for conducting a repeated measures ANOVA were evaluated. The z scores calculated for the GSR (skin conductance), NASA-TLX, response time and the gesture response time data under various conditions fell within the acceptable threshold of ± 3 , indicating that there were no notable outliers. For certain conditions, the standardisation values (z-scores) calculated for false responses and forgotten word counts were within the permissible range, although some outliers were detected. According to the results of the Shapiro-Wilk test, the residuals of skin conductance measured during different levels of cognitive tasks across all gesture techniques for each subject conformed to a normal distribution, indicated by $p > 0.05$ in the S-W statistic. The response time and gesture response times, were approximately normally distributed for most conditions. Additionally, skewness and kurtosis according to the Fisher coefficient were within the acceptable bounds of ± 1.96 [43]. The distribution of residuals for false responses and

forgotten word counts was not normal in nearly all conditions. Furthermore, the Fisher coefficients for skewness and kurtosis fell due to variations in task level and individual user performance that affected false responses and forgot word counts. However, ANOVA, including its repeated measures variant, is notably resilient to normality assumption breaches, allowing for some degree of violation while still yielding valid results [44], even with small sample sizes ($n = 3$) [45].

Homoscedasticity was additionally assessed with Mauchly's test of sphericity. In repeated measures designs, Mauchly's test for sphericity serves a role similar to Levene's test for variance homogeneity. The results of Mauchly's test indicated a breach in the sphericity assumption when examining the impact of load on skin conductance ($\chi^2 = 9.47, p = 0.009$), load on response time and the analysis of technique and load, as well as for the gesture response time, with ($\chi^2 = 21.81, p < 0.001$; $\chi^2 = 28.46, p < 0.001$) and ($\chi^2 = 21.81, p = 0.003$), respectively. Similarly, load and technique, and load for false responses ($\chi^2 = 32.26, p < 0.001$; $\chi^2 = 13.55, p = 0.001$), as well as for forgot word count ($\chi^2 = 39.40, p < 0.001$; $\chi^2 = 14.87, p < 0.001$). Consequently, the degrees of freedom (df) were adjusted in repeated measures ANOVA with Greenhouse-Geisser corrections for the impact of the load on the conductance of the skin ($\epsilon = 0.701$), load and technique in response time ($\epsilon = 0.58$; $\epsilon = 0.552$) and for the analysis of technique and load on gesture response time ($\epsilon = 0.67$). Similarly, load and technique for false responses ($\epsilon = 0.54$; $\epsilon = 0.64$) and forgot word count ($\epsilon = 0.52$; $\epsilon = 0.63$). These df adjustments do not alter the computed F -ratios, but do change the p -values to accommodate the sphericity assumption. The df presented here are slightly rounded. The analysis demonstrated statistically significant effects of techniques on skin conductance, response time, gesture response time, false responses, forgot word counts and NASA-TLX scores.

4.1. Result Based on Physiological Measures

Table 3 displays a noteworthy primary impact of the technique (GCI versus Dactylology) on the GSR ($F_{(1,18)} = 11.42, p < 0.005, \eta_p^2 = 0.39$, which represents a large effect size), highlighting a significant distinction in the levels of skin conductance between GCI ($M = 6.65 \mu\text{S}$, $SD = 2.65$) and the Dactylology technique ($M = 7 \mu\text{S}$, $SD = 2.79$) while performing the task. This implies that executing the task with GCI resulted in lower skin conductance compared with the Dactylology method, with the gesture technique accounting for 39% of the variance in skin conductance. The results corrected using Greenhouse-Geisser indicate that the average skin conductance varied marginally between load levels ($F_{(1.40,25.22)} = 0.97, p > 0.05, \eta_p^2 = 0.07$, suggesting a small effect size). This finding implies a minimal impact of task load on skin conductance. The interaction effect was not significant ($F_{(1.76,31.73)} = 0.80, p > 0.05, \eta_p^2 = 0.07$, indicating a smaller effect size). This implies that GCI and Dactylology independently affect skin conductance under varying cognitive load conditions.

4.2. Result Based on Performance of Participants

Table 3 highlights that the primary impact of techniques (GCI compared to Dactylology) on the response time was not significant ($F_{(1,18)} = 1.51, p = 0.235, \eta_p^2 = 0.07$, reflecting a small effect size), demonstrating a lower considerable difference in response time between the GCI ($M = 116.31 \text{ s}$, $SD = 84.54$) and the Dactylology technique ($M = 107.48 \text{ s}$, $SD = 79.26$) when performing the task. This implies that executing the task with GCI versus the Dactylology technique leads to Dactylology performing with less response time. Further, results revealed a significant variance in mean response time across different load levels ($F_{(1.16,20.89)} = 132.08, p < 0.001, \eta_p^2 = 0.88$, suggesting a large effect size). This indicates that task load significantly affected response time. The interaction effect

was not significant ($F_{(1.1,19.8)} = 0.54, p = 0.48, \eta_p^2 = 0.02$, indicating a very small effect size). This suggests that the GCI and Dactylology techniques operate independently in different cognitive load situations. There is a notable primary impact of the technique on gesture response time, illustrating significant differences between GCI and Dactylology ($F_{(1,18)} = 44.56, p < 0.001, \eta_p^2 = 0.71$, denoting a substantially large effect size). Specifically, the gesture response time for GCI ($M = 7.06$ s, $SD = 2.60$) was shorter compared to the Dactylology technique ($M = 11.57$ s, $SD = 5.02$) when performing the task. This implies that using GCI results in faster gesture response times and accounts for 71% of the variance. In addition, the proposed GCI achieved approximately 39% lower gesture response time than Dactylology, reducing the average gesture response time from 11.57 s to 7.06 s. The variation in gesture response time between load levels was statistically significant ($F_{(1.61,29.06)} = 21.66, p < 0.001, \eta_p^2 = 0.54$, denoting a large effect size). This indicates a notable influence of task load on gesture response time. The interaction effect was not significant ($F_{(1.33,24.10)} = 2.48, p = 0.12, \eta_p^2 = 0.12$, indicating a smaller effect size). This suggests that GCI and Dactylology function independently under varying load conditions.

The primary impact of techniques (GCI versus Dactylology) on false responses ($F_{(1,18)} = 1.41, p = 0.255, \eta_p^2 = 0.07$, reflecting a minimal effect size), showing not significant differences between the GCI ($M = 1.33$, $SD = 2.65$) and Dactylology techniques ($M = 1.07$, $SD = 2.23$) regarding false responses during the task. This suggests that executing a task via GCI does not differ significantly from performing it using the Dactylology technique. The significant difference in mean false responses between load levels ($F_{(1.08,19.45)} = 12.42, p = 0.002, \eta_p^2 = 0.40$, implying a medium to large effect size). This signifies that task load has a significant influence on false responses. The interaction effect was not significant ($F_{(1.29,23.23)} = 2.55, p = 0.11, \eta_p^2 = 0.12$, suggesting a smaller effect size), indicating that GCI and Dactylology function independently across different levels of cognitive load. In addition, a notable primary impact of technique (GCI vs. Dactylology) on forgot word count ($F_{(1,18)} = 5.31, p = 0.033, \eta_p^2 = 0.22$, reflecting a medium to large effect size), highlighting a distinct difference between the GCI technique ($M = 0.43$, $SD = 0.89$) and the Dactylology technique ($M = 0.89$, $SD = 2.04$) in relation to the forgot word count for task execution. This implies that using the GCI technique results in fewer forgotten words than using Dactylology, with the gesture technique accounting for 22% of the variance in the forgotten word count. The forgot word count averages varied significantly between different load levels ($F_{(1.05,18.93)} = 12.56, p = 0.002, \eta_p^2 = 0.44$, indicating a medium to large effect size). This implies a significant impact of cognitive load on forgot word count. The interaction effect is significant ($F_{(1.26,22.74)} = 9.13, p = 0.004, \eta_p^2 = 0.33$, suggesting a medium to large effect size). This implies that both GCI and Dactylology interact with technique and varying levels of cognitive load.

4.3. Subjective Results Based on NASA-TLX

Table 3 presents a marginal primary impact of technique (GCI versus Dactylology) on NASA-TLX score ($F_{(1,18)} = 0.54, p = 0.47, \eta_p^2 = 0.03$, indicating a very small effect size), indicating a very little marginal difference between GCI ($M = 55.33$ score, $SD = 20.2$) and Dactylology technique ($M = 57.14$ score, $SD = 20.64$) in terms of NASA-TLX score to perform the task. This suggests that performing the task using GCI was almost the same as performing the same task using the Dactylology technique.

Together, the results of the data collected from 19 participants, including skin conductance, response time, gesture response time, false responses, forgot word count, and NASA-TLX scores, revealed distinct differences between the two techniques being compared. Statistical analysis indicated a significant difference in the skin conductance levels, suggesting varying levels of physiological changes associated with these techniques. The gesture

response time and the forgot word count showed a significant difference between the two techniques, which clearly demonstrates that the proposed GCI technique resulted in fewer false responses and forgot word counts. Although the response times and the false responses did not show a significant difference. Moreover, across all load conditions, except for the skin conductance, the difference is statistically significant. Furthermore, the NASA-TLX scores, which assess subjective workload, showed minimal variation between the techniques. In addition, paired-samples *t*-tests and Wilcoxon signed-rank tests were conducted for each load condition and outcome measure, as presented in Table 4. The results consistently showed significantly lower gesture response times for GCI than Dactylogy across low, medium, and high load conditions ($p < 0.005$). GCI also exhibited significantly lower skin conductance under low and medium load conditions and a significantly lower forgot word count under high load conditions. Although differences in overall response time, false responses, and NASA-TLX scores were not statistically significant, GCI generally demonstrated lower physiological load, faster gesture execution, and fewer memory-related errors than Dactylogy. The Wilcoxon signed-rank test results were consistent with the paired-samples *t*-test findings, providing additional support for the robustness of the observed effects.

Table 4. Descriptive statistics and results of paired-samples *t*-tests and Wilcoxon signed-rank tests comparing GCI and Dactylogy techniques across all measures.

Test Variable	GCI		Dactylogy		$t_{(18)}$		Medians		Wilcoxon Test	
	Mean	SD	Mean	SD	<i>t</i>	<i>p</i>	GCI	Dact.	<i>W</i>	<i>p</i>
Low GSR	6.52	2.74	6.94	2.85	−3.07	0.007 *	6.79	7.31	30.0	0.007 *
Medium GSR	6.63	2.66	7.07	2.89	−2.48	0.023 *	6.91	7.06	37.0	0.018 *
High GSR	6.79	2.68	7.00	2.78	−1.44	0.168	6.77	7.41	37.0	0.018 *
Low RT	45.69	14.96	43.06	17.12	0.80	0.436	41.99	35.76	71.0	0.353
Medium RT	92.52	27.35	87.09	36.04	0.86	0.402	84.66	75.56	58.0	0.145
High RT	210.71	77.42	192.28	74.45	0.97	0.347	184.22	171.35	59.0	0.156
Low GRT	8.51	2.91	14.35	5.70	−5.468	<0.001 **	7.47	11.92	0.0	<0.001 **
Medium GRT	5.75	1.58	9.67	4.00	−5.505	<0.001 **	5.57	8.40	0.0	<0.001 **
High GRT	6.91	2.45	10.68	4.13	−4.225	0.001 **	6.37	9.52	7.0	<0.001 **
Low FR	0.10	0.31	0.26	0.80	−0.766	0.454	0.00	0.00	3.0	0.462
Medium FR	0.94	1.47	0.52	1.34	−0.954	0.353	0.00	0.00	15.0	0.372
High FR	2.15	3.32	3.21	3.72	−1.80	0.089	1.00	2.00	17.0	0.083
Low FWC	0.00	0.00	0.00	0.00	—	—	0.00	0.00	—	—
Medium FWC	0.36	0.76	0.15	0.50	0.94	0.360	0.00	0.00	6.0	0.330
High FWC	0.94	1.64	2.52	2.91	−3.002	0.008 *	0.00	2.00	2.0	0.009 *
NASA-TLX	55.33	20.20	57.14	20.64	−0.74	0.470	55.67	65.00	71.5	0.542

** Significant at 0.005 level; * Significant at 0.05 level.

5. Conclusions

This work proposes Hand Gesture-based Human-Computer Interaction (GCI) techniques with the goal of improving daily life through more natural and efficient user interactions. The proposed GCI technique significantly outperformed the existing technique in several key areas. In particular, the GCI resulted in substantially fewer false responses and forgot word count under various load conditions. This indicates that the proposed technique offers higher accuracy in recognising gestures, which could translate into more reliable and effective user experiences. Regardless of the overall response time, a closer examination of the individual command generation times (gesture response time) revealed 71% of variance, and the proposed GCI technique had a 39% faster gesture response time. In addition, physiological data (Galvanic skin response), as reflected in skin conductance, revealed 39% of variance in skin conductance, a significant difference, suggesting that the

proposed GCI technique may cause a more relaxed reaction than the existing Dactylology method. The NASA-TLX scores for the proposed method showed only a deviation of 3%, with minor differences between the techniques, indicating that the participants found both approaches to be similarly demanding. Together, the results highlight that the participants were able to perform tasks more accurately and efficiently with the GCI. The combination of reduced false responses, shorter response times for command execution (gesture response time), and favorable physiological responses underscores the superiority of the GCI in most scenarios tested, demonstrating its potential for enhancing user interaction in practical applications. Although the sample was representative of the characteristics of the target population, future research should include a larger and more diverse sample to improve the reliability of the results. Furthermore, incorporating participants from different age groups, as well as individuals who have acquired blindness at various stages, provides deeper insights and improves the applicability of the proposed work. The findings of this study offer preliminary evidence to support the potential of the proposed GCI technique. The results suggest that GCI could be a promising method for enabling computer interactions among visually impaired people.

Author Contributions: Conceptualization, D.L., B.S. and A.B.; Methodology, D.L. and B.S.; Software, D.L.; Validation, D.L.; Formal analysis, D.L., B.S. and S.-S.A.; Investigation, D.L.; Data curation, D.L. and A.B.; Writing—original draft, D.L. and B.S.; Writing—review & editing, B.S., A.B. and S.-S.A.; Visualization, B.S., A.B. and S.-S.A.; Supervision, B.S.; Funding acquisition, S.-S.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: All measurements were carried out according to the protocol approved by the Ethics Committee of the Durgapur National Institute of Technology. Participants received detailed instructions about the task, consented to testing procedures, and provided their consent to participate in the study.

Informed Consent Statement: We, Durgesh Lohar, Bibhash Sen, and Anupam Basu, hereby grant permission to publish our research paper. The code for the application design can be requested from one of the corresponding authors.

Data Availability Statement: All data are available in the main text. In addition, information can be requested from one of the corresponding authors.

Acknowledgments: We are thankful to Charudatta Jadhav, Principal Scientist, Head Accessibility Research at Tata Consultancy Services, Mumbai for his creative and critical inputs during the development of the work. We are grateful to Himanshu Ranjan (Jivan Jyoti NGO, Bokaro), Netraheen evang Mookbadhir Vidyalaya (Giridih), Voice of World NGO (Kolkata) and Ramkrishna Mission Boys Blind Academy (Narendrapur) for their voluntary participation. The authors thank the students of the National Institute of Technology, Durgapur, West Bengal, India, for their voluntary participation, with the proper ethical clearance obtained.

Conflicts of Interest: The authors declare no conflict of interest.

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