Cognitive Workload Assessment of Prosthetic Devices: A Review of Literature and Meta-Analysis

Junho Park, *Student Member, IEEE*, and Maryam Zahabi, *Member, IEEE*

***Abstract*—Limb amputation can cause severe functional disability for the performance of activities of daily living. Previous studies have found differences in cognitive demands imposed by prosthetic devices due to variations in their design. The objectives of this article were to 1) identify the range of cognitive workload (CW) assessment techniques used in prior studies comparing different prosthetic devices, 2) identify the device configurations or features that reduced CW of users, and 3) provide guidelines for designing future prosthetic devices to reduce CW. A literature search was conducted using Compendex, Inspec, Web of Science, Proquest, IEEE, Engineering Research Database, PubMed, Cochrane, and Google Scholar. Forty-three studies met the inclusion criteria. Findings suggested that CW of prosthetic devices was assessed using physiological, task performance, and subjective measures. However, due to the limitations of these methods, there is a need for more theoretical and model-based approaches to quantify CW. Device configurations such as hybrid input signals and use of multimodal feedback can reduce CW of prosthetic devices. Furthermore, to evaluate the effectiveness of a training strategy for reducing CW and improving device usability, both task performance and subjective measures should be considered. Based on the literature review, a set of guidelines was provided to improve the usability of future prosthetic devices and reduce CW.**

***Index Terms*—Human–machine interface, literature review, mental workload, meta-analysis, prosthesis.**

I. Introduction

MORE than 2.1 million people with amputations live in the USA and about 185 000 amputations occur each year [1], [2]. Limb amputation can cause severe functional disability for the performance of activities of daily living (ADLs).

Amputees use prosthetic devices on a regular basis to perform ADLs. Without these devices, ADLs may not be possible or may require additional effort and time [3], [4]. However, existing devices are often reported to be challenging to use, leading to poor utilization and device rejection [5], [6]. In an article assessing the usability of different prosthetic devices, it was found that 53% of passive hand users, 50% of body-powered hook users, and 39% of myoelectric hand users rejected prosthetic hands. The main reasons for rejection were identified as poor dexterity, glove durability, and lack of sensory feedback [7]–[9]. Other articles indicated that 40% to 60% of amputees were not satisfied with their lower-limb prostheses mainly due to issues such as discomfort, excessive weight, difficulty of use, and pain [10], [11]. Related to that, 31% of armed forces service members with lower-limb amputations rejected their prosthesis due to the lack of satisfaction and usability issues [12], [13].

Using prosthetic devices requires substantial amount of cognitive resources [14]–[18], which can be an underlying cause for device rejection. Previous articles have found that devices that impose high cognitive workload (CW) can reduce task performance, which can negatively affect user satisfaction, reduce device usability, and ultimately might lead to frustration and prosthetic device rejection [19]–[21]. These cognitive resources are used to compensate for the loss of motor control and to mitigate the loss of somatosensory feedback from the amputated limb [16], [18], [22]–[25]. Therefore, using prostheses can cause a lack of cognitive capacity available to conduct other mental activities [16], [18]. High CW can also reduce primary task performance [26]. For example, an amputee may find it difficult to avoid obstacles or walk in uneven terrain. In case of upper-limb amputation, most of the current control strategies use limited information [i.e., shoulder movements or recorded electromyography (EMG) signals] for activating several degrees of freedom of the prosthetic devices, which is not intuitive and results in high CW [27]. Assessment of CW can provide an understanding of the underlying attentional resources that are engaged during task execution and support the evaluation/development of prosthetic devices [4].

A. Cognitive Workload Assessment Techniques

CW assessment techniques are typically categorized into three broad categories including physiological measures, subjective rating scales, and performance measures [28]. Physiological measures (e.g., heart rate variability) allow the understanding of physiological processes through their effect on body, rather than through task performance or perceptual ratings [29]. Subjective ratings quantify humans' understanding and judgments of their experienced demand. Performance measures are classified into two major categories including primary and secondary task measures. Primary task measures evaluate operator's performance on the task of interest. Examples of primary task performance measures of CW include speed, accuracy, reaction or response times, and error rate. Secondary task measures provide an index

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The authors are with the Wm Michael Barnes '64 Department of Industrial and Systems Engineering, College Station, TX 77843 USA (e-mail: junho.park@tamu.edu; mzahabi@tamu.edu).

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of the remaining operator capacity while performing primary tasks, and are more diagnostic than primary task performance measures [29]. Examples of secondary tasks performance measures include *n*-back, verbal shadowing, and pursuit tracking task.

Besides the conventional measures of CW, cognitive performance modeling (CPM) technique is another approach to assess or predict CW. CPM methods such as goals, operators, methods, and selection rules (GOMS) can provide representations of human performance, including learning time, execution time, number of cognitive/perceptual/motor operators, and task errors [30]. These models can predict the amount of time that an expert need to retrieve information from memory, select from decision options, and execute motor movements. These features enhance the interpretability of CPM approaches as compared to other CW measurement techniques such as physiological and subjective measures [20]. Furthermore, as compared to some of the physiological measures of CW [e.g., electroencephalogram (EEG)], which are intrusive and can be contaminated by body motion, CPM approaches are not intrusive and the models can be modified and applied in different applications. CPMs can be coded, compiled, and run using software applications such as Cogulator and CogTool [31], [32].

B. Cognitive Workload Assessment of Prosthetic Devices

Prior articles have investigated CW of different prosthetic devices using various physiological (e.g., EEG, heart rate, respiratory rate, and skin conductance) [33]–[35] or subjective measures [e.g., NASA-Task Load Index (NASA-TLX)] [36], [37]. However, there is a lack of a systematic review that identifies what prosthetic design features or configurations lead to the differences in CW. In addition, prior articles were only focused on specific prosthetic device configurations. For example, some articles were focused on direct control (DC) or pattern recognition (PR) controllers [19]–[21], [38]–[43], whereas other investigations were focused on assessing workload in hybrid methods such as surface EMG with force myography (FMG) [44], [45]. Other investigations compared different feedback modalities in prosthetic devices such as auditory, visual, or vibrotactile feedback [34], [35], [46]–[48]. Furthermore, some articles assessed the impact of training on CW of prosthetic users. However, these assessments were limited to specific prosthetic configurations (e.g., body-powered or EMG-based devices) [34], [49]–[51] or training duration [52], [53]. Thus, there is a need for an integrated analysis on the impact of training on reducing CW of prosthetic users. Furthermore, only one article used CPM approach to assess CW of prosthetic devices although the method has been used extensively in other domains such as driver workload assessment and usability evaluations [20], [54].

The objectives of this review were to 1) identify the range of CW assessment techniques used in prior articles comparing different prosthetic devices, 2) identify the device configurations or features that reduce CW of users, and 3) provide a set of guidelines for designing future prosthetic devices to reduce CW.

II. Method

The literature review was performed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [55]. The detailed description of our method including search strategy, eligibility and selection criteria, and data analysis is described below.

A. Information Sources and Search Strategy

A systematic literature search was conducted using Compendex, Inspec, Web of Science, Proquest, IEEE, Engineering Research Database, PubMed, Cochrane, and Google Scholar databases. The search was completed in November, 2020. Manual search was also conducted in Google Scholar, as it is the most comprehensive search engine [56]–[59]. The search terminologies included "*workload* AND *prosth** AND *limb*." In the advanced setting, we limited the search to include only journal articles, conference proceedings, and theses/dissertations.

B. Eligibility Criteria

To be included in this review, articles had to fulfill the following criteria:

1) The article had to include quantitative information on cognitive (or mental) workload.
2) The article had to meet the definition of prosthesis for this review, i.e., "A device to replace missing upper or lower limb functionality" [60], [61]. Limb functionality refers to activities such as reaching, grasping, or walking (for lower limb).
3) Study participants could be either amputees using actual prosthetic devices or able-bodied participants using bypass prostheses.
4) The article had to be written in English.
5) The article should be published in or after 2005 for upper limb (the year that Defense Advanced Research Projects Agency started the Revolutionizing Prosthetics Program) [62] and in or after 1999 for lower limb (the year that fully microprocessor-controlled prosthesis made walking with the prosthesis feel and look more natural and provided lower-limb amputees with a solution that was more responsive to changes in walking speed) [63].

As shown in Table I, about 60% (26/43) of the articles were conducted with able-bodied participants using bypass devices. Approximately 12% (5/43) of the articles involved both able-bodied and amputee participants. About 28% (12/43) of the articles were conducted with amputees. For those articles with able-bodied participants, bypass devices were developed using various input signals such as EMG, inertial measurement unit (IMU), FMG, and motion tracking. Also, bypass devices were used to study effects of feedback modality and training schedule on CW. Therefore, bypass devices with able-bodied participants were included in the article as they are devices that allow an able-bodied user to activate a terminal device with similar controls that an amputee would use to operate a custom-made prosthesis [90]. Furthermore, based on our review and previous articles on prosthetic devices, recruiting amputee

TABLE I
OVERVIEW OF REVIEWED STUDIES

Ref.	Location/ participant	Prosthesis Type	Human-Machine Interface Configuration					CW Assessment Technique (significance)		
			Input Signal			Output Control				
			EMG	Brain Signal	Others	Physical device	Virtual environment	Physiological	Subjective	Performance
[20]	U/Amputee	Actual	✔(DC /PR)			✔		Pupil size (S)	-	Primary task (Number of transported pins) (S), CPM (S)
[34]	L/Amputee	Actual			✔(Passive)	✔		HR, SC, ST (all N/A)	NT (N/A)	Secondary cognitive task
[35]	U/ Able-bodied	Bypass			✔(Tendon-driven)	✔		Blink rate (S), SC (S)	NT (S)	-
[38]	U/ Able-bodied	Bypass	✔				✔(3D)	EEG (S)	-	-
[39]	U/Amputee	Actual	✔(DC /PR)			✔		-	-	Primary task (CRT, B&B, JHFT, SHAP, ACMC) (S)
[40]	U/Amputee	Actual	✔(DC /PR)			✔		-	-	Primary task (B&B, JHFT, SHAP, CRT) (S)
[41]	U/Amputee	Actual	✔(DC /PR)			✔		-	-	Primary task (B&B, JHFT, SHAP, CRT, Cubbies) (N/A)
[42]	U/Amputee	Actual	✔(DC /PR)			✔		-	-	Primary task (B&B, JHFT, CRT, AM-ULA) (N/A)
[64]	U/Able-bodied	Bypass	✔		✔(IMU)	✔		-	NT (S)	-
[65]	U/ Able-bodied	Bypass	✔		✔(IMU)	✔		-	NT (S)	-
[43]	U/Mixed	Bypass		✔			✔(2D)	EEG (S)	NT (N/A)	-
[19]	U/ Able-bodied	Bypass	✔(DC /PR)			✔		Pupil size (S)	-	Primary task (Number of transported pins) (S)
[21]	U/ Able-bodied	Bypass	✔(DC /PR)			✔		Pupil size (S)	-	Primary task (Number of transported pins) (S)
[44]	U/ Able-bodied	Bypass	✔		✔ (FMG)	✔	✔(2D)	-	NT (N/A)	-
[45]	U/ Able-bodied	Bypass	✔		✔ (FMG)	✔		-	NT (N/A)	-
[46]	U/ Able-bodied	Bypass			✔(Tendon-driven)	✔		EEG (S), HR (S), HRV, SC, RR (S)	NT (S)	-
[47]	U/ Able-bodied	Bypass			✔(Tendon-driven)	✔		-	NT (N/A)	-
[48]	U/Amputee	Actual	✔			✔		-	NT (S)	-
[53]	U/ Able-bodied	Bypass			✔ (Motion tracking)		✔(2D)	-	NT (S)	-
[66]	U/Mixed	Bypass/ Actual	✔(PR)			✔		EEG (S)	NT (N/A)	-
[67]	U/ Able-bodied	Bypass	✔				✔(3D)	EEG (S)	-	-
[68]	U/ Able-bodied	Bypass	✔			✔		Gaze data (S), EEG (S)	-	-
[69]	L/Mixed	Bypass/ Actual			✔ (Energy storing prosthetic feet)	✔		EEG (S)	NT (S)	Secondary cognitive task
[70]	U/Mixed	Bypass	✔			✔	✔(3D)	EEG (S)	NT (S)	-
[71]	U/ Able-bodied	Bypass	✔			✔	✔(3D)	EEG (S)	-	-

TABLE I
(CONTINUED.)

Ref.	Location/ participant	Prosthesis Type	Human-Machine Interface Configuration					CW Assessment Technique (significance)		
			Input Signal			Output Control				
			EMG	Brain Signal	Others	Physical	VE	Physiological	Subjective	Performance
[72]	L/Amputee	Actual			✔(Passive)	✔		EEG	NT (S)	Secondary cognitive task
[73]	L/Amputee	Actual			✔(Passive)	✔		EEG	NT (S)	-
[74]	U/Mixed	Bypass/ Actual	✔			✔		-	NT (S)	-
[75]	U/Mixed	Bypass/ Actual	✔		✔(IMU)	✔	✔(3D)	-	NT (N/A)	-
[76]	U/ Able-bodied	Bypass	✔ (PR)				✔(2D)	-	NT (N/A)	-
[77]	U/ Able-bodied	Bypass			✔(Motion tracking)		✔(2D)	-	NT (S)	-
[78]	U/ Able-bodied	Bypass		✔	✔(Motion tracking)		✔(2D)	-	NT (S)	Secondary cognitive task
[79]	U/ Able-bodied	Bypass			✔(Motion tracking)	✔		-	NT (S)	Primary task (Task completion time)
[80]	U/ Able-bodied	Bypass			✔(Motion tracking)		✔(2D)	-	NT (S)	-
[81]	U/ Able-bodied	Bypass			✔(Motion tracking)		✔(2D)	-	NT (S)	-
[82]	U/ Able-bodied	Bypass			✔(Motion tracking)		✔(2D)	-	NT (S)	-
[83]	U/Amputee	Actual	✔			✔	✔(2D)	-	-	Primary task (Task completion time)
[84]	L/Amputee	Actual			✔(Micro-processor feet)	✔		-	-	Secondary cognitive task
[85]	U/Amputee	Actual	✔			✔		-	-	Primary task (Task completion time) (S)
[86]	U/ Able-bodied	Bypass	✔			✔		-	NT (S)	-
[87]	U/ Able-bodied	Bypass	✔			✔		-	NT (S)	-
[88]	U/ Able-bodied	Bypass	✔			✔		-	NT (S)	-
[89]	L/ Mixed	Bypass/ Actual			✔(Energy storing prosthetic feet)	✔		EEG (S)	-	Secondary cognitive task

(Alphabetical order) ACMC: assessment for capacity of myoelectric control, AM-ULA: activities measure for upper limb amputees, B&B: box and block, BF: breathing frequency, CRT: clothespin relocation task, EEG: electroencephalography, DC: direct control, FMG: force myography, HR: heart rate, HRV: heart rate variability, IMU: inertial measurement unit, JHFT: Jebsen hand function test, L: lower limb, NT: NASA-TLX, N/A: descriptive data only, PR: pattern recognition, RFID: radio frequency identification, RR: respiratory rate, S: significant, SC: skin conductance, SHAP: Southampton hand assessment procedure, ST: skin temperature, U: upper limb.(Alphabetical order) EEG: electroencephalography, IMU: inertial measurement unit, L: lower limb, NT: NASA-TLX, N/A: descriptive data only, PR: pattern recognition, S: significant, U: upper limb.

participants for human subject experiments are challenging and therefore several articles used able-bodied participants to assess the usability and CW of prosthetic devices. Thus, inclusion of bypass devices in our article might be helpful in providing a more comprehensive design guideline for assessing CW of prosthetic devices. All publications including journal articles, conference proceedings, and theses/dissertations were eligible.

C. Study Selection

Initially, the relevance of literature returned through the searches was evaluated via a review of the titles. Literature deemed relevant via title review was assessed for relevance again via abstract review. Finally, the full text of literature deemed relevant by both title and abstract were reviewed by the authors ($n = 159$). Of the initial records found ($n = 9261$), 43 articles were found to meet the eligibility criteria and were included in this review per PRISMA methodology shown in Fig. 1. Among the 43 articles, there were 32 journal articles, 7 conference proceedings, and 4 Ph.D. or master theses.

The relevant articles were reviewed by the authors in order to confirm relevance to the present article and to summarize the findings. For each article, a structured summary was developed including study citation, objective, methodology, findings, and conclusions.

D. Data Extraction

The data extraction and variable coding for meta-analysis were conducted based on the information provided in each article (e.g., numbers, tables, or figures). Among the 43 articles, 25 articles were excluded due to lack of sufficient number of data points (i.e., three data points per recommendations from [91]) for each comparison category such as PR vs. DC prosthetic configurations. Therefore, the meta-analysis was conducted on the remaining 18 articles.

TABLE II
HYPOTHESES (HYPOTHESIS NUMBER IN PARENTHESES)

Input signal	Output control	Feedback modality	Training	Lower limb
Hybrid approach will reduce CW compared to the non-Hybrid approach (H1) PR configuration will reduce CW compared to the DC configuration (H2)	Use of virtual environments as an output control will reduce CW compared to physical devices (H3)	Auditory feedback will reduce CW compared to the visual feedback (H4) Multimodal (Auditory + Visual) feedback will reduce CW compared to the visual feedback (H5)	CW after training is lower than CW before training (H6)	CW in seating posture is lower than CW during walking (H7)

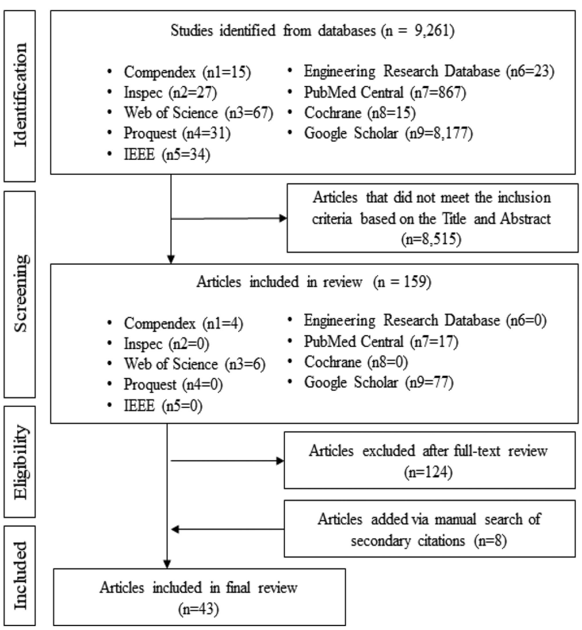


Fig. 1. Literature review process based on PRISMA methodology.

For the overall NASA-TLX score, the average of six subdimensions including mental demand, physical demand, temporal demand, effort, performance, and frustration was calculated due to the lack of reporting weights of each category in prior articles. However, this procedure has been used and validated in previous articles [92].

E. Hypotheses

Based on the literature review results, a list of hypotheses (H) was formulated which is presented in Table II. For input signals, it was hypothesized that the hybrid approach will generate lower CW than the nonhybrid approach (H1) due to its versatility in terms of sources of input. Hypothesis 2 (H2) was formulated based on the findings of our prior article [19]. Multiple resource theory (MRT) [93] was applied to formulate hypotheses 3–5. Since virtual environments (VEs) can provide visual and/or auditory feedback to participants, they might reduce CW compared to physical devices. In addition, since prosthetic device users use visual resources to interact with the device, using another modality (i.e., auditory) could generate lower CW than visual feedback. Hypotheses 6 and 7 were formulated to capture the effect of training and posture in lower-limb prosthetic devices, respectively.

F. Data Analysis Approach

The meta-analysis was conducted using Revman 5.3, a meta-analysis software where we calculated heterogeneity (I^2) for each group of comparison (both within-subject design and between-subject design). On average, I^2 was calculated as 38%, which based on Cochrane's guide [94], indicates that there was no heterogeneity issue. The statistical test and procedures used were based on [95] and were similar to the procedure used in other meta-analysis articles [96]. The meta-analysis plot was generated using MATLAB 2020.

A regression analysis was conducted on NASA-TLX scores of 20 upper-limb articles using JMP Pro 15.0.3. Box-Cox transformation on the dependent variable satisfied both normality and equal variance assumption. To verify differences in levels of significant effects, Tukey's honest significant difference *post-hoc* multiple comparison was applied. A significance level of $\alpha = 0.05$ was set as a criterion for the article.

III. RESULTS

A. Cognitive Workload Assessment Techniques in Previous Articles

A review of literature on upper-limb articles revealed that CW of prosthetic devices was assessed using a combination of physiological, subjective, or task performance measures (Fig. 2). Physiological measures included various types of brain activity measures such as P200 (which represents some aspect of higher order perceptual processing, modulated by attention), P300 (an event-related potential component elicited in the process of decision making), late positive potential (LPP, an event related potential that reflects facilitated attention to emotional stimuli), and frontal theta/parietal alpha (FT/PA) [35], [38], [43], [66]–[68], [70], [71]. A few articles used cardiac [35], respiratory [35], skin [35], and eye-tracking measurements [19]–[21], [35]. Skin measurements included skin conductance and temperature. Eye-tracking measures included blink rate and pupillometry measures such as pupil diameter [19]–[21]. Among all the CW measures, NASA-TLX was the most frequently used method (28 out of 43 articles) [34], [35], [43]–[48], [53], [64]–[66], [69], [70], [72]–[82], [86]–[88]. The main reason for frequent

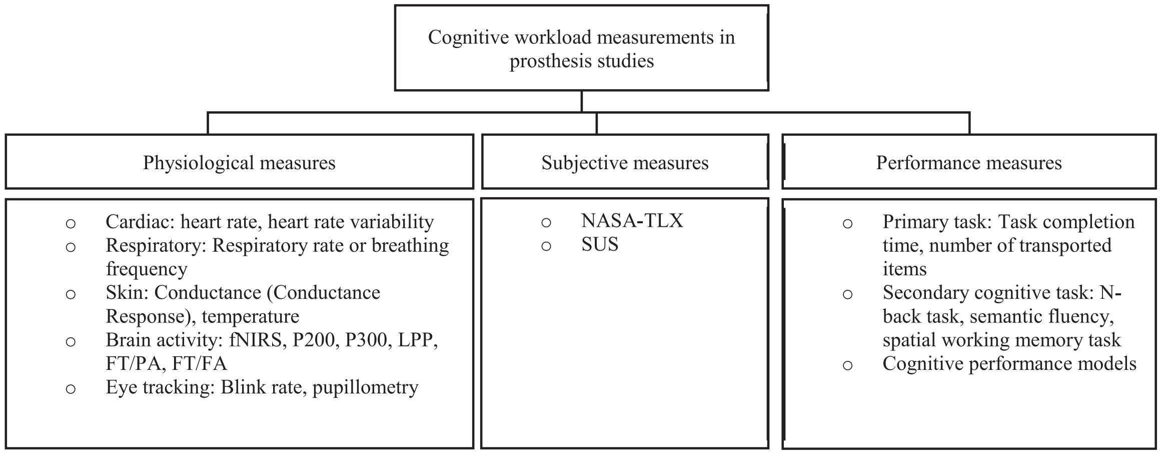


Fig. 2. Cognitive workload assessment techniques in prosthesis studies.

use of NASA-TLX was determined as its capability to assess CW in motor tasks [58], [66], [92] and consideration of overall workload as well as the magnitude of each factor [49], [50].

Primary and secondary task performance were used as CW measures in 16 articles [19]–[21], [34], [39]–[42], [69], [72], [78], [79], [83]–[85], [89]. Primary task measures were mainly used when the participants performed ADL tasks and were defined in terms of task completion time and the number of transported items [39]–[41], [79], [83], [85]. CW was also assessed using secondary task performance measures when participants were asked to perform verbal, semantic, or numerical cognitive tasks along with the ADL tasks or other primary tasks during the experiment (e.g., participants counted backward from 100 to 1 with three steps while they were moving an object with their prosthetic device [42]).

Only one article used CPM approach to assess CW of prosthetic devices [20]. The finding of this article comparing DC and PR control modes suggested that CPM approaches such as GOMS models can be used to assess cognitive demands of using upper-limb prostheses [20].

Six lower-limb articles met the criteria of this review [34], [69], [72], [73], [84], [89]. Heart rate, skin conductance, skin temperature [34], and EEG signals [69], [72], [73], [89] were used as physiological measurement techniques in these articles. In addition, some articles used NASA-TLX as a subjective measure of CW [34], [69], [72], [73]. Secondary tasks or dual tasks under walking or seating condition were also used in few studies to assess CW [34], [69], [72], [84]. It was found that participants prioritized between the difficulty of walking (primary task) and the secondary cognitive tasks in different environmental conditions (e.g., walking on uneven terrain). Therefore, to reduce CW, not only secondary tasks but also primary tasks and environments should be carefully designed [34], [69], [84].

B. Prosthetic Device Configurations

We made a structure of human–machine interfaces for prosthetic devices based on reviewed articles. These interfaces can be categorized in terms of input signals (signals captured from human to control the device) and outputs controls (Fig. 3). In terms of input signals, prosthetic devices can be controlled using EMG signals, brain signals, and/or other methods. There are various methods in "others" category such as body-powered devices or devices controlled by FMG, IMU, or motion tracking. Outputs can be generally categorized in two groups of physical devices and VE. Most of the upper-limb articles used EMG as an input signal for controlling the physical device. Lower-limb prosthetic devices included passive, energy-storing prosthetic feet, and microprocessor-controlled devices. In addition, some articles used bypass input signals with sensors and displayed virtual prosthesis motions on two-dimensional (2-D) or (3-D) screens.

1) Inputs:

a) EMG signals: About 60% (26 out of 43 articles) of the articles used EMG as an input signal, which was the most frequently used input signal (Table II). This finding is consistent with other articles [49], [97]–[99] that found myoelectric control is an appropriate technique concerned with the detection, processing, classification, and application of input signals to control human–machine interfaces in rehabilitation. Most comparisons of CW have been made between the DC and PR controllers. It was found that the PR controller imposed less CW on the user as compared to the DC mode due to intuitive muscle contractions [20].

Various feedback modalities were combined with EMG-based configurations to improve task performance and reduce CW. The most heavily used feedback modality was vibrotactile feedback [45], [48], [64], [65]. For example, participants received vibrotactile feedback that came from uniformly placed vibrotactors providing information on contact, prosthesis state (active function), and grasping force. Auditory and visual modalities were also used in a few articles [35], [46], [47]. For example, the flexion of the fingers was divided into eight different positions, which were identified by different piano major triads for the palmar grasp. As a visual feedback, a green LED was used to indicate when to start and finish each trial. The participant was asked to open his hand completely and wait for the LED to turn ON, then, start closing the hand until the bottle was fully grasped.

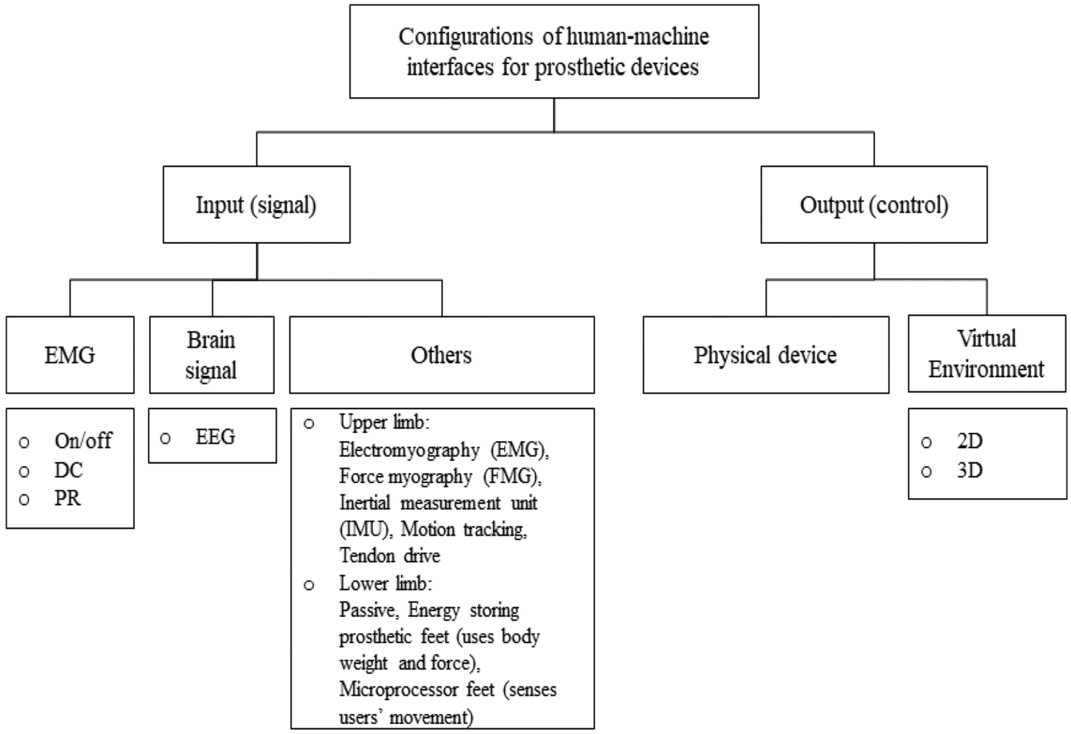


Fig. 3. Configurations of human–machine interfaces for prosthetic devices.

b) Brain signal: EEG [43], [78] was used to provide input signals to control non-EMG-based devices in order to perform ADLs. However, using EEG as input signals was more cognitively demanding and required higher effort (attention) than manual control [100]. Furthermore, EEG signals are highly susceptible to interference from skeletal muscle activity and often require the application of elaborate filtering methods that may result in loss of meaningful signal information. However, articles that used the hybrid approach (i.e., combination of EEG and EMG signals) found reduction in CW as compared to the EEG or EMG signals alone [78].

c) Others: Body-powered prosthetic devices are controlled by body movements. For example, upper-limb body-powered devices, or cable-operated limbs, work with a harness and a cable around the opposite shoulder of the injured arm. The participant can pull the cable to open the prosthetic hand (hook) by shoulder movements. Passive devices (for lower limb) [34], [69], [72], [84], [89] were used in five articles to compare their capabilities with other prosthetic devices or to compare task performance or CW in various feedback modalities. Force measurement unit and IMU were used with EMG signals as a hybrid approach and generated lower CW as compared to EMG control inputs [44], [45], [75].

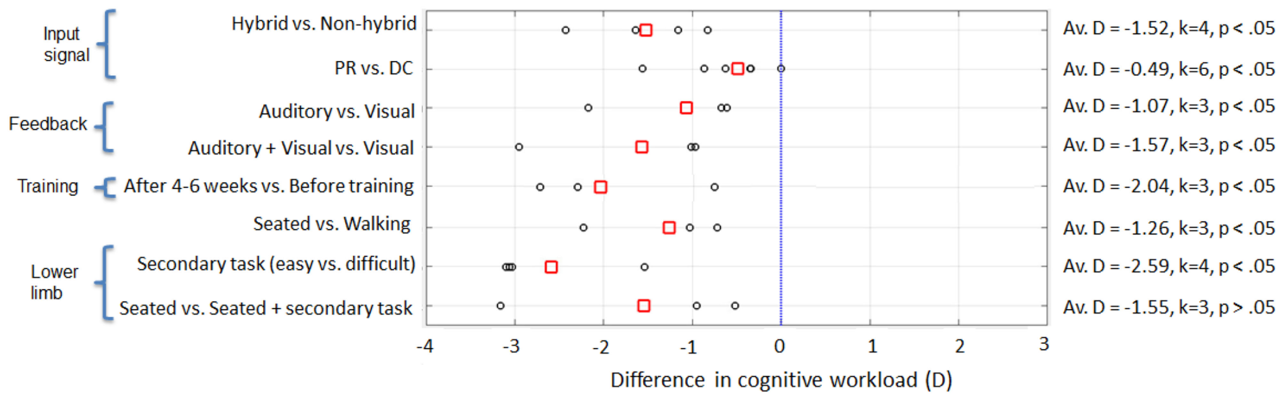
Motion tracking was also used to control prosthesis and 2-D or 3-D displays [53], [77], [78], [80]–[82]. Head movements were classified as a gesture or pattern for controlling the device's movements and animations in the VE. In addition, using motion capture systems was found to be a more appropriate approach for capturing head movements instead of using skin attachments [53], [81], [82]. Lower-limb articles used passive controllers (i.e., prosthetic devices that look like a natural lower limb) [34], [72], [73], energy storing prosthetic feet (i.e., devices that use body weight and force as inputs) [69], [89], and microprocessor-controlled devices (i.e., devices that sense users' movement) [84].

2) Outputs:

a) Physical device: About 77% of the articles (33/43) used physical devices as an output (Table I). Major EMG-based devices included DC or PR controllers. A few articles also used ON/OFF threshold setup (i.e., a prosthetic hand that is operated with a constant speed in clockwise and counterclockwise directions with a full stop). Some EMG-based devices used EMG signals in combination with FMG [44], [45], RFID [75], IMU [64], [65], [75], and vision module [75] as a hybrid method. The findings indicated that CW in the hybrid approach was lower than devices using EMG signals alone.

b) Virtual environment: About 35% of the articles (15/43) used VE as an output. The articles with VE setup used nonimmersive (i.e., 2-D displays) [43], [44], [53], [76]–[78], [80]–[83] or immersive systems (i.e., 3-D displays) [38], [67], [70], [71], [75]. None of the articles used head-mounted displays. VE could be used for testing the capability of human, through practice, to acquire new sensorimotor mappings to adapt to novel kinematics or dynamics as well as to learn how to manipulate a device [82].

However, VE can be challenging for participants in that they might be able to intentionally control the movements in prosthetic devices while allocating less attention to task performance, which leads to high stability in prosthesis movements and low task performance [68]. No lower-limb article used 2-D or 3-D



* Black circles represent the difference (D) in CW between the two conditions. A negative D indicates that the CW of the former condition was lower than the latter. The red square represents the average D in each category, k represents the number of studies in each category and p indicates the *p*-value.

Fig. 4. Meta-analysis results.

VE as an output. Instead, these investigations used passive or active transfemoral or transtibial prosthesis devices.

C. Meta-Analysis

Fig. 4 summarizes the findings of meta-analysis. Black circles represent the difference (D) in CW between the two conditions. A negative D indicates that the CW of the former condition was lower than the latter. The red square represents the average D in each category, k represents the number of articles in each category, and p indicates the p-value.

If the red square is on the left side of the vertical blue dotted bar, it means that the former condition is better than the latter in terms of CW. For example, in the first comparison, the red square is on the left side, meaning that the CW of using a hybrid approach is significantly lower than that of a nonhybrid configuration.

1) Comparison of Different Prosthetic Device Configurations in Terms of Input Signals: Based on the meta-analysis, it was found that CW was significantly lower when hybrid signals were used as an input as compared to the nonhybrid approach ($p < 0.05$). Hybrid configurations include a combination of EMG or brain signals with other input signals such as EMG + IMU [64], [65] and motion tracking + brain signal [78]. Hybrid input signals were found to have lower CW than single input signals (i.e., brain signal, EMG, and motion tracking only). Within the EMG-based interfaces, CW was significantly lower when the PR controller was used as compared to the DC in performing simulations of ADLs such as the clothespin relocation task, Jebsen hand function test, and cubbies task ($p < 0.05$) [19]–[21], [39], [41], [100].

2) Comparison of Feedback Modalities in Prosthetic Devices: The analysis on feedback modalities indicated that using auditory feedback was less cognitively demanding as compared to the visual feedback ($p < 0.05$) [35], [46], [47]. However, using multimodal feedback (i.e., visual and auditory) was more beneficial than using visual feedback alone ($p < 0.05$) [35], [46], [47]. The feedback was provided on the task performance. For example, auditory feedback was provided to let the user know whether he/she grasped the object with sufficient force [35]. Altogether, the comparison between different feedback modalities suggests using multimodal visual and auditory feedback to reduce CW.

3) Effect of Training on Cognitive Workload: Findings suggested that upper-limb amputees experienced less CW after continuous training for 4–6 weeks at home ($p < 0.05$) [39], [41], [83] (Fig. 4). These articles assessed participants' cognitive load before and after 4–6 weeks of training. Under 6 weeks of training, participants were exposed to prosthetic devices for at least 124 h. During four weeks of training, participants received at least 38 h training on the devices.

4) Cognitive Workload Assessment in Lower-Limb Articles: CW was higher in the walking condition than the seated condition ($p < 0.05$) [34], [69], [72]. However, there was no significant difference in CW between the seated condition and seated condition with secondary task ($p > 0.05$). The findings suggest that walking requires substantial cognitive resources for amputees with lower-limb prosthetic devices and performing difficult secondary tasks during this activity significantly increases CW.

TABLE III
STUDY VARIABLES AND LEVELS FOR REGRESSION ANALYSIS

Variable	Levels
1. Input signal	Hybrid, EMG, EEG, Others (e.g., motion tracking)
2. Output control	Physical prosthesis, Virtual environment

D. Regression Analysis

The objective of this analysis was to identify the effect of prosthetic device configurations on CW. Data coding for the regression analysis is shown in Table III. Two variables were identified based on the literature review including: 1) input signals and 2) output controls. It is important to note that the

TABLE IV
RESULTS OF REGRESSION ANALYSIS

Variable*	p-value	F ratio	Level	p-value (95% C.I.)	Parameter estimate
Input signal	.0005**	F(3,37)=7.46	Hybrid	.01 (-19.60, -2.04)	-10.82
			EMG	.82 (-7.91, 9.85)	0.97
			EEG	.98 (-18.67, 18.12)	-0.25
			Others (ref)		
Output control	.42	F(1,37)=0.67	Physical device	0.42 (-2.45, 5.77)	1.66
			Virtual environment (ref)		

*Input signals: Signals captured from human to control the device, Output control: including physical devices or virtual environment.**An α level of 0.05 was used to determine statistical significance for the regression analysis.

TABLE V
SUMMARY OF HYPOTHESIS TESTS

Hypothesis	Test Result	Hypothesis	Test Result
H1	Supported	H5	Supported
H2	Supported	H6	Supported
H3	Refuted	H7	Supported
H4	Supported		

TABLE VI
COMPARISON OF CW ASSESSMENT TECHNIQUES

Technique	Pros	Cons
Physiological	Continuous & objective [20, 29]	Intrusiveness, susceptible to temperature and humidity [110]
Subjective	Have high face validity [20]	Discrete, ability to predict task performance is uncertain [29, 111], recall bias, and individual differences [92]
Task performance	Useful to test changes of CW using direct modification on the task [20]	Lack of interpretability [29], lack of scientific rigor, and plausible compensatory effect [20]
Cognitive performance modeling	High interpretability, less intrusive, high versatility (can be edited and embedded in various situations) [112]	Need time and effort to learn the modeling techniques, need validation process with human data

feedback modality was initially included in the model; however, it was removed due to the lack of sufficient number of observations. The analysis was focused only on upper-limb articles as there were only six relevant lower-limb articles and their workload measurements were heterogeneous. The overall CW was determined based on the overall NASA-TLX score reported in prior articles.

Based on Table IV, the type of input signal had a significant impact on overall CW ($p < 0.05$). Among the input signals, the hybrid approach significantly reduced CW (parameter estimate $= -10.82$), while others significantly increased CW (parameter estimate $= 10.11$). However, there was no effect of output control on CW ($p > 0.05$). The model predicting the overall CW was specified according to (1):

$$\text{Overall cognitive workload} = \alpha + \beta_{\text{Input\_Signal}} \cdot \text{Input}_{\text{Signal}} + \beta_{\text{Output}_{\text{Control}}} \cdot \text{Output}_{\text{Control}} \quad (1)$$

where α is the intercept, $\beta_{\text{input\_Signal}}$ and $\beta_{\text{output\_Control}}$ are the parameters associated with the study variables listed in Table IV.

E. Summary of Hypothesis Tests

Table V illustrates the summary of hypothesis tests based on meta-analysis and regression results. The results are further discussed in the following section.

IV. DISCUSSION

This article identified the determinants of CW associated with using prosthetic devices using two approaches including a meta-analysis and regression analysis. The meta-analysis provided a comparison between different variables in terms of CW. Furthermore, the regression analysis reinforced the meta-analysis results and revealed the impact of device configurations (input and output) on CW. From this discussion, a set of guidelines was formulated in Table VII.

A. CW Assessment Techniques

This review revealed that a majority of articles used EEG, NASA-TLX, and task performance measures to assess CW of prosthetic devices. EEG signals were used frequently to measure CW since in most of the articles conducted with upper-limb prosthetic devices; the participant was in a static posture without any head or body movement. This static posture would be helpful to gather and analyze EEG signals from participants as these signals can be easily contaminated by head or body motion. In terms of statistical analysis, it was hard to generalize or elicit insights on CW due to various measurement techniques such as P200, P300, LPP, FT/PA, FT/frontal alpha ratio, and insufficient number of articles per each category to conduct statistical analysis.

TABLE VII
SUMMARY OF GUIDELINES FOR DESIGNING PROSTHETIC DEVICES WITH LOW COGNITIVE WORKLOAD

Issues	Guideline	References
Input signal	[Upper limb]	
	1. Use hybrid input signals including: • EMG + IMU or EMG + FMG	[44, 48, 64, 65]
	2. Use PR instead of DC in EMG-based prosthesis	[19-21, 39-42, 49, 86]
	3. Avoid using motion tracking or tendon-driven devices alone to control prosthetic devices. Instead, use them as a combination with other input signals (e.g., EMG)	[35, 46, 47, 53, 77]
	4. Provide more degrees of freedom for wrist movement (flexion-extension, radial-ulnar deviation, and rotation)	[74, 79]
Output control	1. Use EMG-based physical devices instead of non-EMG based physical prosthetic devices	[19-21, 39-42, 45, 48, 49, 64-66, 74, 79, 83, 85]
	2. Use VEs to provide adaptable and rich media for assessment and training of motor deficits	[118, 119]
Feedback modality	[Upper limb]	
	1. Use multimodal feedback modality (Auditory + Visual) instead of unimodal feedback (Visual)	[35, 46, 47, 50]
	[Lower limb]	
	1. Use vibrotactile feedback with visual feedback	[34]
Training strategy	1. To evaluate the effectiveness of a training strategy, consider both task performance and subjective measures (e.g., NASA-TLX).	[34, 49-53]
	2. Provide training for at least four weeks.	[39-41, 76, 83]

Secondary tasks were frequently used in lower-limb articles to assess CW of prosthetic devices while walking (i.e., primary task). Use of secondary tasks in this condition is preferred over physiological measures of CW since bio sensor signals might be contaminated by whole body movement while walking. However, complexity of the secondary tasks or environmental conditions can reduce the performance of walking, or the primary task [84]. In addition, if the amputees are acclimated to the prosthesis and the environment is stable, the impact of cognitive burden can be limited, and therefore physiological measurements can be used instead of task performance measurements to capture subtle changes in CW under these conditions [101].

One possible alternative to assess CW is the CPM method. Although CPM was used only in a case study with one amputee participant under DC and PR conditions, the method has the potential to be applied to other configurations and experimental conditions, considering its capability to predict task performance and calculate memory chunks [20]. The models can calculate task performance, the number of cognitive/perceptual/motor operators, and memory chunks to identify bottlenecks in the task. These models have been widely applied to other domains such as human–computer interaction research, aviation, health care, usability testing, and cybersecurity [102]–[108]. However, it is important to note that CPM approaches assume expert performance, and therefore the methods might have limited application to novice prosthetic users.

Advantages and limitations of each CW assessment technique were summarized in Table VI. A detailed comparison of these techniques based on sensitivity, intrusiveness, cost, and accuracy can be found in [109]. Physiological measures allow the understanding of psychological processes through their effect on the body, rather than through task performance or perceptual ratings [29]. Therefore, the principal advantage of physiological measures is that these measures are continuous and objective. However, some signals can be contaminated by head or body movements (e.g., neuroimaging or EEG measures), especially in experiments using prosthetic devices or electrode caps [20].

Majority of articles used NASA-TLX to measure CW since the method is unobtrusive and can be easily collected after the experiment sessions. Subjective measurement techniques such as NASA-TLX quantify humans' understanding and judgments of their experienced demand. While these methods have high face validity, their interpretation, and ability to predict performance is uncertain [29]. These measures also provide discrete rather than continuous values, and prior articles have found dissociation between subjective and performance measures [111]. Furthermore, subjective measures are limited due to recall bias and substantial individual differences [92].

Performance measures are classified into two major categories, including primary and secondary task measures. Primary task measures evaluate the operator's performance on the task of interest. Examples of primary task measures of workload include speed, accuracy, reaction or response time, and error rate. Secondary task measures provide an index of the remaining operator capacity while performing primary tasks and are more diagnostic than primary task measures [29]. Examples of secondary tasks include *n*-back, verbal shadowing, and pursuit tracking task. Performance measures have advantages in that they evaluate participants' performance on the task of interest directly, and this is useful where the demands exceed operators' capacity such that performance degrades from baseline or ideal level [29]. However, they often lack scientific rigor, making interpretation of the results difficult. Unknown or uncontrolled factors may affect results rather than the intended manipulations in the article. Also, due to the protective (compensatory) effect of increased effort in the task, measuring performance might not be sufficient to evaluate the participant's state. For example, the performance does not reflect information about the costs involved in the adaptive response to stress [29].

B. Device Configuration: Input Signals

Hybrid input configurations such as EMG signals in combination with IMU or FMG were less cognitively demanding as compared to EMG or EEG input signals alone [64], [65], [75]. Combination of EMG and IMU reduced task completion time since they were more intuitive than myocontrol configuration alone. This active support can help the user perform a larger set of tasks including easy (e.g., reaching or grasping an object) and complex tasks (e.g., clothespin and cups relocation) while decreasing the rejection rate of the device [113], [114]. Thus, the combination of EMG and IMU can improve prosthetic device usability in terms of effectiveness, satisfaction, and efficiency [115]. In addition, a combination of FMG and EMG signals showed higher overall stability (i.e., lower variance) over time than the EMG signals alone [44], [45]. Using the hybrid configuration, participants did not have to memorize so many different movement patterns in order to perform simple tasks. Therefore, use of hybrid input methods can improve prosthetic device usability and frequency of use by amputees to perform ADLs [75]. Among the EMG-based controllers, the PR mode was the least cognitively demanding prosthetic controller [39]–[41], [83]. This was mainly because patterns are generated from the user attempting an actual movement (e.g., forming a fist). Thus, this identification of user intention can reduce CW, which is not possible in other EMG-based controllers such as DC. In terms of device usability, the PR mode is better than the DC since it requires more natural arm gestures to control the device, which requires PR rather than recall from memory [116]. However, even in PR, unintentional hand movement can occur [19]. Articles have identified errors related to the PR control, which resulted in unintentional prosthesis movement and reduced device reliability [41], [83]. However, it was found that these errors reduced by additional training and as the participants learned to make more distinguishable movements [117].

C. Device Configuration: Output Control

Some articles found that non-EMG-based devices were significantly more cognitively demanding as compared to EMG-based prosthesis. This was mainly due to the difference in eye-hand coordination performance. The eyes fixate on a target to provide spatial information before the hands are engaged in a movement [118]. In EMG-based prosthetic devices, the output control is attached close to the upper limb and its shape is similar to human arm, which makes the movement more natural (less cognitively demanding) for the participant. However, in non-EMG-based devices such as EEG-based prostheses, the movement of the device is not always similar to the actual limb because the input signal location (head) and control location (hand) are separate [43], [100]. Thus, the operator needs more attention (higher CW) to move, control, and check the status of the arm. Therefore, from the usability point of view, non-EMG-based devices need to be more advanced to improve effectiveness, efficiency, and satisfaction.

According to recent articles [119], [120], VE can provide adaptable and rich media to create conditions for the assessment and training of motor deficits. VEs can mimic arm extension, flexion, supination, and pronation based on the input commands. Furthermore, objects like a virtual ball and basket can be created and placed within the VE [70]. The main advantage of the VE is its rich and adaptive versatility in training and assessment [71]. Enhanced technology is currently being explored in prosthetic limb training. It has been shown that VEs help users to form a robust mental model to perform the ADLs [121], which are especially important in the initial training phase of using a myoelectric prosthesis. Since VEs can provide visual and/or auditory feedback to participants, they can also help to reduce CW [38], [50], [51], [67], [70], [71].

D. Device Configuration: Feedback Modality

Findings suggested that using combined auditory and visual feedback modalities could reduce CW. Participants mainly rely on their visual attention to control their prosthetic device [35], [46], [47] and to perform ADLs. Based on MRT [93], additional visual feedback in this situation can cause attentional overload. For example, if only visual feedback is provided, participants should visually focus on the task environment to perform the task while continuously monitoring the visual display to check the status of their performance. Thus, to avoid attentional resource competition in the same modality, it is recommended to use other modalities of information presentation (such as auditory or vibrotactile [34], [50], [64], [65]) as task performance feedback modality. Use of auditory feedback can also improve task performance while reducing CW, which can increase device usability [115], [122]. However, vibrotactile feedback should be used with caution. Upper-limb prosthetic users slightly agreed with the positive effect of vibrotactile feedback to improve performance accuracy [50]. However, if the task required continuous visual attention, there was no significant difference in CW (based on eye-tracking measures) with or without the vibrotactile feedback [85]. Some lower-limb articles found that using a combination of vibrotactile and visual feedback was less cognitively demanding than a single feedback modality [34]. Furthermore, a majority of participants preferred mixed feedback modality instead of visual feedback alone [50].

Another consideration is related to task complexity and training [113]. The feedback was beneficial only for complex tasks such as clothespin and cups relocation task. After a participant was sufficiently trained, he or she could develop a feedforward strategy, thus, the feedback became redundant. This shows a need for adaptive feedback based on the skill level of a prosthetic device user.

E. Training

Participants perceived less CW after 4–6 weeks of training with the prosthetic device. This might have been due to the improvement in quality of control over the device and execution of movements, which led to less mental effort to perform the ADLs [39], [42], [83]. However, this recommendation should be stated with caution and requires additional context. First, our meta-analysis was based on subjective measures of workload (i.e., NASA-TLX) and did not include the findings of usability evaluations. In some upper-limb articles, task performance and error rate, and therefore device usability improved after four and six weeks of training [41]. Other articles recommended training duration of 30 days to determine device rejection rate [123]. Second, it should be noted that there might be discrepancies between participants' self-report and objective task performance. For example, although they perceived low CW based on subjective measures after 4–6 weeks of training, they might not achieve optimal task performance [39], [41], [49], [83].

F. Limitations

This article had some limitations. First, some reviewed articles did not provide the exact descriptive statistics values (i.e., mean and standard deviation). To resolve this issue, we contacted the authors and could obtain some of those exact values [4], [33], [39], [48], [49], [51], [52], [64], [65], [83], [100]. For the articles that we could not find the exact values, the mean and standard deviation of different conditions were extracted from the figures [4], [43]–[45], [70], [101]. However, to ensure the quality of data extraction based on graphs, we compared the estimates with the exact values (for those articles that we had the exact values) and the results were similar, which validated our approach. The second limitation was that the meta-analysis could not be performed on physiological measures due to the lack of the number of articles with matched independent and dependent variables.

Finally, this article included investigations which used bypass prosthetic devices since a majority of prior articles used able-bodied participants to assess the usability and CW of prosthetic devices. However, there are many factors (e.g., device weight, pain, motivation, perceived functional ability, and satisfaction with device) that might influence amputees' mental demands on any given day. These factors cannot be replicated in bypass device users, so the results obtained from this article should be interpreted with caution to the actual population of interest.

V. Conclusion

The first objective of this article was to identify the range of CW measures used in prior articles comparing different prosthetic devices. It was found that CW measures can be categorized into physiological (e.g., heart rate and pupillometry data), and subjective and task performance (i.e., primary and secondary task). Among all the measures, the NASA-TLX questionnaire was the most frequently used method to measure CW in using prosthetic devices.

The second objective of the article was to identify the device configurations or features that led to the lowest CW for the users. It was found that the hybrid approach (e.g., EMG signals in combination with other input signals) resulted in the lowest CW as compared to other configurations (e.g., motion tracking) or nonhybrid approaches. Regarding the feedback modality, multimodal feedback was the most effective feedback to reduce CW, as compared to visual and auditory feedback modalities alone. Although the use of vibrotactile feedback was found to be effective in reducing CW of lower-limb prosthetic devices, its advantages were not clear for upper limbs. In addition, to evaluate the effectiveness of a training strategy for reducing CW and improving device usability, both task performance and subjective measures should be considered.

The final objective of the article was to provide a set of guidelines for designing future prosthetic devices to reduce CW. A set of guidelines (Table VII) was established based on the findings to reduce CW with appropriate input signal, output control, feedback modality, and training schedule.

The results of this article can be beneficial in design and development process of future prosthetic devices in order to reduce CW. By recognizing the identified issues in prosthetic device configurations, feedback, and training, developers may be better able to make appropriate design changes toward more effective, efficient, and satisfying prosthesis use. In addition, the guidelines might be beneficial in providing design recommendations to improve the usability of prosthetic devices.

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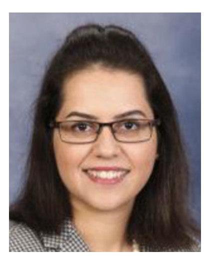
Junho Park (Student Member, IEEE) received the B.S. degree in industrial engineering (minor: psychology) from Yonsei University, Seoul, South Korea, in 2008, and the M.S. degree in industrial engineering from Seoul National University, Seoul, South Korea in 2010. He is currently working toward the Ph.D. degree in human-systems engineering at the Industrial and Systems Engineering Department, Texas A&M University, College Station, TX, USA.

From 2010 to 2015, he was a Researcher with Korea Institute for Defense Analysis in Center for Military Planning Division. From 2015 to 2019, he was an Associate Research Fellow, he conducted force requirement analysis and evaluation research and cognitive decision-making modeling studies as a Principal Investigator. His research interests include human factors in assistive technologies and cognitive performance modeling.



Maryam Zahabi (Member, IEEE) received the B.S. and M.S. degrees in industrial and systems engineering from Sharif University of Technology, Tehran, Iran, in 2011 and 2013, respectively, and the Ph.D. degree in industrial and systems engineering (minor: statistics) from North Carolina State University, Raleigh, NC, USA, in 2017.

She is currently an Assistant Professor with the Industrial and Systems Engineering Department, Texas A&M University, College Station, TX, USA. Her research interests include applying human systems engineering theories and principles in design and analysis of complex human-in-the-loop systems. In particular, she is interested in usability evaluation and cognitive load assessment of assistive technologies and cognitive performance modeling applications in different domains.