SPECIAL ISSUE: User Centered Design for Exoskeleton & Exosuit Usage

Static, Dynamic, and Cognitive Fit of Exosystems for the Human Operator

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Objective: To define static, dynamic, and cognitive fit and their interactions as they pertain to exosystems and to document open research needs in using these fit characteristics to inform exosystem design.

Background: Initial exosystem sizing and fit evaluations are currently based on scalar anthropometric dimensions and subjective assessments. As fit depends on ongoing interactions related to task setting and user, attempts to tailor equipment have limitations when optimizing for this limited fit definition.

Method: A targeted literature review was conducted to inform a conceptual framework defining three characteristics of exosystem fit: static, dynamic, and cognitive. Details are provided on the importance of differentiating fit characteristics for developing exosystems.

Results: Static fit considers alignment between human and equipment and requires understanding anthropometric characteristics of target users and geometric equipment features. Dynamic fit assesses how the human and equipment move and interact with each other, with a focus on the relative alignment between the two systems. Cognitive fit considers the stages of human-information processing, including somatosensation, executive function, and motor selection. Human cognitive capabilities should remain available to process task- and stimulus-related information in the presence of an exosystem. Dynamic and cognitive fit are operationalized in a task-specific manner, while static fit can be considered for predefined postures.

Conclusion: A deeper understanding of how an exosystem fits an individual is needed to ensure good human–system performance. Development of methods for evaluating different fit characteristics is necessary.

Application: Methods are presented to inform exosystem evaluation across physical and cognitive characteristics.

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HUMAN FACTORS
Vol. 62, No. 3, May 2020, pp. 424–440
DOI:10.1177/0018720819896898
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Keywords: exoskeleton, anthropometry, range of motion, executive function, somatosensation

BACKGROUND

Exosystems, a category that includes exoskeletons and exosuits, are wearable technology that have potential to provide significant benefits to users, including increased strength or endurance, improved motor performance, and enhanced capability. Exosystems may be passive (providing a structural support for the operator) or active (generating a motion of the operator using powered components). Passive exosystems include protective systems that redistribute load to reduce musculoskeletal injury (e.g., Levitate Technologies' Airframe, SuitX's BackX, Lockheed Martin's Fortis), as well as protection in the space environment (e.g., NASA MKIII planetary suit, Extravehicular Mobility Unit, Boeing CST-100 Starliner suit). Active exosystems include augmenting load handling (e.g., Sarcos' Guardian XO), increasing endurance (e.g., Dephy ExoBoot, Lockheed Martin Onyx), as well as medical rehabilitation and mobility (e.g., Ekso Bionics GT, Parker Indego). Effective performance depends on a good "fit" between the system and the user. Although formal definitions of fit remain elusive, subjective and qualitative aspects of fit have informed research thus far.

Broadly, fit is an optimized status between the human and their immediate environment (Choi et al., 2009) where immediate environment begins with clothing or worn devices and extends to the workplace. Proper fit entails "equipment ease," a term denoting balance between the size of wearable equipment and the size of the wearer. However, far from being a static or one-size-fits-all descriptor, equipment ease in one body region may affect the ease in other regions with changes in posture or with movement (Huck et al., 1997). Equipment ease has direct implications for the performance of wearable equipment. Improper fit (an example of which could be too much or too little relative motion) can lead to inefficiencies such as decreased active range of motion (ROM) of the user (Choi et al., 2019), as well as an increased likelihood of overexertion, fatigue, discomfort (e.g., increased tissue contact pressure deformation), and injury (e.g., muscle atrophy [Hesse et al., 1999]). The impact of poor fit on mobility may also lead to deeper changes in motor-plan selection, as well as increased attention toward task completion, increasing overall physical and cognitive workload, and risking diminished operational performance.

Initial sizing and fit evaluations of exosystems are currently based on scalar anthropometric dimensions and subjective assessments. As fit depends on ongoing interactions related to the task setting and user, attempts to tailor equipment have limitations when optimizing for this limited definition of fit. Scalar dimensions provide valuable information on the overall size of the individual, but provide limited guidance on shape or posture both in static poses and while moving. For example, a family of sizes inherently makes assumptions about dimensional ratios underlying the equipment that will not hold for entire populations (e.g., ratio of thigh circumference to leg length) (Gordon et al., 2014). Custom sizing becomes cost-prohibitive for large populations needing precision component dimensions for each user. To be effective, a subject-specific sizing approach must consider 3D body shape, posture, and shape deformation across a variety of mobility tasks. For example, a passive exosystem used for life-support like the spacesuit embodies a tradeoff between arm length and glove mobility (Benson & Rajulu, 2009). The authors state that "if a suit is sized to fit the crewmember when their arms are outstretched, the fingers are forced back out of the gloves when they pull their arms close to the chest. If, on the other hand, the suit is sized for the fingers to be snug when working close to the chest, the fingertips will press against the glove when the arms are at other postures." With the spacesuit, the limitations in dynamic mobility impose predefined motions (Gast & Moore, 2011) that operators must learn and adopt to complete their tasks. The resulting interaction between fit of the wearable system and task requirements can impose constraints, costing the user conscious cognitive workload and limiting directed attention to relevant operational activities. The spacesuit example was presented as these challenges have been previously documented; however, these emergent issues are also relevant for other passive and active exosystem applications.

We consider exosystem fit on three key characteristics: (1) static, (2) dynamic, and (3) cognitive. In this paper, we define these characteristics, review measurement methods, and discuss the interactions between these characteristics.

METHODS

A targeted literature review was performed to inform a conceptual framework that defines three characteristics of fit. This review was not meant to provide a systematic summary of all research related to fit characteristics and is not a meta-analysis to generalize the effect of fit characteristics on performance. The review is provided to highlight methods in use in the literature and to guide the distinctions between types of fit examined. In describing the fit characteristics, references were selected from a variety of experimental methods. An evaluation of the references was performed following the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018). Of the 157 papers referenced, 53 (34%) did not fit the MMAT categorization of an empirical study as they were either review papers, methods papers, or device design papers. Of the remaining papers, 25 papers (16%) were experimental trials with randomization of the conditions of interest; 26 papers (17%) were quantitative studies that included repeated measures, but were not clearly randomized across all conditions; 52 papers (33%) included quantitative descriptions that either were case-controlled studies or provided characteristic measures; and 1 paper (Gast & Moore, 2011) (1%) was only qualitative in content. We did not exclude papers for being quantitative descriptions as many studies of fit are characteristic in nature. Within the review, it was deemed relevant to include reference to these methods. As exosystem evaluations expand, it will be important to design and report studies that are well aligned with the associated research questions. Future systematic literature reviews should be performed to evaluate the effect of specific fit characteristics on operational performance.

RESULTS AND DISCUSSION

Defining the Characteristics of Fit

Static fit. Static fit refers to the alignment between dimensions of the human and exosystem in one or a small number of predefined, standardized postures. Static fit considers the anthropometric characteristics of a user, as well as the sizing of equipment components. This fit characteristic is relevant for exosystems that require kinematic alignment with user body segments to enable comfort and prevent injury due to inappropriate application of forces in static postures. Static fit can be adjusted through selecting a different equipment size or adjusting components of the equipment (e.g., lengthening straps, adding padding). This section presents measures, assessments, and limitations of static fit.

Measures of static fit. Static fit is most commonly defined through the anthropometric dimensions of users collected in a minimally clad configuration (traditional anthropometry) or in equipped configurations (encumbered anthropometry; Choi et al., 2019; Garlie & Choi, 2014; Jones et al., 2013). Anthropometry includes size data (i.e., linear dimensions) collected using standard anthropometers (e.g., calipers, tape measures) or extracted from three dimensional (3D) scan images, as well as 3D scan images themselves as shape data that provide information about a user's external surface and contour (Hsiao, 2013; Hsiao et al., 2015; Jones et al., 2018; Margerum et al., 2010; Park et al., 2017). Traditional anthropometric databases (Gordon et al., 2013, 2014; Harrison & Robinette, 2002) have been used to quantify anthropometric characteristics recorded in standardized postures, develop sizing systems, evaluate population accommodation rates, and generate digital human models for various target populations. Encumbered anthropometry studies include equipped size, weight, shape, and bulk in various ensemble configurations (Choi, Garlie et al., 2019; Garlie & Choi, 2014; Hsiao, 2013; Jones et al., 2013), as well as 3D surface coverage of a body within the geometry of equipment or a device (Choi et al., 2009; Hsiao et al., 2009; Jones et al., 2014, 2015; Li et al., 1999).

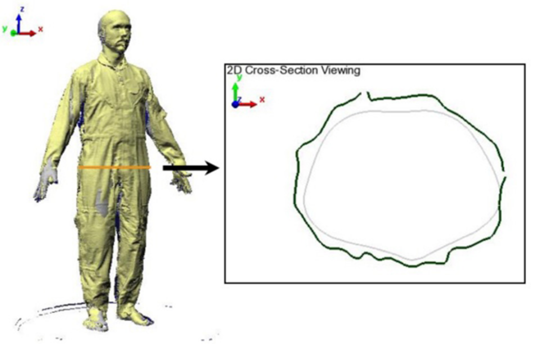

Figure 1. Two-dimensional cross-sectional view at buttock (most protruding) level of encumbered scan with flight suit (Choi et al., 2009). The gray line is the surface of the body; the green line is the surface of the flight suit.

In practice, evaluation of the static alignment between a user and equipment considers subjective comfort (e.g., too tight, too long, too loose) and quantitative measures (e.g., ease at chest, sleeve length from ulnar stylion) at relevant body locations while trying on different sizes (Choi et al., 2011; Hsiao et al., 2007). Quantitative measures can be assessed through traditional methods or by 3D scans (Choi et al., 2009; Hsiao et al., 2015; Jones et al., 2015; Li et al., 1999; Loker et al., 2005), and evaluated in terms of 3D body shape models (i.e., parametric body shape modeling [Hsiao et al., 2009; Jones et al., 2018; Park & Reed, 2015; Park et al., 2017]). Figure 1 shows an example quantifying ease at a specific location using a cross-section extracted from a 3D scan, which may be expressed as the difference between two surface lengths or as the space between the body and equipment in the azimuth direction from the center of the body (termed radial ease [Wang et al., 2006]). Radial ease provides insight into how space is distributed around the body, which is especially important for rigid equipment (e.g., helmet, ballistic hard armor plate, exoskeleton).

Traditionally, quantitative measures across users are combined with subjective assessments to define quantitative fit criteria (e.g., Tables 3 and 4 within [Choi et al., 2011]) that refer to "the way in which an item is required or expected to fit" Choi et al., 2009. Depending on the level of complexity of the equipment, static fit criteria for more complex systems require considerations of 3D body shape information that captures the geometric dimensions.

Matching a 3D human shape to an exoskeleton for an individual user is analogous in some respects to the fit of orthotics and prosthetics (Doshi et al., 1998; Faustini et al., 2006; Wu et al., 2003). In these domains, efforts have focused on improving the fit and performance of orthoses by gathering high-resolution 3D body shape data (Bagaria et al., 2015; Koutny et al., 2012) and improving reproducibility (Telfer et al., 2012) and reliability (Carroll et al., 2011). Subject-specific models of 3D body shape have also been used to design exoskeletons (Reimer et al., 2014). However, the use of custom-fit or subject-specific products is limited in that it is dependent on an iterative process that may involve several prototypes and static fit tests with individual end users.

Alternatively, 3D anthropometric modeling methods yield statistical models that quantify morphological variations within the population as functions of overall descriptors such as age, sex, stature, and body weight (see example models at http://humanshape.org [Jones et al., 2018; Park et al., 2017; Park & Reed, 2015]). Parametric models of human body shape provide good guidance on shape that may be useful in the design and evaluation of exoskeletons. For example, Kim (2017) generated human shape models to quantify the effects of body size and shape on posture alignment within spacesuit configurations. Static fit criteria generated using a 3D approach will enable rigorous design and evaluation of exosystem geometry and sizing, ultimately leading to better systems that work efficiently for a wider range of the population.

Assessment of static fit. Quantitative measures of static fit are used to produce a pass or fail rate of a test sample (who fits and does not fit in each size) as well as a population accommodation rate (the proportion of the target population that fits in any size), a final sizing system (necessary and unnecessary sizes), and a size tariff (how many of which size should be produced; Choi et al., 2009, 2011). Complex exosystems will require a rigorous and careful design to accommodate the desired population with an acceptable static fit. Attempts to accommodate 100% of a population are generally cost- and design-prohibitive. Instead, designs typically aim to accommodate a central proportion of a target population, excluding extreme sizes and shapes during the design process. The U.S. Military Standard 1472G Design Criteria for Human Engineering (Department of Defense, 2012) identifies the "central 90 percent of the target user population" as the preferred accommodation rate, although this concept is difficult to define in multidimensional and single-tail accommodation problems (e.g., when any human dimension smaller than the equipment dimension statically fits).

Applying the preferred accommodation percentage independently to each critical anthropometric dimension results in a final accommodation rate that is always less than the univariate accommodation rate and often deficient (Gordon et al., 1997; Hsiao, 2013; Robinette & Hudson, 2006). Consider a hypothetical lower-body exosystem that must fit on a small number of critical dimensions (knee height, calf circumference, crotch height, and thigh circumference). Table 1 demonstrates the effects of using the traditional univariate accommodation approach for a system needing to fit these four dimensions using U.S. Army male data (Gordon et al., 2014). The "central 90% accommodation" for each dimension results in only accommodating 74% of the target population. The decrease in accommodation occurs because individuals with extreme values of one dimension are not necessarily the same individuals with extreme values of another as demonstrated in Figure 2 (Robinette & Hudson, 2006). Population accommodation requires a

TABLE 1: Example of Applying the 90% Accommodation Rate to Individual Dimensions

Order of Inclusion	Anthropometric Measure	Individual Dimension Accommodation	Joint Population Accommodation
1	Knee height (mid-patella)	5th–95th percentile	90%
2	Calf circumference	5th–95th percentile	81%
3	Crotch height	5th–95th percentile	78%
4	Thigh circumference	5th–95th percentile	74%

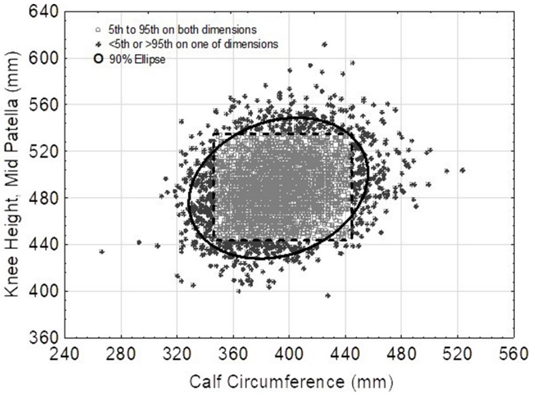

Figure 2. The ellipse represents the central 90% for the dimensions of knee height and calf circumference using a multivariate approach, and the square boundary demarcates the 5th and 95th percentile cases on both dimensions as an example of a univariate approach. Discrepancies between univariate and multivariate approaches are highlighted with solid markers for personnel who are smaller than 5th or greater than 95th percentiles on one or more dimensions, and hollow markers for 81% of personnel who are between 5th and 95th percentiles on two dimensions.

multivariate approach to account for a wide range of human variation simultaneously.

The limits of static fit. Scalar dimensions provide valuable information on the overall size of the individual, while 3D models can provide guidance on static shape and posture. Relevance of the selected postures when evaluating static fit should be considered (e.g., functionally relevant vs. standardized postures). As static fit is concerned with the alignment between the human and exosystem, it is important to have relevant anthropometric measures of the target users, as well as the exosystem components. While exosystem adjustability may allow more users to statically fit a system, care must be taken to assess the efficacy of the system when lengthening or shortening motion arms, when increasing or decreasing tension, or through the differing direction of applied forces. Ensuring proper static fit is a necessary but not wholly sufficient aspect of assessing the comprehensive human–exosystem fit. While anthropometric models can suggest a preliminary static fit configuration, subjective comfort and feedback might alter the static fit an end user ultimately wears, necessitating fit checks prior to using exosystems in operational settings. Furthermore, the ability to comfortably statically fit into or wear an exosystem in some postures does not ensure that the exosystem will maintain dynamic fit throughout movements. Measuring the continued fit of the system through dynamic movement is another critical characteristic of comprehensive fit.

Dynamic fit. Dynamic fit refers to how the human and equipment move and interact with each other through functional ROM activities and task performance, and is defined formally in the context of a specific activity. This characteristic is relevant as exosystems should minimize restrictions on mobility and minimize internal human–exosystem opposing forces such that operational tasks can be performed. When the kinematics of the human–exosystem are misaligned, forces exerted by the operator are countered by forces internal to the human–exosystem rather than transmitted to the environment. This inappropriate coupling creates inefficiency, increases fatigue and metabolic cost, and can lead to injury.

Exosystem dynamic fit assessment must parameterize the human–exosystem interface to define the relative alignment of the kinematic linkages between the two systems (e.g., the location of human joint center locations with respect to the exosystem, and human soft tissue deformation with respect to exosystem allowances during motions). The selected dynamic motions should align with intended use case scenarios. Similar to static fit concerns, the dynamic fit measures should consider the large range of human anthropometric variability. In this section, we present experimental measures of dynamic fit and computational models that can be used for design and evaluation.

Experimental measures of dynamic fit. Dynamic fit is measured through isolated and task-specific ROM, torque required to exert external force through a ROM, functional task performance, relative motion between the human and exosystem, metabolic consumption, and surface pressures at the interfaces between the human and equipment. Examples of these measures in the literature are provided in this section.

Joint-specific and functional ROM restrictions are quantified with standard anthropometric equipment for body-borne armor systems (Choi et al., 2019; Jones et al., 2014; Mitchell, 2013), and with 3D motion capture (Hu et al., 2007; Reid et al., 2014) and inertial measurement units (Bertrand et al., 2014; Di Capua & Akin, 2012; Fineman et al., 2018) for spacesuits. Similar strategies of using anthropometric body scans and inertial sensors have also been used for assessing firefighter gear, such as investigating static fit on dynamic fit for fire boots and turnout suits (McQuerry, 2020; Park et al., 2015, 2019). The differences in ROM measures between unequipped and increasing equipped configurations are typically considered. Due to extra torque required to move pressurized spacesuit joints, additional characterizations of dynamic fit for spacesuits are considered, including changes in the external force exertion capability using dynamometers (Gonzalez et al., 2002; Morgan et al., 1996; Reid et al., 2014; Valish & Eversley, 2012) and maximal grip and pinch strength (Amick et al., 2016; Hu et al., 2007). These measures help identify restrictions associated with the spacesuit as they deform through a ROM cycle. These studies indicate an interaction between joint torque, wearable geometry, and movement direction.

The military uses a functional task assessment, the Load Effects Assessment Program (LEAP), which includes evaluating decrements in sequential timed mobility tasks to quantify the performance differences due to soldier equipment (Bossi et al., 2016; Jones et al., 2014; Mitchell et al., 2016). Recent efforts examine LEAP performance using IMUs (Vitali et al., 2019). Changes in gait kinematics or alternate mobility tasks are also used to evaluate the effect of exosystems (Gordon et al., 2013; Gregorczyk et al., 2010; Wehner et al., 2013), body armor (Dempsey et al., 2013; Hasselquist et al., 2008; Park et al., 2013), and spacesuit configurations (Cullinane et al., 2017; Fineman et al., 2018). In addition to ROM, relative motion between the human and spacesuit is measured (Fineman et al., 2018). For exoskeletons, small relative motions between the human and exosystem are considered as a way to prevent unwanted mobility restriction as mechanical designs do not perfectly match the motion of human joints (Cenciarini & Dollar, 2011). However, it is unclear how much or little relative motion should be permitted to enable performance benefits.

Studies also directly quantify the surface pressures between body-borne equipment and the body. For example, pressure sensors are used to measure the human–equipment interface of operators donning a backpack (Jones & Hooper, 2005; Lenton et al., 2018) and human–spacesuit interfaces (Anderson et al., 2015; Anderson & Newman, 2015; Reid et al., 2014). A customized glove was designed (Amick et al., 2016) with multiple integrated sensors (including force-sensitive resistors, thermocouples, and a humidity sensor) to conduct a quantitative evaluation of a spacesuit glove. Sensors measuring human–exosystem interaction pressures have also been developed to evaluate injury mechanisms related to dynamic fit during motion tasks (de Rossi et al., 2011; Donati et al., 2013; Rathore et al., 2016; Tamez-Duque et al., 2015). In addition, exosystems have used pressure sensors (as on/off or proportional input) or load cells within a controller to drive motion for lower (Dollar & Herr, 2008; Galle et al., 2014;

Long et al., 2016; Wu et al., 2015) and upper extremity (Diftler et al., 2014; Lee et al., 2008; Siu et al., 2018) systems. Previous efforts (Schiele & van der Helm, 2009) showed the alignment between an upper extremity exoskeleton and human joint could become offset more than 10 cm even when the two axes were well aligned statically at the start of a movement and that these discordant kinematics generated unwanted internal forces on the human. Discordant kinematics may lead the user to fight exosystem assistance and create additional forces between the human and exoskeleton as opposed to transmitting those forces to the surrounding environment.

A surrogate for dynamic fit is metabolic cost, which many assistive exosystems aim to reduce (Collins et al., 2015; Mooney & Herr, 2016; Panizzolo et al., 2016) and spacesuits aim to minimize (Carr & Newman, 2007; Mcfarland & Norcross, 2014; Norcross et al., 2010). While a useful metric for assessing the physical workload associated with using an exosystem, it has limited utility in differentiating and quantifying issues associated with fit. To understand the root causes of metabolic changes associated with using an exosystem, the other more direct measures of dynamic fit are necessary, such as the torque required to exert external force through a ROM, the interaction pressures between the human and equipment, or the functional ROM. These direct measures would inform specific locations that may be driving the observed increases in metabolic cost. However, a measured change in dynamic fit could also be caused by poor cognitive fit, as later discussed.

These current approaches characterize differences in a measure between the human alone versus with the exosystem. However, the relationship between task performance limitations and decrements in dynamic fit measures is not well understood. Future work should consider how these measures can inform exosystem mechanical and controller design to minimize interface discomfort and unwanted differences in functional performance.

Computational models of dynamic fit. The examination of dynamic fit prior to physical prototype evaluations can be enabled using deformable 3D anthropometric models that can be parameterized to provide the relevant body shape changes across relevant motions. Current methods exist to create nondeformable anthropometric models from 3D body shape and surface contours captured using laser scanners (Jones et al., 2018; Park et al., 2017; Park & Reed, 2015). To enable statistical modeling within and across scans, a standardized 3D mesh template is fit to each processed scan, defined by a set number of segments, joint locations, and linkages, to ensure anatomical homology (i.e., a similar structure; Figure 3). The fitting process involves two steps: (1) a template mesh is morphed using a radial basis function (RBF) interpolator to roughly match the overall body shape based on the manually collected landmarks; (2) the RBF-morphed template is then further adapted to achieve the geometric details using an implicit-surface fitting method (Park & Reed, 2015).

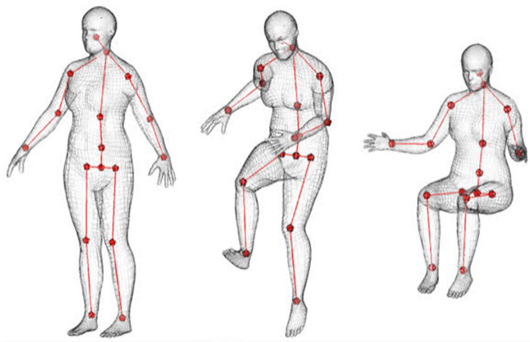

Figure 3. An example of a posable template fit in postures. The postural changes were driven by the skeletal linkage. Body landmarks, joint locations, and skeletal linkage are shown in red.

The body changes shape across the functional ROM. Thus for dynamic fit assessment, there is a need for modeling surface deformation near joint locations (e.g., hips, knees, shoulders, elbow). In addition to laser scans, motion capture methods have been used to quantify skin surface deformations (Obropta & Newman, 2015; Wessendorf & Newman, 2012). Many posable human modeling systems are available (e.g., RAMSIS, Jack, Max Planck tools). Among the fully posable template model available, some are linked to parametric shape models (Loper et al., 2015), but none are available that can efficiently model the interactive effects of the exosystem.

Among other things, the effects of flesh deformation due to forces between the exosystem and human must be accurately modeled. Currently, flesh deformations require finite-element models that are computationally expensive and not well integrated with other needed modeling capability, such as simulation of the musculoskeletal system (Stirling, Arezes et al., 2019).

While deformable anthropometric models could assist analyzing exosystem dynamic fit during the prototyping processes, the models do not guarantee that a user will be able to efficiently move with the system. Human motor control includes feedforward and feedback mechanisms that may be affected by the presence of an exosystem. Measuring the cognitive characteristic of fit provides additional insight into exosystem usability.

Cognitive fit. Cognitive fit refers to supporting the perception–cognition–action decision process of the human when wearing the exosystem. This characteristic is relevant to exosystem fit as the operator's cognitive capability must be maintained such that operational tasks, including decision making, can be adequately performed. The operator should be free to process task- and stimulus-related information, as well as to choose and complete the appropriate physical actions that the exoskeleton supports. Issues related to cognitive fit include somatosensation, executive function, and motor-action selection.

Somatosensation. Somatosensation includes sensory feedback related to touch, pressure, temperature, and movement of the muscles and tendons. Here we specifically consider touch (a response to skin deformation and motion) as well as proprioception (a response to changes in the length and loads on the muscles and tendons). Somatosensory assessments often include the Semmes–Weinstein monofilament test (Bell-Krotoski & Tomancik, 1987), the ability to sense or repeat a joint orientation (Casadio et al., 2018), and the ability to match a visual target with a limb motion. Touch and proprioception provide the ability to sense posture and movement of one's body, enabling dexterous movement performance. These mechanical inputs blend with vestibular and visual systems to enable balance and error correction within a motor task (Dietz, 2002). The perception of sensory feedback, positions, and postures depend on a variety of factors (e.g., aging [Adamo et al., 2007], relative orientations of body segments [van Beers et al., 1998], and visual feedback [Wann & Ibrahim, 1992]). Even when an exosystem is appropriately fit statically and dynamically to a user, the system will affect sensations needed for successful task completion. Interfering with proprioception may compromise a person's ability to control the interaction forces arising from multijoint motions (Dietz, 2002; Gordon et al., 1994; Sainburg & Ghez, 2019), although visual monitoring can partially compensate for the changes in proprioceptive information (Ghez et al., 1990). Vibrotactile cues have enhanced proprioception in an upper extremity reaching task (Krueger et al., 2017; Tzorakoleftherakis et al., 2015), in postural balance at a super-threshold level (Kinnaird et al., 2016) and a subthreshold level (Priplata et al., 2003), as well as in locomotor tasks (Sienko et al., 2013). An important part of cognitive fit will be whether the exosystem affords sufficient proprioception to perform coordinated motor actions.

Executive function. Executive function refers to cognitive processes that enable goal-directed behavior, including inhibition of behavior (cognitive and motor), working memory (holding and working with information in the mind), and cognitive flexibility (ability to adjust priorities; Diamond, 2013). Stirling et al. (Stirling, Siu et al., 2019) provide a human factor description of several key components of executive function as they relate to exosystem design and evaluation, including the concepts of mental models, attention, workload, and situation awareness. The mental model is an evolving memory structure providing a dynamic representation of the environment, as well as descriptive interrelationships for a set of objects or events (Rouse & Morris, 1985; Stirling et al., 2019). It directs attention and inhibits interfering stimuli, resulting in a dynamic understanding of the environment or task, and budgeting limited cognitive resources for task completion. Operators will develop a mental model of the expected exosystem responses that may be a function of their posture or environment (e.g., during stair ascent a different power is experienced than during level ground).

Inhibition of motor response may occur for the operator to synchronize their motion with a poorly tuned exosystem. Increased attentional demand for an operational task will increase the cognitive workload and weaken both cognitive and motor performance (Huang & Mercer, 2001; O'Shea et al., 2002; Taylor & Thoroughman, 2008). An exosystem that requires focused attention (e.g., due to triggering a mode change, verifying assistance levels, or creating additional concentration when stepping) can lead to limitations in performance on additional concurrent tasks. Measurements of executive function align with these different considerations. For example, inhibition of motor action can be examined using a go/no-go (Rubia et al., 2001) or Simon task (Simon & Rudell, 1967). Workload can be measured objectively using secondary task methods (Wickens, 2002) or subjectively (Hart & Staveland, 1988). Directed attention can be measured through response times to cues in the environment (Kahneman, 1973; Wickens, 2008), head postures (Murphy-Chutorian & Trivedi, 2009), or eye tracking (Duchowski, 2007). Additional efforts have examined executive function by measuring brain region activity during a task (Mehta & Parasuraman, 2013).

Executive control can either initiate desired actions or inhibit undesired motions due to cues in the environment (Diamond, 2013). Human performance has been represented at three levels (Rasmussen, 1983): skill-based behavior, rules-based behavior, and knowledge-based behavior. Skill-based behavior occurs without conscious control, converting sensory inputs into actions according to autonomous sensorimotor patterns. For expert actions that are nominally skill-based, directing attention at the motor activity can weaken the skilled performance by diverting perceptual resources from the surrounding context (Beilock & Carr, 2001; Beilock et al., 2002; Masters, 1992). Rules-based behavior involves conscious consideration of remembered procedures or supplementary checklists. Knowledge-based behavior combines expertise with desired goals to develop a procedure. Learning of motor skills can progress through these behavioral levels during adaptation or training (Stirling et al., 2019; Wentink et al., 2003). Depending on user experience with an exosystem, the user mental model may be used at a conscious or subconscious level, affecting attentional demand and the ability to complete goal-direction physical or cognitive tasks.

Motor action selection. The central executive maps goals to commands for many underlying muscle units through intermediary levels (reflexes, synergies, and internal models) in a movement-system hierarchy. As the lowest level of this hierarchy, reflexes are well-documented innate sensorimotor nervous arcs that translate incoming stimulation directly into motor response through spinal activity and without executive control (Kandel et al., 2013). The quickest reflexes leave no time for central-executive intervention, but slower reflexes offer wider margin for goals to change reflex expression (Kurtzer, 2015). Measuring reflexes usually involves asking participants to maintain stable postures, introducing often unexpected stimulation, and measuring the size, intensity, and direction of the reflex response (Yamagata et al., 2018). Exosystem design might benefit from leaving short-latency reflexes unconstrained and using longer-latency reflexes as points of entry through which exosystems might blend into dynamic movements.

Synergies are groups of muscles and/or joints that coordinate using synchronous or phase-related excitation by the central executive (Coscia et al., 2018; Delis et al., 2018; Prevete et al., 2018) or through repeated experience (Bruton et al., 2018; Latash, 2018; Salvietti, 2018). Measuring excitation-sharing synergies involves applying dimensional-reduction methods to electromyography (EMG) of multiple muscles to identify the fewest linear combinations of muscle activations explaining most of the EMG variance (Routson et al., 2014). Measuring experientially driven synergies involves estimating the Jacobian null space for geometrical models of task-relevant joint postures and segments, that is, a subspace specifying all anatomical configurations supporting goal completion (de Freitas & Scholz, 2010). Whether innately fixed or experientially flexible (Santello et al., 2013), synergies could inform exosystem control policy design (Salvietti, 2018), and selected policies can modify muscle synergies, offering support for designed modulation of muscle recruitment (Steele et al., 2017).

Internal models compute motor commands and sensorimotor predictions based on goals, body dynamics, and current-state sensory impressions. Predictions include expected sensory stimulation (Mussa-Ivaldi et al., 2011; Schaefer et al., 2012) and machine–systems behavior (Liu & Scheidt, 2008). Prediction errors lead to internal-model updates for better selection of subsequent movements (Cullen & Brooks, 2015; Opsomer et al., 2018; Schaefer et al., 2012), allowing unconscious adaptations (Mussa-Ivaldi et al., 2011). Theoretical perspectives vary in envisioning the relative richness or sparsity of logical detail in internal models. Richly detailed internal models specify anatomical destinations and intensities of neural excitation (Jeannerod, 2001; Jeannerod & Decety, 1995). In this view, co-contraction of muscles aids forming new models in dynamic motor learning (Heald et al., 2018). A more minimal internal model relies on prestressed bodily tissues to preferentially favor neutral positions without executive intervention (Bizzi et al., 1992; Gomi & Kawato, 1996). In this view, executive intervention provides excitation when muscles stretch beyond an equilibrium point, adapting synergies for novel circumstances when somatosensory inputs suggest contextual changes (Feldman, 2016).

Measuring internal models involves measuring motor trajectories, response times, and accuracy in the presence and absence of environmental manipulations. However, these measures are typically made in very controlled environments. Movement systems certainly adapt to exoskeletons (Cain et al., 2007), but future research might evaluate how specific internal-model variants incorporated within the control policy might support human operation of exoskeletons in varied environments. Further, concurrent cognitive tasks affect adaptation timelines (Taylor & Thoroughman, 2008), highlighting the importance of executive control in motor adaptation. A challenge will be enabling internal-model updates during concurrent cognitive and sensory processing. Exosystems might reshape internal models that humans use to represent task dynamics.

The dynamical process of forming new motor relationships can span multiple time scales as observable through selected motions (state dynamics), parameters driving the state (parameter dynamics), and new coordination patterns or motoric solutions (graph dynamics; Saltzman & Munhall, 1992). Although exosystems can modulate muscle recruitment in controlled environments, they will have to be robust to motoric engagement in varied task environments capable of generating new graph dynamics (Stephen et al., 2009). Further, these relationships and parameter dynamics may be environment- and individual-specific as initial optimal exosystem control methods highlight variability in torque profiles across subjects (Zhang et al., 2017). Cognitive performance is always ready to discover new operational solutions transferrable across diverse circumstances (Dixon et al., 2012), and overly rigid commitment to internal models can compromise the ability to navigate such diversity (Brooks, 1991). So, a long-range challenge for cognitive fit of exosystem design is to leverage what behavior fewer internal models might support but, at the same time, allow room for motor engagement where users discover novel task approach.

Relationship Between Fit Characteristics

The components of fit are not independent and interact with each other. For example, modifying the static fit of a system by changing the equipment ease can affect the dynamic fit as measured through ROM (e.g., body armor [Choi, Mitchell et al., 2019], protective overalls [Huck et al., 1997], protective gloves [Tremblay-lutter & Weihrer, 1996], and firefighter gear [Park et al., 2015, 2019]). Reductions in cognitive fit, as measured through visual response times, have been observed even when exoskeletons are statically and dynamically fit to the operator (Bequette et al., 2018). As mentioned in the introduction, the spacesuit provides an example of static fit complexities. However, this system also provides an example of the relationships across fit characteristics. A well-known issue with current planetary spacesuit designs is that the ROM permitted by the spacesuit is not well aligned with the natural ROM during human gait (Cowley et al., 2012). The limited overlap means that there is a poor dynamic fit and operators will move their legs differently when walking in the spacesuit. As these motions are learned, the difficulty in moving changes the normally subconscious gait cycle to a conscious motion, redirecting attention and potentially affecting operational task performance. Increased hip circumduction in gait similar to the limitations of a spacesuit decreases metabolic efficiency (Shorter et al., 2017), which leads to increased fatigue and risk for operational performance decrements.

Spacesuits are required for life support, but other exosystems are proposed to reduce musculoskeletal injury risk. For example, consider a passive upper extremity exoskeleton designed to off-load a worker in an industrial environment. The worker is highly skilled at performing a precision task (e.g., welding) and performs the task at a skill-based level where the tactile and proprioceptive feedback leads to subconscious motor selection. The use of the exosystem changes the sensory feedback sent to the central nervous system, which may then create inappropriate motor actions until the internal models are updated to respond based on the updated sensory and environmental cues.

Another important consideration for static, dynamic, and cognitive fit interactions is the underlying evaluation timelines. Static and dynamic fit, once optimized, are fairly constant over time, while cognitive fit evolves as the user adapts to the exosystem. Further research is needed to understand long-term adaptation to exosystems when a user may transition between using and not using the system, as well as transitioning between exosystem use-cases. Improved understanding of the factors that affect adaptation can also be used to develop appropriate training paradigms.

CONCLUSIONS

Exosystem fit has three key characteristics: (1) static, (2) dynamic, and (3) cognitive. When considering fit for exosystems, evaluation frameworks are needed that consider each of these fit characteristics, as well as their interactions. Static, dynamic, and cognitive fit complement each other. While fit prediction is commonly based on static fit, an assessment of dynamic fit provides information about the relationship between body size, shape, and mobility. Alternately, the anthropometric dimensions, specifically 3D body shape, of users who execute the acceptable level of performance could be the basis of the size prediction. Operators will require time to adapt to the new sensory feedback to update their internal models and achieve an adapted response. However, this adapted response may still limit performance through the motor actions required or the additional attentional focus. Baseline measures that could predict adaptation could inform initial control systems, just as static fit measures could inform initial sizing. Testing frameworks that progress from simple to complex environments (Mudie et al., 2018) enable evaluating integrated system risks while minimizing overall risk. The operationally relevant performance metrics can be considered in context with the selected system design decisions. The causes of operational deficiencies should be quantified with appropriate test methods across the fit characteristics that allow the underlying causal factors to be differentiated. The selection of test measures to include for an individual evaluation will naturally depend on the exosystem development stage. Current ongoing efforts within the ASTM F48 committee are focused on the next steps of developing recommendations and guidelines for specific measures to include based on the type of task, domain of usage, and stage of evaluation. Future systematic literature reviews should be performed to assess how these fit characteristics affect operational performance.

KEY POINTS

- Exosystem fit is defined across three characteristics (static, dynamic, and cognitive). These characteristics are not independent and interact with each other within defined motor tasks.
- Given that the static fit evaluates the alignment between human and the equipment, understanding the anthropometric characteristics of the

target users as well as the geometric features of the equipment is critical.

- Dynamic fit assesses how the human and equipment move and interact with each other during functional ROM and task performance, with a focus on the relative alignment of the kinematic linkages between the two systems.
- Cognitive fit considers the stages of human information processing including somatosensation, executive function, and motor selection. Cognitive capabilities should remain available to process task- and stimulus-related information in the presence of an exosystem.

ACKNOWLEDGMENTS

This work was partially supported by NASA Grant NNX15AR20G (LS), NSF Award 1905524 (LS), NASA Space Technology Research Fellowships NNX16AM71H (RF), and the U.S. Army Combat Capabilities Development Command Soldier Center research project 18-114 (JP, HC). It has been approved for public release: distribution is unlimited.

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Date received: May 13, 2019
Date accepted: December 2, 2019