CHAPTER 30

# ARTIFICIAL INTELLIGENCE AND ROBOTICS IN REHABILITATION

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This chapter provides an overview of applications of intelligent technologies in contemporary rehabilitation practice and research. Within the context of the chapter, we focus primarily on current trends and future capabilities in ubiquitous computing, especially smart environments, intelligent mobile and wearable devices, and other assistive technologies. We also explore the application and study of robotics in rehabilitation practice and research. This is followed by a discussion of the broader implications for rehabilitation practice and research.

## INTRODUCTION

Technological advances, particularly in artificial intelligence (AI) and robotics, are revolutionizing the methods and capabilities of rehabilitation research and practice. Smart homes, for example, can assist inhabitants with everyday functioning and alert care providers if assistance is required. Intelligent mobile and wearable devices are available to collect data, and provide users with information to assess health and monitor progress toward individualized rehabilitation goals. Moreover, socially and physically assistive robots can be used to help people recuperate after illness or injury, or to help bridge gaps caused by sensory, motor, or cognitive impairments. These technologies are playing an important role in helping people to improve their functional abilities, independence, and overall well-being.

Our goal with this chapter is to provide an overview of intelligent technologies in contemporary rehabilitation practice and research. We begin by summarizing current trends and future capabilities in ubiquitous computing, especially smart environments, intelligent mobile and wearable devices, and the application and study of robotics in rehabilitation practice and research. Although a comprehensive review of all intelligent technologies and evidence of their effectiveness in rehabilitation is outside the scope of this chapter, we do provide several examples of their application to demonstrate their capabilities. We also discuss *assistive technologies* (AT; equipment or systems designed to maintain or improve the functional capabilities of people), and the *human activity assistive technology model* as a basic conceptual framework for conducting research and practice. We conclude with a discussion of the broader implications for rehabilitation practice and research, including ethical considerations.

## UBIQUITOUS COMPUTING AND AMBIENT INTELLIGENCE

*Ubiquitous computing* (also referred to as *pervasive computing*) entails embedding computational capability into everyday objects so they can communicate information (Abowd et al., 1999; Fogg, 2002; Weiser, 1993). The continual reduction in size of electronic devices (e.g., microprocessors and sensor technology),

http://dx.doi.org/10.1037/0000129-031
*Handbook of Rehabilitation Psychology, Third Edition*, L. A. Brenner, S. A. Reid-Arndt, T. R. Elliott, R. G. Frank, and B. Caplan (Editors-in-Chief)

as well as the use of wireless technology, make it possible to do this in such a way that systems are transparent (unobtrusive) and fully integrated (Luxton, June, Sano, & Bickmore, 2015). Ubiquitous computing systems can be designed so that data is captured *implicitly*, through passive sensing, or *explicitly*, by periodically surveying people, such as via a kiosk, smart mobile device, or through speech (voice processing).

*Ambient intelligence* (AmI) is a type of ubiquitous computing that refers to intelligent electronic environments that are sensitive and responsive to the presence of people within them (Aarts & de Ruyter, 2009; Aarts & Wichert, 2009; D. J. Cook, Augusto, & Jakkula, 2009; Vasilakos & Pedrycz, 2006). For example, ubiquitous computing systems embedded within a person's home or other rehabilitation setting can be aware of the needs, preferences, and functioning of inhabitants by analyzing situational data in real time, such as a person's physical location within the environment and other relevant information, such as the time of day. *Context awareness* refers to how technologies infer the current activity state of the user (e.g., smart home inhabitant) and the characteristics of the environment in order to manage information content and information distribution (D. J. Cook et al., 2009; O'Connor & Riek, 2015).

Recent gains in speech recognition, natural language processing (NLP), eye and face tracking, and gesture recognition provide users with multiple ways for interacting with intelligent technologies in a naturalistic manner. For example, it may be difficult or impossible for some people to effectively use keyboards or touch screens as an input device. Verbal interaction can allow people with physical or visual impairments to communicate with and control devices and eye trackers can enable respirator users to do the same.

AI can also assist with other basic but important "behind the scenes" functions such as preserving battery life by being aware of the situation (e.g., shutting down equipment when it is not in use). Basic functions such as battery life may be especially important when considering the use of technologies in critical health contexts, such as patient monitoring (Luxton et al., 2015), fall detection (Casilari & Oviedo-Jiménez, 2015), or when performing resuscitation (Gonzales, Henry, Calhoun, & Riek, 2016).

## INTELLIGENT MOBILE AND WEARABLE DEVICES

Intelligent mobile and wearable devices make excellent data collection platforms for health-related data, as well as contextual data relevant during rehabilitation. Consumer wearable devices from companies such as Apple, Fitbit, Jawbone, or Nike can be used to collect physiologic, behavioral, environmental (e.g., from ambient sensors), biological, and self-reported assessments (Luxton et al., 2015; Patel, Park, Bonato, Chan, & Rodgers, 2012; Piwek, Ellis, Andrews, & Joinson, 2016). A principal advantage of wearable technologies, such as smart watches, is that they are in physical contact with users for extended periods of time and they do not require the user to interact with a keyboard or touch screen while wearing them (Luxton et al., 2015).

Fall detection systems (FDS; Acampora, Cook, Rashidi, & Vasilakos, 2013; Gasparrini, Cippitelli, Spinsante, & Gambi, 2014) are an example of a technology germane to rehabilitation that uses intelligent sensors placed within an environment and/or as a wearable device. The goal of these systems is to detect falls and automatically alert medical staff, emergency services, or family members if assistance is required (Casilari & Oviedo-Jiménez, 2015). Casilari and Oviedo-Jiménez (2015) pilot tested such a system that uses fall detection algorithms implemented in a smartphone app and a smartwatch (both provided with an embedded accelerometer and a gyroscope) to track and analyze movements of simulated patients. The system was designed to discriminate falls from the conventional activities of daily living by simultaneously and independently analyzing the data from the two devices (they can interact via Bluetooth connection). Machine learning algorithms allow these types of systems to learn the behavioral patterns and characteristics of individuals over time and therefore help to reduce false positives. Moreover, systems can be designed to assess environmental risks, such as household lights that are off or proximity to fall hazards (e.g., stairwells) and preemptively alert inhabitants or care providers.

A growing number of mobile apps for use in rehabilitation are now available to health care professionals, clients, and family members. These include point-of-use tools for accessing health-related information, clinical decision support tools, medical imaging, mood and behavior trackers (e.g., pain diaries), physiological monitors, and assistive tools. (For general reviews regarding available mobile health apps, see Boulos, Brewer, Karimkhani, Buller, & Dellavalle, 2014; Luxton, McCann, Bush, Mishkind, & Reger, 2011; Martínez-Pérez et al., 2014; Ventola, 2014). Mobile devices also offer a way to facilitate live chatting with health care or other support professionals, text messaging interventions (e.g., behavioral reminders), scheduling and appointment reminders, and synchronous video-based tele-rehabilitation services (Kuemmel & Luxton, 2015; Luxton et al., 2011).

Integrated systems, such as our example in Figure 30.1, may collect data seamlessly from several types of sensors and data inputs. Data can be collected from sensor networks embedded within the environment (e.g., motion sensors) or worn on the user (e.g., physiological sensors) and sent via wireless connections to other mobile devices, a desktop computer, or other central processing system for analysis. Fully automated systems can be built to analyze and monitor data 24/7 and alert health care professionals and/or family members if needed. Synchronous video-based telehealth services could also be provided. Moreover, robots that provide physical assistance functions (e.g., lifting items, opening doors), monitoring, and therapeutic social functions may also be placed in these environments (Chan, Estève, Escriba, & Campo, 2008). The Care-O-bot 4, from Fraunhofer IPA (depicted in Figure 30.1), for example, is a commercially available configurable robot designed to provide assistive functions in the home.

## INTELLIGENT VIRTUAL AGENTS

An *intelligent virtual agent* (IVA) is a computer-generated, animated, artificial intelligent virtual character that can be designed to take on the visual appearance of humans, animals, or any other form imaginable (Hudlicka, 2015; Prendinger & Ishizuka, 2004). Their design can range from cartoonlike agents to highly detailed and lifelike three-dimensional agents. IVAs can been deployed on personal computers and on mobile phones and tablet computers, or even on robots (Luxton et al., 2015). Speech recognition and natural language processing (NLP) can allow the virtual agent to converse with the user through basic text interface or through verbal conversation. IVAs typically have a knowledge-engine with information that it uses

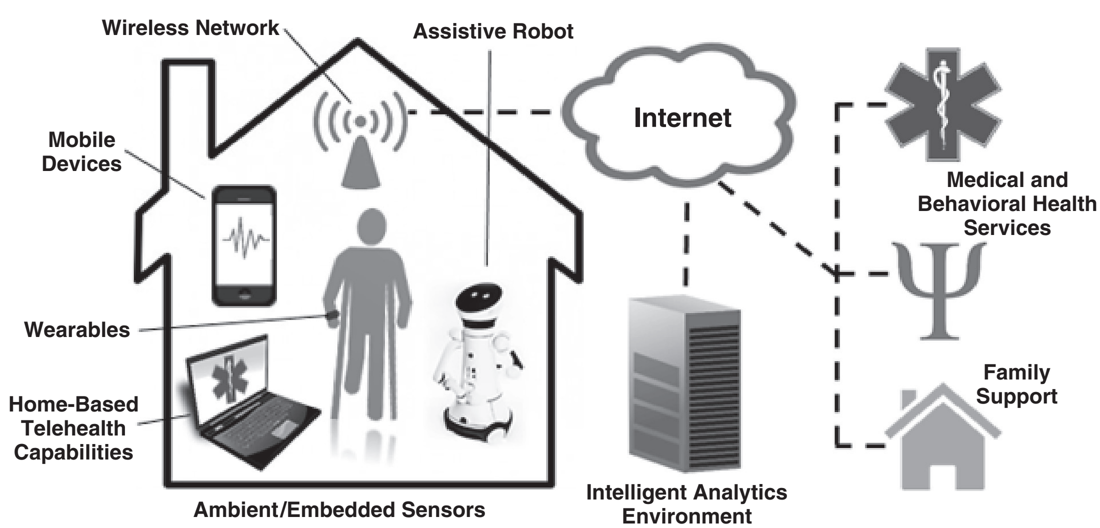


FIGURE 30.1. Integrated smart environment system.



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in conversation to enable it to understand, reason, and sometimes exhibit emotions.

*Virtual affective agents* are IVAs that are capable of affective interaction through recognition of human emotions and expression of emotions by the agent (Hudlicka, 2015; Hudlicka et al., 2008). Systems can be designed to detect mood states through analysis of language as well as through sensors that detect nonverbal information such as facial expressions and eye gaze (Luxton, 2014a). Affective agents may also be designed with the capability to explicitly model emotions, thereby enabling the agents to display nuances of emotional and social intelligence (e.g., awareness of social cues and user goals; Hudlicka, 2015). This capability gives these systems some ability to form and maintain relationships with human users, as well as to adapt in real time to the changing states and needs of the user. IVAs with this ability are sometimes called *relational agents*. As noted by Hudlicka (2015), it is important for agent developers to balance the need for agent expressiveness, the complexity of the associated processing required for them to function, and the needs of the users within the given interaction context.

IVAs, such as virtual humans, provide many potential benefits for rehabilitation and health care in general. For example, IVAs that simulate patients can be used for training purposes (Talbot, Sagae, John, & Rizzo, 2012). They can be designed to simulate various disorders or conditions in order to allow trainees to practice their interviewing skills and gain experience. The U.S. military, for example, has tested the use of lifelike virtual military veterans with depression and suicidal thoughts to teach military clinicians and other personnel how to recognize the risk for suicide (Kenny, Parsons, & Rizzo, 2009). Virtual patient simulations used in instruction have shown to be associated with better learning outcomes compared to conventional educational methods without simulations (Hirumi et al., 2016).

IVAs have also been developed for providing clinical care and coaching tasks (Luxton, 2015). For example, Bickmore and colleagues (2010) developed and tested a virtual nurse for use in hospital discharge planning and found that patients preferred to receive the discharge planning from the virtual human because they spent more time with the patient and never seemed rushed. Other studies suggest that IVAs can make users feel better understood while also reducing social anxiety (Bailenson & Yee, 2005; Gratch, Wang, Gerten, Fast, & Duffy, 2007; Kandalaft, Didehbani, Krawczyk, Allen, & Chapman, 2013; Kang, Gratch, Wang, & Watt, 2008; Lucas, Gratch, King, & Morency, 2014).

Other advantages of IVAs who stand in for human coaches and care providers are that they will not experience burnout or fatigue, and they may potentially be more reliable than humans (Luxton, 2014b). That is, they could be programmed with and learn skills that are applied consistently while also adapting to the client/patient's needs and preferences (Luxton, 2014b). They may also be capable of sensitivity and adaptation to specific aspects of a patient's culture, such as race/ethnicity or socioeconomic status. For example, a virtual human rehabilitation psychologist could modify its physical appearance and mannerisms (e.g., eye contact), speech dialect, use of colloquialisms, and other characteristics to match a given cultural group. This capability could help the system to develop and enhance rapport with a client, contributing to improved rehabilitation outcomes.

The application of IVAs that "stand in" for human rehabilitation professionals suggests that they may become a competitive threat to the rehabilitation workforce. There is indeed growing concern and evidence in many industries, including health care, that AI will replace human professionals (Brynjolfsson & McAfee, 2012; Luxton, 2014a). It is most likely, however, that IVAs will be used to assist rehabilitation professionals and enhance what they do, rather than replace them. There are also opportunities for rehabilitation psychologists to contribute to the design and testing of IVAs and to assure that they are put to use in ways that are ethical and effective at improving outcomes for clients.

## VIRTUAL REALITY, AUGMENTED REALITY, AND SERIOUS GAMES FOR REHABILITATION

*Virtual reality* allows people to become immersed within and interact with three-dimensional computer-generated simulated environments (Rizzo, Buckwalter,

& Neumann, 1997; see also Chapter 31, this volume). Virtual reality can be used to create virtual humans or other simulated life forms (e.g., virtual pets) that humans can interact with inside of virtual environments (e.g., in computer games). In therapeutic applications, virtual reality affords the capability to create and control environmental stimuli such that behavioral reactions to them can be practiced and recorded for clinical assessment, intervention, and rehabilitation goals (Schultheis & Rizzo, 2001). *Augmented reality* allows computer-generated virtual reality to be superimposed over live "real world" video imagery (Caudell & Mizell, 1992; Craig, 2013; Hugues, Fuchs, & Nannipieri, 2011). This allows information about the surrounding environment of the user to be available for interaction and digital manipulation in order to augment the user's perception of the world.

Virtual and augmented reality systems have been used for motor function training and recovery after stroke (Merians et al., 2002) and in pain management (Sato et al., 2010). Mirror therapy, for example, entails the use of a glass mirror to provide visual feedback to the brain. Augmented reality mirror systems use a high-resolution video screen and video cameras to simulate a mirror reflection. Thus, the technology allows a person to look into the simulated mirror to see a computer-generated image (e.g., a limb) or other images created by augmented reality. Sato and colleagues (2010) developed and tested a virtual mirror visual feedback system and applied it to the treatment of complex regional pain syndrome and found that it may be an effective alternative treatment for complex regional pain syndrome.

*Serious games* are computer games developed for training and learning purposes (as opposed to games designed solely for entertainment purposes; Hudlicka, 2015). In health care, serious games are used for training and education purposes for health care professionals (e.g., emergency room triage, nursing care, surgery) as well as for therapeutic and educational purposes for patients and clients (e.g., education about diet and exercise, coaching to increase physical activity, pain management, social skills training; Horne-Moyer, Moyer, Messer, & Messer, 2014). The skills to be learned or practiced are embedded within the game tasks and can be customized to the user's specific learning needs or therapeutic goals. The game aspect provides the benefit of motivating users (i.e., behavioral reinforcement) while also making the training or tasks more engaging.

One example of serious gaming for rehabilitation are exergames. These are video game—like simulations that allow a user to, for example, relearn basic motor skills by practicing them in a virtual environment. By combining a virtual mirror therapy component, these simulations can allow users to observe their own movements "in the game."

Desai and colleagues (2016) developed and tested an exergame for rehabilitation that uses low-cost, commercially available cameras such as Microsoft Kinect V2, to create a 3D model of the person and immersing the model in interactive virtual environments. These researchers designed games, such as a bowling simulation and a shotput game as well as a virtual trivia game requiring elbow rotation movement. Results of their initial test on ten participants (with no known disabilities) showed the games to be fun and realistic, and at the same time engaging and motivating for performing exercises. This example, while a preliminary test of this technology for rehabilitation, shows promise as a cost-effective tool for both in-office and in-home rehabilitation. Desai and colleagues (2016) also noted that this particular system does not require sensors to be worn by the user, thus it is less cumbersome and restrictive of physical movements.

## ROBOTICS TECHNOLOGY IN REHABILITATION

*Robots* are "physically embodied systems capable of enacting physical change in the world" (Riek, 2015, p. 185). They enact this change with effectors which can move the robot (locomotion), or objects in the environment (manipulation). Robots typically use sensor data to make decisions. They can vary in their degree of autonomy, from fully autonomous (the robot makes all decisions itself) to fully teleoperated (an operator makes all decisions for the robot), though most modern systems have mixed initiative, or shared autonomy. More broadly, *robotics technology* includes affiliated systems, such as related sensors, algorithms for processing data, and so on (Riek, 2015).

*Robotics* is a field of study that began in the industrial domain, studying the "intelligent connections between perception and actions" (Siciliano & Khatib, 2016, p. 2), though in the past few decades it has shifted to supporting people across nearly every human environment and exploring problems relating to teaming with real people in the real world (Iqbal & Riek, 2017; Riek, 2013).

This shift has been referred to in the literature as *human-centered robotics*, and an emerging area in the past decade focusing on problems in this space is known as *human-robot interaction* (HRI; Riek, 2015).

In health care, robots have tremendous potential to help people receiving rehabilitative care and their caregivers, as well as the clinical workforce itself. Robots can provide both physical and cognitive support to these individuals, across multiple types of care settings, and across the lifespan (Riek, 2017). These applications are discussed within the context of rehabilitation below.

## Physically Assistive Robotics

Robots have been used extensively in physical rehabilitation applications across multiple clinical areas, including helping patients recover motion after a stroke (Johnson, Rai, Barathi, Mendonca, & Bustamente-Valles, 2017; Matarić, Eriksson, Feil-Seifer, & Winstein, 2007), recovering or supplementing lost function (Maciejasz, Eschweiler, Gerlach-Hahn, Janson-Troy, & Leonhardt, 2014), and supporting mobility (van den Heuvel, Lexis, Gelderblom, Jansens, & de Witte, 2015). For example, Lancioni, Sigafoos, O'Reilly, and Singh (2012) described several robot-based intervention studies that aimed to increase activity engagement and ambulation among a small number of participants ($n = 56$) with severe physical and cognitive disabilities. The mobile robots used in the studies helped to improve participants' engagement with the physical world while also increasing their independence. Other recent advancements have included providing care receivers with additional physical reach, such as with wheelchair-mounted robot arms or smart, on-body prostheses, and multi-setting mobility capabilities, such as via exoskeletons or accessible personal transportation devices (Riek, 2017).

Another key area for physically assistive robots is as an aid to the clinical workforce itself. This is a population often overlooked in the technology literature, yet who are under constant physical and cognitive overload, and are at great risk for burnout and suicide (Card, 2018). They could greatly benefit from additional assistance in their work. For example, physically assistive robots can be used to help health care providers accomplish nonvalue-added tasks that detract from care delivery, such as removing waste, fetching supplies, cleaning rooms, or helping lift patients (Riek, 2017). Robots can also help treat patients with highly infectious diseases, which can further protect the clinical workforce (Kraft, Chu, Hansen, & Smart, 2016). Recent work in robotics has explored ways that robots can physically adapt to people in real time, by modeling their motion and altering their movement accordingly, as well as by predicting future behavior (Iqbal, Rack, & Riek, 2016; Nikolaidis, Forlizzi, Hsu, Shah, & Srinivasa, 2017). These concepts may prove particularly useful in future robots that provide physical rehabilitative support to people with disabilities, as well as to clinicians, by providing affordances for intuitive human-robot/human-agent teaming.

## Socially Assistive Robotics

Socially assistive robotics represent a juncture between assistive robotics and socially intelligent robotics (Riek, 2015). As can be seen in Figure 30.2, socially assistive robots can be designed to be anthropomorphic, animal-like (zoomorphic), or machinelike (Riek, Rabinowitch, Chakrabarti, & Robinson, 2009). Roles that these robots can take in health care, and specifically in rehabilitation, include companion, coach or instructor, or play partner (e.g., in play therapy). Paro, for example, is a robotic baby seal used to provide therapy for patients with dementia (Shibata & Wada, 2011) and RoboKind's Milo is a small anthropomorphic robot that teaches social behaviors for young persons with autism.

FIGURE 30.2. **Example robots used for rehabilitation from Dr. Riek's lab. Clockwise from left: (a) the Toyota Human Service Robot is a mobile robot used to encourage activity in older adults and to assist with activities around the house; (b) stuffed animal robots, like the Hasbro companion pet robot, are often used to alleviate symptoms of loneliness and depression; (c) table top social robots, like Jibo, are being used to provide cognitive support to people with autism and dementia; and (d) mobile telepresence robots, like the Double (shown at the bottom center and right), provide prehabilitation support to workers. For more information, see Lee and Riek (2018) and Woodworth, Ferrari, Zosa, and Riek (2018). Parts a–c copyright 2018 by L. D. Riek. Reprinted with permission. Part d from "Preference Learning in Assistive Robotics: Observational Repeated Inverse Reinforcement Learning," by B. Woodworth, F. Ferrari, T. E. Zosa, and L. D. Riek, 2018, *Proceedings of Machine Learning Research*, *85*, p. 11. Copyright 2018 by B. Woodworth, F. Ferrari, T. E. Zosa, and L. D. Riek. Reprinted with permission.**

Application domains of socially assistive robotics include support for older adults, individuals with physical recovery/rehabilitation and training needs, and individuals with cognitive, developmental, and social disorders (Tapus, Mataric, & Scassellati, 2007). Socially assistive robotics are highly useful for facilitating active rehabilitation exercises (Tapus et al., 2007). For example, Eriksson, Mataric, and Winstein (2005) tested a "hands-off" therapist robot that assists, encourages, and socially interacts with patients who have suffered a stroke. These authors note that the shared physical context and physical movement of the robot, encouragement, and continuous monitoring supported patient compliance with rehabilitation exercises.

## IMPLICATIONS FOR REHABILITATION PRACTICE AND RESEARCH

The development, evaluation, and practical use of technologies in rehabilitation require the identification and measurement of relevant outcomes. As noted by Smith (2016), there is great complexity around outcomes in the field of rehabilitation in general, so target outcomes must be simplified and well organized. The multitude of emerging technologies used in diverse rehabilitation contexts and populations adds to this complexity.

## The Need for Conceptual Models

Conceptual models are useful for rehabilitation professionals because they can provide a theoretical basis for advancing research and improving practice. Specifically, conceptual models can help to classify areas of inquiry (and outcomes), evaluate design and alternatives, and analyze data across different populations and contextual circumstances (Lenker & Paquet, 2003). The *human activity assistive technology model* (HAAT; A. M. Cook & Hussey, 1995) is one longstanding conceptual model involving assistive technologies (for review of additional models, see Lenker & Paquet, 2003). Assistive technologies (AT) can range from low-tech devices, such as a walker, to high-tech devices, such as sophisticated smart room environments (A. M. Cook & Polgar, 2015; Mihailidis, Boger, Craig, & Hoey, 2008). Formal definitions of AT, such as from the United States, The Assistive Technology Act of 1998 (amended in 2004) and from the World Health Organization (WHO) focus on individuals with disabilities—a fact that some have argued is based too strictly on the medical model (Hersh & Johnson, 2008). ATs are also described in the context of rehabilitation and in educational settings, which are not limited to "disabled persons" or older persons. The primary difference is the applicability to broader populations and the goals concerning the use of the technology. For education, the principal goal is enabling participation and learning. For rehabilitation, it is the restoration of functioning.

As shown in Figure 30.3, the HAAT model has four components: the human, the activity, the assistive technology, and the context in which these three components exist. Essentially, the HAAT model describes an AT system in terms of a person (human) who is using an AT device to accomplish a desired task (activity) within a

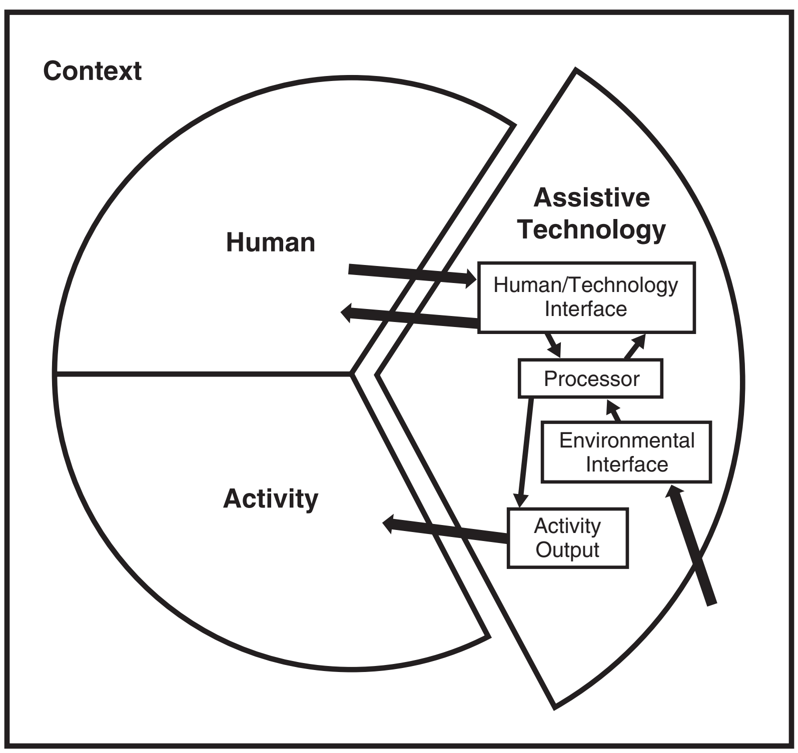


FIGURE 30.3. The human activity assistive technology model showing the assistive technology component. From *Assistive Technologies: Principles and Practice* (4th ed., p. 26), by A. M. Cook and J. M. Polgar, 2015, St. Louis, MO: Elsevier Mosby. Copyright 2015 by Elsevier Inc. Adapted with permission.

particular context (environment). Each component should be considered both independently and in combination with the others when designing, selecting, applying, and evaluating AT devices (Lenker & Paquet 2003).

According to A. M. Cook and Hussey (1995), the *human* element refers to physical, cognitive, and affective aspects of the participant. The *physical* element has to do with the physical attributes and functioning of a person, such as their coordination, strength, balance, and physical structure (i.e., anatomy). The *cognitive* element refers to measurable constructs such as attention, alertness, and problem-solving abilities, as well as other varying deficits of attention, judgment, insight, and so on. The *affective* element may include attitudes associated with the experience (e.g., frustration) as well affective symptoms associated with psychiatric conditions such as depression. The *activity* component refers to the process of doing something, such as daily living activities (e.g., dressing, hygiene, mobility), work activities (e.g., home management, educational, vocational activities), or play and leisure activities (e.g., activities related to enjoyment, relaxation, and self-expression). The *context* refers to social and cultural contexts, as well as environments and physical conditions. Lastly, the *AT technology* component (i.e., the device or devices) is described as having a human-technology interface, a processor (typically, an electronic computer or a mechanical device), and an activity output (Lenker & Paquet, 2003).

As noted by Lenker and Paquet (2003), the HAAT model aims to characterize system performance, rather than confining focus to human or device performance. The approach also considers aspects of human factors engineering and occupational therapy: the former entails analysis of how task characteristics of and environments influence human performance and the later aims to improve human performance in purposeful activities.

## Quality of Care and Economic Considerations

The development of intelligent technologies in rehabilitation and health care in general has the potential to improve the quality of care while also providing economic benefits. One way that these technologies can improve overall quality of care is by the amount of health- related data that can be collected to assess patient outcomes. As noted earlier, mobile devices such as smartphones and ambient home technologies can collect data in real time, with more frequent data collection, and in the environments that people live in, thus providing richer data to measure improvements in functioning and outcomes of treatments. These technologies also have the potential to improve adherence to treatment and rehabilitation plans by providing users with behavioral reminders (e.g., to conduct a daily exercise regimen) and feedback regarding use and progress toward goals (Luxton et al., 2015). Moreover, assistive technologies can also improve safety outcomes by providing real-time monitoring and alerts when increased assistance is needed.

Intelligent technologies in rehabilitation and health care can also provide significant economic benefits for health care providers and consumers of services. The increased accessibility and lower costs of intelligent technologies that provide services may make available opportunities for longer term treatments that might otherwise be restricted by managed-care costs (Luxton, 2014b). Thus, patients will have the opportunity to participate in longer term therapies and also receive periodic checkups that improve outcomes while also greatly reducing costs.

While initial development costs of fully interactive, intelligent rehabilitative systems may presently be high, depending of the complexity of the system, they can provide economic benefits. For example, they can potentially address treatment access gaps and be part of stepped care—the process whereby the least resource intensive care is provided to the most people first, with more intensive care provided to patients who need it the most (Bower & Gilbody, 2005). Clients could seek initial consultation and be assessed or screened by a virtual human and referred to more intensive care if needed.

## Privacy and Data Security Considerations

The technologies presented in this chapter entail specific privacy and electronic data security requirements that may need to be met, such as those enforced by the Health Insurance Portability and

Accountability Act (HIPAA) in the United States. With HIPAA, the health care service provider must assure compliance whenever a user is to transmit protected health information to a health care provider (if they are considered a covered entity). Although business associate agreements (BAAs) are required, they do not remit clinicians or their employers of all responsibility if consumers are harmed (Luxton, Nelson, & Maheu, 2016). HIPAA requires that several standards be met, including the availability of "audit trails" that make records of interactions accessible to authorities when needed, as well as "breach notification tools" that inform clinicians of breaches, such as when a transmission is illegally hacked.

It is important to note that physiological data that are collected, stored, and transmitted by ubiquitous computing technologies could also be used to identify a person (Luxton, Kayl, & Mishkind, 2012). This extends far beyond video and audio data—even basic actigraphy can reveal identifiable health information, and even "anonymized" data can be easily de-anonymized (Piewek, Ellis, Andrews, & Joinson, 2016). Thus, systems that collect such data, whether mobile apps, ambient intelligence systems or robots, might fall under the same regulatory requirements when used in the context of health care. Moreover, the technologies that we have discussed in this chapter also pose privacy issues associated with third parties (e.g., bystanders, family members). For example, cameras or microphones in smart environments may also collect images and sounds from residents and guests who are not aware of the data collection (Luxton, June, Sano, & Bickmore, 2015).

To help address these ethical quandaries, researchers and practitioners are encouraged to consult resources such as the Connected and Open Research Ethics (CORE) tool, a dynamic online resource which provides ethical practices and guidelines (Torous & Nebeker, 2017). Other professional organizations have also recently released codes of ethics guiding research practice in these technologies, including the IEEE, which may also provide a valuable resource to researchers (Chatila, Firth-Butterflied, Havens, & Karachalios, 2017; Riek & Howard, 2014).

## CONCLUSION

The technologies and methods presented in this chapter provide many exciting opportunities to enhance rehabilitation services and research. Improvements in existing technologies and future ones not yet developed will further advance rehabilitation capabilities and methods. These systems can provide numerous benefits to rehabilitation professionals, care providers, and clients.

While all of the specific technologies presented in this chapter can be expected to advance the field of rehabilitation psychology, it is likely that the integration of these technologies will provide the most significant opportunities for the field in the years ahead. For example, assistive robots with onboard IVAs can facilitate interactive communication and therapeutic bonds with the client. The system could also receive information (e.g., physical activity) from an ambient sensor network at home and, through the use of machine learning techniques, predict and adapt interventions that optimize rehabilitation outcomes, safety, and user satisfaction. The integration of these technologies also poses some challenges, including the need to design for interoperability and additional privacy risks (e.g., data security). Researchers and clinicians will need to consider the additional complexities and requirements of these systems.

Several limitations warrant mention. More research, especially clinical trials, are needed to evaluate the effectiveness of these technologies in the rehabilitation context. Unfortunately, the clinical trials that are needed to make informed decisions about the efficacy and benefits of various technologies can take many years to go through funding, implementation, and results and simply cannot keep up with the rapid evolution in many types of technology. Disruption technologies (or disruptive innovations) present a particular problem. New technologies and methods are constantly being brought to the marketplace, and while this progress is a good thing, it also requires new research and sometimes entire paradigm shifts in how care or services are provided. Technology access limitations is a related issue. Some people will simply not have access to technologies due to lack of economic resources and infrastructure (e.g., Internet access). This presents an ethical issue that needs to be considered by policy makers, researchers, and practitioners.

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