# Exploring the Relationship between Clinicians, Patients, and Wearable Health Sensors

A Research Paper submitted to the Department of Engineering and Society

Presented to the Faculty of the School of Engineering and Applied Science
University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science, School of Engineering

**Sean Lynch**

Spring 2022

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Advisor

Sean M. Ferguson, Department of Engineering and Society

## STS Research Paper

### Introduction

Over the last decade there has been an emergence of wearable health devices and sensors as a result of both advancements in technology and an increasing interest in personal health and wellness. Popular wearable devices such as smartwatches and wristbands are expected to increase in demand and dominate the consumer market, while healthcare practitioners are using wearable devices to assist them in investigating a patient's health and wellbeing. Wearable devices offer clinicians significant advantages, such as improvements in the quality of health monitoring, reduction in patient costs, and potentially faster patient recovery time for certain injuries. In addition, these health sensors, along with artificial intelligence, can be used to assist decision-makers and healthcare systems in providing more personalized recommendations and prescriptions. Unfortunately, however, these devices can also be responsible for less favorable outcomes. Patients are vulnerable to unintended changes in their behavior, increase in anxiety concerning their health, and lack of data accuracy and privacy. The doctor-patient relationship has traditionally consisted of a patient seeking assistance and a specialized doctor using his or her training to assess the patient's health and identify potential treatment plans. While this relationship has evolved over time with the emergence of new technologies, practices, and knowledge, personalized recommendations and prescriptions have always remained a difficult task. Now, with the assistance of these devices and sensors, this feat is possible and as patients turn to wearable technology to interpret their individual health and recovery status the doctor-patient relationship undergoes inevitable changes. This paper explores the relationships between clinicians, patients, and wearable sensors, and the effect that these sensors have on how patients' health and injury recovery are monitored.

Actor-network theory (ANT) is an approach to social theory that describes the phenomenon of an ANT network, which is a "heterogeneous amalgamation of textual, conceptual, social, and technical actors" (A-Ritzer, 2004). In this methodology, both humans and nonhumans can be analyzed as actors within a specific network, where the acts performed by an actor affect the stability and organization of the network. Through this paper, the network consisting of clinicians, patients, and wearable health sensors will be examined. Specifically, readers will have a firm understanding of how this network is organized, how it is "increasingly transportable", and how the actors have become "functionally indispensable" (A-Ritzer, 2004). Wearables have become a centralized space in which both patients and clinicians shape their behaviors to fit the requirements of the sensor and the preferences of the other human actors. In addition, the physiological input of the patient is filtered through the sensors, which act as a center node between the patient and clinician. This paper will first show how patients perceive and interact with sensors, secondly how patients and clinicians communicate with each other through the sensors, and thirdly clinicians' preferences and interpretations of the data from the sensors.

**Patients' Perceptions and Interactions with Wearable Sensors**

Body-worn sensor systems can be defined as "non-invasive systems that are worn to obtain clinically relevant information" (Bergmann & McGregor, 2011). Research has found that patients are primarily interested in a sensor system that is "compact, embedded and simple to operate and maintain" (Bergmann & McGregor, 2011). They share strong beliefs on the design and usability of the sensors and believe that the technology should not alter their daily behavior and routine. Specifically, the sensors should be "small, unobtrusive, and preferentially incorporated into everyday objects" (Bergmann & McGregor, 2011).

In order to adhere to patient preferences, self-tracking health monitors encourage behavior change most commonly through "nudges." Nudging has been popular in fields such as economics and public policy as a means to "influence decisions and behavior suggestions, [provide] positive reinforcement, and other non-coercive means" (Karlsen & Andersen, 2019). Digital nudging has been successful across a variety of technologies because it provides the user with recommendations and information that "both motivates and helps the user choose the suggested behavior" (Karlsen & Andersen, 2019). There are two common ways in which wearables send digital nudges: the first can be through physical contact (Gilmore, 2017) such as a vibration, and the second can be visually via an alert or message. The nudges aim to both encourage the user to pursue a certain action and to notify them when they have reached some sort of target without disrupting the person's daily routines. For example, an Apple Watch may notify its user that they have reached 10,000 steps that day, or that they have only reached 5,000 steps and are below the daily target. This type of notification acts as "a sort of compass to help individuals navigate a world of choices" (Schüll, 2016). Users are compared to a standard value and the nudges encourage them to meet or exceed that value. In a study conducted in 2020, middle-aged male and female participants used a variety of wearable health sensors over the course of four to six weeks and researchers analyzed their response to the sensors' nudges (Toner et al., 2021). Rather than blindly adhere to the advice of the nudges, participants actively made sense of the notifications and information they were receiving and developed their own interpretations as to whether they should act on that advice or not. Participants also believed that they did not need to consistently know how they compared "in relation to some arbitrary ideal" and were dismissive of the data when it conflicted with their own knowledge of their body. In some cases, the nudges actually resulted in participants feeling anxious and confused, and they consciously disregarded the information. Without the supervision and expertise of a medical professional, nudges can serve as the only communication source between the sensor and user, and the frequency that they are delivered in, the data that they are providing, and the timing of the notification can all negatively affect a user's willingness to act from it.

In the medical setting, patients have expressed more interest, trust, and willingness to change their behavior based on the use of their wearable sensors. In a study conducted in 2019, pregnant women at a rural health clinic were asked to answer survey questions in regard to their views on using wearable technology to track their health during pregnancy (Runkle et al., 2019). A 21-item e-survey was administered and respondents expressed that they did not have privacy concerns with the technology and were open to behavior changes based on the personalized recommendations from the technology. Similarly, a study in 2020 was conducted to understand patients' experiences with wearable sensors that identify epileptic seizures (Simblett et al., 2020). The researchers conducted semi-structured interviews on the effectiveness and desirability of wearable sensors after the interviewees had worn either one or multiple sensors. While several interviewees expressed positive experiences with the sensors, concerns arose around the visibility, support, and stability of the sensors. They noted how properly putting the device on and keeping it attached to their body was not only difficult but oftentimes needed assistance from the research team. In addition, sensors that had wires attached to them were an annoyance for several participants when pursuing "personal care activities." The ability to remove a wearable easily and comfortably was a strong preference for several participants. Overall, patients value the information and insights derived from wearable sensors but have difficulty properly wearing the sensors and pursuing everyday activities with them attached to their bodies. To eliminate patients' difficulties with putting and keeping the sensors on, designers are integrating the sensors into clothing, a technology known as "smart textiles". Two approaches for making sensor networks wearable include "[making] the sensors themselves into a fabric-like material, such as piezoelectric fabric capable of shape sensing and sound detection" or "[embedding] non-fabric-like sensors into textile allowing them to be worn" (Nesenbergs & Selavo, 2015). Either way, both technologies simplify how patients directly interact with the sensors.

**How Patients and Clinicians Interact Through Wearable Sensors**

The introduction of wearable sensors has allowed clinicians to oversee patients' health without face-to-face interaction through a practice known as outpatient monitoring. The two most common methods for outpatient monitoring are patient reported outcome measures (PROM) and telemonitoring. PROM involves a patient self-reporting their perspective via a descriptive analysis sent to the clinician, whereas telemonitoring passively tracks physiological data by using information technology which can be viewed by the patient and clinician. In addition to the fact that PROM collects subjective data, it poses shortcomings by only gathering a person's symptoms periodically as opposed to continuously, and also requires great effort from the patients to provide accurate and thorough descriptions (Maldaner et. al, 2019). Telemonitoring, on the other hand, is limited to the quality of the wearable sensor and the accuracy of the data. Quantifying self-hybrid models (QSHMs) intersects these two, as it accounts for both a patient's qualitative assessment and the quantitative variables from the sensors. Most wearable sensors are monitored using telemonitoring, however QSHMs offer the advantage of "combining subjective symptoms with objective criteria" (Appelboom et al., 2014).

The combination of PROM and telemonitoring is unique as it meets the demands of the both the patients and clinicians. PROM encourages the patient to be an advocate for themselves and control the flow of information, mitigating the risk of inaccurate sensor data and accounting for symptoms that the wearables may not track. In circumstances where clinicians are untrustworthy of a patient's self-reporting, telemonitoring provides them with objective data that can make their recommendations more trustworthy and meet medical compliance standards.

**Clinicians' Preferences and Interpretations of the Wearable Sensors**

Clinicians and patients not only interpret wearable sensors differently, but also prioritize different features of the technology. Clinicians are primarily interested in the sensors' data collection methods and accuracy, such as their limited recording time, how they should be properly placed on a patient, and the ability to quickly receive data in real-time. All medical professionals, be it physicians, nurses, or psychologists, have the responsibility of "interpreting recommendations, educating and motivating patients, monitoring responses to recommended behaviors, and providing feedback" (Miller et al., 1997). Therefore, they must prioritize the functionality and efficiency of the sensors in order to mitigate error in their recommendations and feedback to the patients.

Wearable sensors gain a clinician's trust through a clinical decision support system. A clinical decision support system (CDSS) is a "computer system designed to impact clinician decision making about individual patients at the point in time that these decisions are made" (Berner, 2010). CDSSs assists clinicians by improving medical decisions with "targeted clinical knowledge, patient information, and other health information" (Sutton et al., 2020). They contain three parts: the knowledge base, the inference engine, and a communication system. In practice, the two different types of CDSSs are known as knowledge-based and non-knowledge based. Knowledge-based often rely on if-then rule engines, for example if a particular test yields a certain result, then the clinician is advised to administer a specific dosage of medication to the patient. In addition, they can be based off "probabilistic associations of signs and symptoms with diagnoses, or known drug-drug or drug-food interactions" (Berner, 2010). Non-knowledge based CDSSs, on the other hand, use machine learning to identify patterns and trends in the data. Popular non-knowledge-based methods include artificial neural networks and genetic algorithms. Artificial neural networks (ANN) act the same way the human brain does and learn from examples. Genetic algorithms are based on the theories of Darwin and "reproduce themselves in various recombination's in an effort to find a new recombinant that is better adapted than its predecessors" (Berner, 2010). The inference engine of a CDSS connects the method from the knowledge base with the actual patient data, and then lastly the communication system is used to "get the patient data into the system and get the output of the system to the user who will make the actual decision" (Berner, 2010).

Throughout the outpatient monitoring process, data from wearable sensors can be used as an input into a CDSS. In other words, the CDSS acts as an intermediary between the data being collected from the wearable sensor and the clinician themselves. The sensor data is communicated wirelessly to the clinician because "wireless communication satisfies the requirements of flexible and convenient interactions" (Yin et al., 2020), expediting the data collection process and facilitating the role of the clinician. One area in the medical field where this technology has become very popular is the monitoring of glucose levels in patients with diabetes. Wearable continuous glucose monitoring (CGM) sensors have been used to greatly improve the treatment and daily management of Type 1 diabetes (Vettoretti et al., 2020).

Professional CGM sensors are administered by a clinician, often for a short period of time, and record a patient's glucose concentration data which can then be viewed by the clinician to make accurate recommendations. Other methods have been developed to connect wearable sensor data to a health decision support system (HDSS) with machine learning knowledge bases. Research conducted in 2017 detailed how data from wearable sensors could be a valuable input into a HDSS in a close-loop system (Yin & Jha, 2017). The researchers proposed a four-tier system, with similar data inputs as a QSHM. The first tier consists of physiological data from a wearable sensor and the second tier is a patient's clinical checkup where the clinician collects patient information through both a line of questioning and observations. The third tier involves the clinician making diagnoses based on medical measurements and other tools, and lastly the fourth tier would use machine learning methods to recommend various "treatments, prescriptions and medications, and future lifestyle suggestions."

The advancement of wearable sensors and CDSSs offer clinicians and patients several benefits, such as improvements in patient safety, reduction in costs, automating administrative functions, and providing diagnostic support (Sutton et al., 2020). CDSSs allow clinicians to monitor a patient's drug dosages and ensure that they are not taking harmful combinations (Vonbach et al., 2008) and also increase safety through reminder systems for other medical events (Sutton et al., 2020). They decrease hospital costs by reducing the quantity and length of patient visits and can reduce patient costs by suggesting cheaper options to medications that insurance companies pay for. Tasks such as ordering tests can be automated, and CDSS for clinical diagnosis, known as diagnostic decision support systems (DDSS), can assist clinicians in processing a patient's symptoms and identifying potential diagnoses (Berner, 2010). However, disadvantages in using wearable sensors and CDSSs include vulnerability to poor data quality and incorrect readings, a lack of transportability and interoperability, alert fatigue, and undesirable alerts (Sutton et al., 2020). Poorly collected data from the sensors will provide the CDSS with false inputs and thus give clinicians incorrect insights. In addition, there can be an unwillingness to share patient data and trust these technologies. Lastly, clinicians are oftentimes in disagreement with an alert and will ignore it if they are not notifying a serious event, for example a life-threating allergic reaction. “Alert fatigue” can occur when numerous alerts, often insignificant, are sent to a clinician.

**Discussion**

This paper explored the relationships between clinicians, patients, and wearable sensors through actor-network theory. The introduction of wearable sensors in the medical setting has proposed several benefits, most notably the reduction in costs for both the clinicians and patients, the ability to conduct continuous health tracking, and the potential for more personalized medical recommendations. However, wearable sensors still pose severe limitations, such as their inability to eliminate “alert fatigue” and in some cases an overwhelming quantity of inappropriate alerts, which can be experienced by both the clinicians and patients. While this paper explored these relationships and expressed the benefits and negative consequences of wearable sensors, there are several limitations. First, few research exists exploring this actor-network and identifying how clinicians and patients interact with one another in the presence of wearable sensors. The evidence used to write this paper separately analyzed how clinicians interact with the sensors and how patients interact with them, as opposed to one closed system. In addition, the use of wearable sensors in the medical field is relatively new and limited to few diseases and illnesses, restricting the types of clinicians and patients that could be used for this study. Future studies could explore this network outside of patients with illnesses such as diabetes and other chronic health conditions, for example how athletes with muscle injuries interact with the wearable sensors. Similarly, studies could analyze how clinicians not associated with a hospital, such as physical therapists or nutritionists, interact with wearable sensors.

# References

Appelboom, G., Camacho, E., Abraham, M. E., Bruce, S. S., Dumont, E. L. P., Zacharia, B. E., D'Amico, R., Slomian, J., Reginster, J. Y., Bruyère, O., & Connolly, E. S. (2014). Smart wearable body sensors for patient self-assessment and monitoring. *Archives of Public Health*, *72*(1). https://doi.org/10.1186/2049-3258-72-28

A-Ritzer, "ACTOR NETWORK THEORY," Encyclopedia.qxd, 2004.

Bergmann, J.H., Chandaria, V., & McGregor, A. (2012). Wearable and Implantable Sensors: The Patient's Perspective. *Sensors*, *12*(12), 16695–16709. https://doi.org/10.3390/s121216695

Bergmann, J. H., & McGregor, A. H. (2011). Body-worn sensor design: What do patients and clinicians want? *Annals of Biomedical Engineering*, *39*(9), 2299–2312. https://doi.org/10.1007/s10439-011-0339-9

Berner, E. S. (2010). *Clinical Decision Support Systems: Theory and Practice (Health Informatics)* (Softcover reprint of hardcover 2nd ed. 2007 ed.). Springer.

Cresswell, K. (2019). Using Actor-Network Theory to Study Health Information Technology Interventions. *Applied Interdisciplinary Theory in Health Informatics*, 87–97.

Di Paolo S, Lopomo NF, Della Villa F, Paolini G, Figari G, Bragonzoni L, Grassi A, Zaffagnini S. Rehabilitation and Return to Sport Assessment after Anterior Cruciate Ligament Injury: Quantifying Joint Kinematics during Complex High-Speed Tasks through Wearable Sensors. *Sensors*. 2021; 21(7):2331. https://doi.org/10.3390/s21072331

Gilmore, J. N. (2017). From Ticks and Tocks to Budges and Nudges: The Smartwatch and the Haptics of Informatic Culture. Television & New Media, 18(3), 189–202. https://doi.org/10.1177/1527476416658962

Haick, H., & Tang, N. (2021). Artificial Intelligence in Medical Sensors for Clinical Decisions. *ACS Nano*, *15*(3), 3557–3567. https://doi.org/10.1021/acsnano.1c00085

Karlsen, R., & Andersen, A. (2019). Recommendations with a Nudge. *Technologies*, *7*(2), 45. https://doi.org/10.3390/technologies7020045

Krupat, E., Yeager, C. M., & Putnam, S. (2000). Patient role orientations, doctor-patient fit, and visit satisfaction. *Psychology & Health*, *15*(5), 707–719. https://doi.org/10.1080/08870440008405481

Lee, S. M., & Lee, D. H. (2020). Healthcare wearable devices: An analysis of key factors for continuous use intention. *Service Business*, *14*(4), 503–531. https://doi.org/10.1007/s11628-020-00428-3

Maldaner, N., Desai, A., Gautschi, O. P., Regli, L., Ratliff, J. K., Park, J., & Stienen, M. N. (2019). Improving the patient-physician relationship in the digital era - transformation from subjective questionnaires into objective real-time and patient-specific data reporting tools. *Neurospine*, *16*(4), 712–714. https://doi.org/10.14245/ns.1938400.200

McCaldin, D., Wang, K., Schreier, G., Lovell, N., Marschollek, M., Redmond, S., & Schukat, M. (2016). Unintended Consequences of Wearable Sensor Use in Healthcare. *Yearbook of Medical Informatics*, *25*(01), 73–86. https://doi.org/10.15265/iy-2016-025

Miller, N. H., Hill, M., Kottke, T., & Ockene, I. S. (1997). The Multilevel Compliance Challenge: Recommendations for a call to action. *Circulation*, *95*(4), 1085–1090. https://doi.org/10.1161/01.cir.95.4.1085

Nesenbergs, K., & Selavo, L. (2015). Smart textiles for wearable sensor networks: Review and early lessons. *2015 IEEE International Symposium on Medical Measurements and Applications (MeMeA) Proceedings*, 402–406.

Runkle, J., Sugg, M., Boase, D., Galvin, S. L., & C. Coulson, C. (2019). Use of wearable sensors for pregnancy health and environmental monitoring: Descriptive findings from the perspective of patients and providers. *DIGITAL HEALTH*, *5*, 205520761982822. https://doi.org/10.1177/2055207619828220

R. S. McGinnis *et al.*, "Wearable sensors capture differences in muscle activity and gait patterns during daily activity in patients recovering from ACL reconstruction," *2018 IEEE 15th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, 2018, pp. 38-41, doi: 10.1109/BSN.2018.8329653.

Schüll, N. D. (2016). Data for Life: Wearable Technology and the design of self-care. *BioSocieties*, *11*(3), 317–333. https://doi.org/10.1057/biosoc.2015.47

Senanayake, S. M. Namal & Malik, Owais. (2012). Wireless Multi-Sensor Integration for ACL Rehabilitation Using Biofeedback Mechanism. ASME International Mechanical Engineering Congress and Exposition, Proceedings (IMECE). 2. 10.1115/IMECE2012-87809.

Simblett, S. K., Biondi, A., Bruno, E., Ballard, D., Stoneman, A., Lees, S., Richardson, M. P., & Wykes, T. (2020). Patients' experience of wearing multimodal sensor devices intended to detect epileptic seizures: A qualitative analysis. *Epilepsy & Behavior*, *102*, 106717. https://doi.org/10.1016/j.yebeh.2019.106717

Smuck, M., Odonkor, C. A., Wilt, J. K., Schmidt, N., & Swiernik, M. A. (2021). The emerging clinical role of wearables: factors for successful implementation in healthcare. *Npj Digital Medicine*, *4*(1). https://doi.org/10.1038/s41746-021-00418-3

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: benefits, risks, and strategies for success. *Npj Digital Medicine*, *3*(1). https://doi.org/10.1038/s41746-020-0221-y

Tedesco, S., Crowe, C., Ryan, A., Sica, M., Scheurer, S., Clifford, A. M., Brown, K. N., & O'Flynn, B. (2020). Motion sensors-based machine learning approach for the identification of anterior cruciate ligament gait patterns in on-the-field activities in rugby players. *Sensors*, *20*(11), 3029. https://doi.org/10.3390/s20113029

Toner, J., Allen-Collinson, J., & Jones, L. (2021). ‘I guess I was surprised by an app telling an adult they had to go to bed before half ten’: A phenomenological exploration of behavioural ‘nudges.’ *Qualitative Research in Sport, Exercise and Health*, 1–15. https://doi.org/10.1080/2159676x.2021.1937296

Trulsson, A., Miller, M., Hansson, G. K., Gummesson, C., & Garwicz, M. (2015). Altered movement patterns and muscular activity during single and double leg squats in individuals with anterior cruciate ligament injury. *BMC Musculoskeletal Disorders*, *16*(1). https://doi.org/10.1186/s12891-015-0472-y

Vettoretti, M., Cappon, G., Facchinetti, A., & Sparacino, G. (2020). Advanced Diabetes Management Using Artificial Intelligence and Continuous Glucose Monitoring Sensors. *Sensors*, *20*(14), 3870. https://doi.org/10.3390/s20143870

Vonbach, P., Dubied, A., Krähenbühl, S., & Beer, J. H. (2008). Prevalence of drug–drug interactions at hospital entry and during hospital stay of patients in internal medicine. *European Journal of Internal Medicine*, *19*(6), 413–420. https://doi.org/10.1016/j.ejim.2007.12.002

Yin, H., & Jha, N. K. (2017). A Health Decision Support System for Disease Diagnosis Based on Wearable Medical Sensors and Machine Learning Ensembles. *IEEE Transactions on Multi-Scale Computing Systems*, *3*(4), 228–241. https://doi.org/10.1109/tmscs.2017.2710194

Yin, R., Wang, D., Zhao, S., Lou, Z., & Shen, G. (2020). Wearable Sensors-Enabled Human–Machine Interaction Systems: From Design to Application. *Advanced Functional Materials*, *31*(11), 2008936. https://doi.org/10.1002/adfm.202008936