Optimizing Surgical Planning to Treat Patellar Instability

Analyzing the Impact of Image Recognition Systems on Physicians in the United States

A Thesis Prospectus
In STS 4500
Presented to
The Faculty of the
School of Engineering and Applied Science
University of Virginia
In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science in Biomedical Engineering

By
Valeria Pabon

October 27, 2022

Technical Team Members:
Allison Kenney and Kate de Jong

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.

ADVISORS

Rider Foley, Department of Engineering and Society

Silvia Blemker, Department of Biomedical Engineering

David Diduch, Department of Orthopaedic Surgery

Introduction

A person who has dislocated their patella, also known as the kneecap, has over a 50% chance of experiencing recurrent dislocations (Martinez-Cano et al., 2021). Recurrent dislocation, which occurs when the patella constantly slides out of its intended position within the femur's trochlear groove during knee flexion and extension, is the main characteristic of patellar instability. Forces generated by muscles and ligaments, such as the quadriceps and medial patellofemoral ligament (MPFL), help to stabilize the patella as it tracks through the trochlear groove. Once there is an imbalance between these forces, the patella will no longer be adequately stabilized and subluxes, meaning it undergoes a partial dislocation (Duchman et al., 2013). This condition is estimated to affect 50 to 77 out of 100,000 Americans while more commonly impacting young athletes (*Patellar Instability*, 2021). Specifically, within the populations of adolescent athletes, patellar instability is seen in every 29 per 100,000 adolescents (Thompson & Metcalfe, 2019). Athletes are at higher risk for this injury because of repeated rapid deceleration and twisting motions that affect the net lateral force that the patella experiences. Since patellar instability is characterized by recurrent dislocations and considering that an increase in the lateral force component can lead to further MPFL rupture, there is an emphasis on surgical treatment to address this condition (Wolfe et al., 2022).

Since various anatomical etiologies, such as soft tissue abrnomalites and trochlear dysplasia, cause recurrent patellar instability, this condition has made it difficult for physicians to treat because of the inability to objectively determine patellar instability (Rhee et al., 2012). This has led to various treatment methods, including non-surgical and surgical interventions, with none being clearly defined as the most effective treatment. In addition, these current procedural planning methods rely on the surgeon's subjective opinions. Therefore, these surgeries may not completely address the problem which leads to a 25% chance of recurrent subluxation post-surgery and a higher probability that patients have to undergo additional surgeries (Zimmermann & Balcarek, 2020).

While many of these surgeries can be effective for some patients, the ability for the surgeon to create a surgical plan that takes into account the patient's bone and muscle anatomy is currently unavailable. Creating a patient-specific musculoskeletal model and simulating its movement may significantly improve the diagnosis and treatment of musculoskeletal disorders, such as patellar instability (Valente et al., 2017). These models can provide more accurate results and allow for specific treatments that are tailored to the patient. This is important for musculoskeletal disorders, like patellar instability, that may present differently in patients and impact age groups and sexes differently (Arshi et al., 2016). By creating a patient-specific computational model that can simulate different surgical approaches, my capstone team will create an assistive tool with a more quantitative approach that surgeons can use when treating patellar instability.

Computational Model for Optimizing Surgical Planning for Patellar Instability

The development of a computational model representative of a patient's musculoskeletal anatomy can provide an assistive tool for subjective surgeries addressing patellar instability. The proposed patient-specific computational model aims to simulate different surgical approaches to determine the approach that produces the most desirable results. Specifically, the model will be focused on the surgical approach of the tibial tubercle osteotomy combined with an MPFL reconstruction due to its popularity in addressing patellar instability (Duchman et al., 2013).

The computational model will be created using the nmsBuilder and OpenSim softwares. MRI data providing the muscle volumes and relevant bone measurements of the patient's leg will be imported into nmsBuilder. The data provided from these MRI images would act as an input for the software to create a static musculoskeletal model with the same muscle and bone anatomy as the patient. The model generated in nmsBuilder can then be imported into OpenSim for kinematic analysis (Valente et al., 2017). In order to simulate surgical intervention for patellar instability, the anatomical dimensions with the bone and muscle landmarks from the patient-specific model will be translated onto an OpenSim generalized model. Through kinematic analysis, the torque and force vectors acting on the patient's patella will be quantified for movements from knee extension to flexion (Sherman et al., 2013). The model can then undergo different surgical approaches by moving the insertion of the patellar tendon laterally to various locations on the tibia and tightening the MPFL. Specifically, the different approaches are simulated by moving the patellar tendon attachment on the tibia, called the tibial tubercle. This movement is done because that is the main goal of the tibial tubercle osteotomy procedure that our model focuses on simulating (Grimm et al., 2018).

The model will undergo kinematic analysis for each surgical approach, including walking, running, and bending movements. These analyses would allow the surgeon to see each surgical approach's torque and force vectors. In order to determine the most effective approach, the resulting net torque and force vector would then be compared to one seen in a healthy patient's knee. This comparison would then allow the surgeon to select the location of the patellar tendon attachment that produces the healthy torque and force vector values. Ultimately, creating this computational model specific to the bone and muscle anatomy of a patient will address subjectivity in surgical planning by quantifying possible surgical outcomes. This project will create a new predictive tool for surgical planning in orthopedic clinics used to increase outcomes of patellar instability surgery.

Analyzing the Impacts of ML Image Recognition Systems on Physicians

While my technical project is a computational model that will optimize surgical planning for treating patellar instability, my Science, Technology, and Society (STS) research will focus on analyzing the impact machine learning image recognition systems have on physicians in the United States (U.S.). Machine learning (ML) systems are an application of artificial intelligence where machines take in data and learn information that would be difficult for humans (Burnham, 2020). ML incorporates computational models and algorithms that imitate the architecture of the neural networks in the brain, allowing the system to learn from data without being explicitly programmed (Pesapane et al., 2018). The most complex form of machine learning involves deep learning. This specific form is increasingly being applied in the healthcare field, specifically for detecting features in imaging data that exceed what humans can view (Davenport & Kalakota, 2019). These ML image recognition systems can recognize and classify patterns from imaging modalities such as X-rays and MRIs. This classification is helpful for disease diagnostics because the images produced from the imaging modalities allow for the visualization of internal body structures, allowing the image recognition model to screen for illnesses (Zhang & Sejdić, 2019). ML image recognition systems can screen for illnesses because the algorithms are trained on an image dataset to extract specific features that allow them to then extract the same features from the image inputs (Huang et al., 2022). However, these systems are considered "black-box" systems, meaning that the input and output data are known, but the process the machine goes through to get the result is not (Rahman & Scali, 2022).

In order to evaluate the sociotechnical relationship between image recognition systems and their impact on physicians, the framework of *technological citizenship* will be used. This framework provides a way to analyze how technology can influence the rights and obligations of citizens within a democracy (Andrews, 2006). The rights of citizens are defined as the rights of access to knowledge, informed consent, and reasonable levels of risk exposure. Additionally, the duties of citizens include achieving technological literacy and protecting the civic good. In order to understand the impact of the implementation of image recognition systems, the rights and duties of physicians that are influenced by this technology must be analyzed. This focus is necessary because there is currently a lack of access to knowledge regarding the demographics of datasets used for algorithm training for ML image recognition systems. Companies that train the algorithms do not always report detailed information on the datasets that are used, which limits the ability of physicians to evaluate how well the technology will perform on their patients (PEW, 2021). This lack of transparency of the datasets may lead physicians to trust the results implicitly without questioning whether the results could be biased. Additionally, due to its "black-box" nature, the algorithm's complexity has impacted physicians' abilities to achieve technological literacy. This complexity makes it difficult to determine how exactly the machine produced the output that it did using the data, making it even harder for physicians to detect unwanted behaviors, such as biased outputs (Rahman & Scali, 2022). By utilizing this framework, the impact of image recognition systems can be analyzed through the assessment of the system’s influence on the rights and duties of physicians.

Research Question and Methods

The research question that is the focus of my STS research is: how has ML image recognition systems affected the rights and duties of physicians in the U.S. when diagnosing patients? This understanding is essential for physicians who rely on this technology for disease diagnostics because the technology's results will ultimately affect their patient's treatment. Therefore, analyzing how this technology impacts physicians is necessary to ensure that the patients receive the most effective treatment possible. The methods that will be utilized to investigate the research question will include a literature review on current image recognition systems that are being tested or have received FDA approval.

In order to find information about FDA-approved technologies, I will look at the list published by the FDA of the 521 AI/ML-enabled medical devices currently marketed in the U.S. (FDA, 2022). As I go through the list, I plan on selecting four of the diagnostic image recognition systems and find their industry reports and diagnostic traning manuals. These sources will give me insight into how the black-box algorithm was presented to its users, showing whether or not enough information was presented for its user to achieve technological literacy. Keywords I will use to find additional sources for the image recognition systems in databases, such as PubMed, include "machine learning," "image recognition," "black-box," and "disease diagnostics." Finally, I plan to present the data I collect by using a table that shows whether the dataset information, specifically the demographics such as sex and race, was provided. This will allow me to address whether or not companies were transparent of their dataset, which is needed to ensure informed consent by the phyisicans since the machine's results could impact the outcome of their patients.

Conclusion

Similar to my capstone project, the use of artificial intelligence in disease diagnostics has the potential to transform and improve the healthcare field. These AI technologies, such as image recognition systems, have the ability to detect diseases early on, allowing for the improvement of treatments. However, the impact of this technology must be taken into account. With that in mind, I expect this research paper to identify ways in which technologies have transformed the rights and obligations of physicians. Specifically, I want to see how the complexity of the technology and the lack of transparency in datasets affect how physicians can treat their patients. This research can increase awareness of the effects of implementing these specific artificial intelligence systems and increase support for better education and transparency for its users.

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