Ice hockey stick fitting using embedded sensors and machine learning algorithms: A pilot study

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Abstract

Hockey sticks are a growing segment of the $850+ million hockey equipment market due to increasing global hockey participation and short product shelf life. While the technologies used to make ice hockey sticks have evolved drastically over the past 20 years, the purchasing experience has changed relatively little: Players still buy equipment mainly in physical stores where they aren't able to test sticks before paying. Stick "fitting" is a process whereby players receive tailored stick recommendations based on their unique needs or shooting style and has gained recent attention from leading ice hockey equipment companies. As such, there is a need for further research of the relationship between objective and subjective evaluations of stick performance and faster, automated stick fitting processes.

The aims of this study were to 1) understand the relationship between subjective perceptions and objective performance metrics with ice hockey sticks and 2) evaluate the feasibility of using inertial sensors and machine learning algorithms for the rapid fitting of ice hockey sticks. Ten left and right-handed participants of high and low caliber performed 80 shots using 4 sticks of different stiffnesses, blade patterns, and kick points.

To address the first aim, an 18-camera Vicon motion capture system was used to capture player and puck kinematics for event detection and calculation of shot speed, accuracy, and puck contact time. Perceptions of shot speed, accuracy, and feel with each stick and overall stick preference rank order were captured separately for slap and wrist shots using 10- and 4-point scales. Significant differences were observed in perceived slap shot speed, slap shot feel, and wrist shot overall preference. No significant differences in shot speed were found: Instead, slap shot contact duration was found to be significantly shorter with the high kick point stick and wrist shot accuracy was found to be significantly lower with the flatter blade pattern. Variable factors mapping using

principal component analysis revealed perceptions of shot speed and accuracy to be closely related to objective measures during wrist shots but not slap shots.

To address the second aim, custom-made inertial measurement units were embedded in a pair of hockey gloves to gather concurrent kinematic measures (linear acceleration and angular velocity) of the hands. Machine learning algorithms using principal components accounting for 95% of the variability in the hand resultant signals correctly classified players' optimal stick flex, blade pattern, and kick point with 90-98% accuracy for slap shots and 93-97% accuracy for wrist shots. Based on these findings, the combination of embedded sensors and machine learning algorithms shows promise in future ice hockey stick fitting applications.

Abrégé

Les bâtons de hockey sur glace sont un segment croissant du marché de l'équipement de hockey de plus de 850 millions de dollars en raison de la participation croissante au hockey à l'échelle mondiale et de la courte durée de conservation des produits. Alors que les technologies utilisées pour fabriquer des bâtons de hockey ont considérablement évolué au cours des 20 dernières années, l'expérience d'achat a relativement peu changé : les joueurs achètent toujours du matériel principalement dans des magasins physiques où ils ne peuvent pas tester les bâtons avant de payer. Le « fitting » des bâtons est un processus par lequel les joueurs reçoivent des recommandations de bâtons personnalisées en fonction de leurs besoins uniques ou de leur style de tir et a récemment attiré l'attention des principales sociétés d'équipement de hockey sur glace. En tant que tel, il est nécessaire de poursuivre les recherches sur la relation entre les évaluations objectives et subjectives des performances du bâton et les processus d'ajustement plus rapides et automatisés du bâton.

Les objectifs de cette étude était 1) comprendre des relations entre la perception subjective des joueurs et les mesures de performance objectives obtenues avec différents bâtons de hockey sur glace et 2) évaluer la faisabilité d'utiliser des capteurs inertiels et des algorithmes d'apprentissage automatique pour effectuer une recommandation rapide et précise de bâtons de hockey sur glace. Dix joueurs de mains gauches et droites de haut calibre ont faire 80 lancés en utilisant quatre bâtons de différentes rigidités, modèle de palette et profils de rigidité.

Pour adresser le premier objectif, un système de capture de mouvement de 18 caméras Vicon a été utilisé pour capturer la cinématique de joueurs et de la rondelle pour la détection d'évènements et le calcul de vitesse, précision, duration de contact pour chaque lancé. Les perceptions de vitesse, précision et sensation du lancés avec chaque bâton et l'ordre de classement de la préférence global

de chaque bâton ont été capturé séparément pour les lancés du poignet et les lancés frappé. Aucune différence significative de vitesse de lancé a été trouvé: Plutôt, le temps de contact des lancés frappé a été trouvé à être significativement plus court avec le bâton de profil de rigidité haut et la précision des lancés du poignet a été trouvé à être significativement plus bas avec le modèle de palette plus plat. La schématique de facteurs variables en utilisant l'analyse de composantes principaux (PCA) a révélé que les perceptions de vitesse de lancer et la précision sont principalement en accord avec mesures objectives durant les lancés du poignet, mais non pour les lancés frappé.

Pour adresser le deuxième objectif, des centrales inertielles fait sur mesure ont été placés dans une paire de gant de hockey pour capturer des mesures cinématiques concurrent (accélération linéaire et vélocité angulaire) des mains. En utilisant les composantes principales montant à 95% de la variabilité des signaux résultant des mains, les algorithmes d'apprentissage automatique ont correctement classifié la rigidité, le modèle de palette et le profil de rigidité optimale pour chaque joueur avec 90-98% de précision pour les lancés frappé et 93-97% pour les lancés du poignet. Basé sur ces résultats, la combinaison de capteurs et algorithmes d'apprentissage automatique montre de l'espoir à l'avenir pour les applications de « fitting » de bâton pour le hockey sur glace.

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Contribution of Authors

Taylor A. Léger, MSc Candidate, Department of Kinesiology and Physical Education, McGill University, was responsible for the research design, processing and analysis of data, and the writing of this thesis. The candidate's supervisor, David J. Pearsall, PhD, Associate Professor, Department of Kinesiology and Physical Education, McGill University, contributed to the research design and analysis of the data.

Shawn Robbins, PhD, Assistant Professor, School of Physical and Occupational Therapy, McGill University, helped develop the data processing pipelines and aided with the statistical analysis. Dr. Robbins was also a member of the thesis advisory committee alongside Dr. Richard Preuss, Assistant Professor, School of Physical and Occupational Therapy, McGill University. Philippe J. Renaud, MSc, Department of Kinesiology and Physical Education, McGill University, played a very important role in the research design, data collection, processing, and analysis, acting as the lab research assistant.

Sean Denroche, MSc Graduate, Department of Kinesiology and Physical Education, McGill University, and Matthew Kelly, MSc Candidate, Department of Kinesiology and Physical Education, McGill University, played important roles in the collection and processing of data.

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1. Introduction

Hockey sticks are a growing segment of the $850+ million USD hockey equipment market due to increasing global hockey participation and short product shelf life (Grand View Research, 2019). It is estimated that hockey sticks alone will reach a market value of $320 million USD by the end of 2025 (More, 2019).

While the technologies used to make sticks have evolved drastically over the past 20 years, the retail landscape has changed relatively little: players still buy equipment mainly in physical stores where they are not able to test it before buying. Further, hockey sticks are more expensive than ever, with high end sticks retailing for up to $350 CAD (Bauer Hockey Ltd., n.d.-b).

At present, few scientific avenues are available to players to determine which stick they should buy. Instead, players rely on marketing information, opinions of sales associates, and their own intuition. This is not the retail model for all sports that require specialized equipment. In fact, it is fairly for golfers and cyclists to undergo a “fitting” process for their clubs and bicycles respectively. During a fitting, a specialist walks the athlete through a series of tests designed to identify the athlete’s anthropometric or kinematic tendencies. The objective is to use this information to arrive at an optimal equipment configuration for the individual.

Today, such services are not available to hockey players below the professional level; however, over the past five years leading hockey stick companies have released their own bespoke tools for assisting with hockey stick fitting. The Bauer *Stick Studio* (United Sport & Cycle, 2019) and CCM *Stick Fitter* (CCM Hockey, n.d.) apps utilize unique but similar methods for determining the ideal sticks for players. Both rely on the manual analysis of slow-motion video on a tablet device. This approach is not feasible for all retailers, as it requires substantial floor space and the assignment of a trained salesperson.

This thesis explores the relationships between perceptions and performance metrics with ice hockey sticks as well as potential future avenues for the improvement of stick fitting using readily available, fast-paced, low-cost technologies.

2. Literature Review

The stick is a central tool in the game of ice hockey. It serves as a functional extension of the player's hands and is the primary means of passing, shooting, and handling the puck (Turcotte et al., 2016).

Since the 1940's, hockey players have modified aspects of their sticks to fit their unique styles of play (Anderson, 2008). What began with the contortion of wooden stick blades became the fine-tuning of whole stick parameters with the introduction of carbon composite technologies to the hockey stick market in the 1990's. Today, players are able to pick and choose from sticks with a variety of stiffnesses, kick points, and blade patterns (Pearsall & Robbins, 2019).

Over the past 50 years, much research has been dedicated to investigating the systematic effects of these parameters on ice hockey player performance in shooting tasks. This has been due to the importance of shooting and scoring in the game of hockey and the stick's contribution to shooting performance.

2.1 Ice Hockey Shooting

There are four main shot types in hockey: slap, wrist, snap, and backhand shots. When and where players use these different shot types is both context and position-specific (Turcotte et al., 2016). The two main shot types are the slap shot and wrist shot. Slap shots are the shot type with the highest associated puck speeds and wrist shots are the most frequently used (NHL, 2020b).

During the slap shot, the player begins by drawing the stick behind the puck and above the ice surface to maximize the path over which forces can be applied to the stick during the downswing and initiate a stretch shortening cycle in the shooting muscles (Robbins et al., 2021). After the downswing, the player contacts the ice behind the puck using the blade of the stick. This ice contact event is proceeded by the deformation, or “loading”, of the blade and stick shaft whereby the player stores strain potential energy in the stick. Skilled players utilize a “rocker” strategy during the early portion of ice contact to achieve earlier stick deformation while less-skilled players do not leverage the spring-like properties of the blade and stick in this way (Lomond et al., 2007). As the stick continues to progress forward, the player will reach a point when they can no longer apply sufficient forces to the stick to keep it deformed. At this time, the stick recoils, springing forward in front of the player. Skilled players are able to coordinate the spatiotemporal “timing” of stick recoil maximize the impulse imparted to the puck and efficiently convert stick strain potential energy to puck kinetic energy (Villaseñor et al., 2006). The amount of strain potential energy stored in the stick during the loading phase is important because the puck remains in contact with the blade for 35-40 milliseconds prior to release (Pearsall & Robbins, 2019). This short duration makes it challenging for the player to achieve maximal puck exit velocities through muscular force and puck momentum alone, thus highlighting the important contribution of the stick to the shot.

The wrist shot is comprised of a similar event sequencing to the slap shot with a few key differences. First, the wrist shot is characterized as a sweeping motion where the blade remains in contact with the ice. Second, the puck remains in contact with the stick blade throughout the shot. Third, players typically grip closer towards the top end of the stick with their bottom hand (Zane, 2012). Consequently, wrist shots are associated with lower degrees of stick bend and puck exit velocities but higher levels of accuracy and quickness of release (Pearsall & Robbins, 2019). The wrist shot begins when the shooter draws the puck back. This is done for the same purpose of the backswing in the slap shot: to increase range of motion and engage the shooting musculature for high puck exit velocities. This allows the player to begin imparting forces to the puck in the forward direction prior to the positive change in velocity of the puck, similar to the way in which athletes utilize countermovement sequencing to maximize vertical jump height. As the puck moves forward, the player applies posterior-superior forces with the top hand and anterior-inferior-medial forces with the bottom hand to the stick (Zane, 2012). In combination with the posterolateral loading on the stick blade due to contact with the ice, a third-class lever is created (Figure 1). This loading causes the stick to deform and recoil as the stick blade progresses forward away from the player through release.

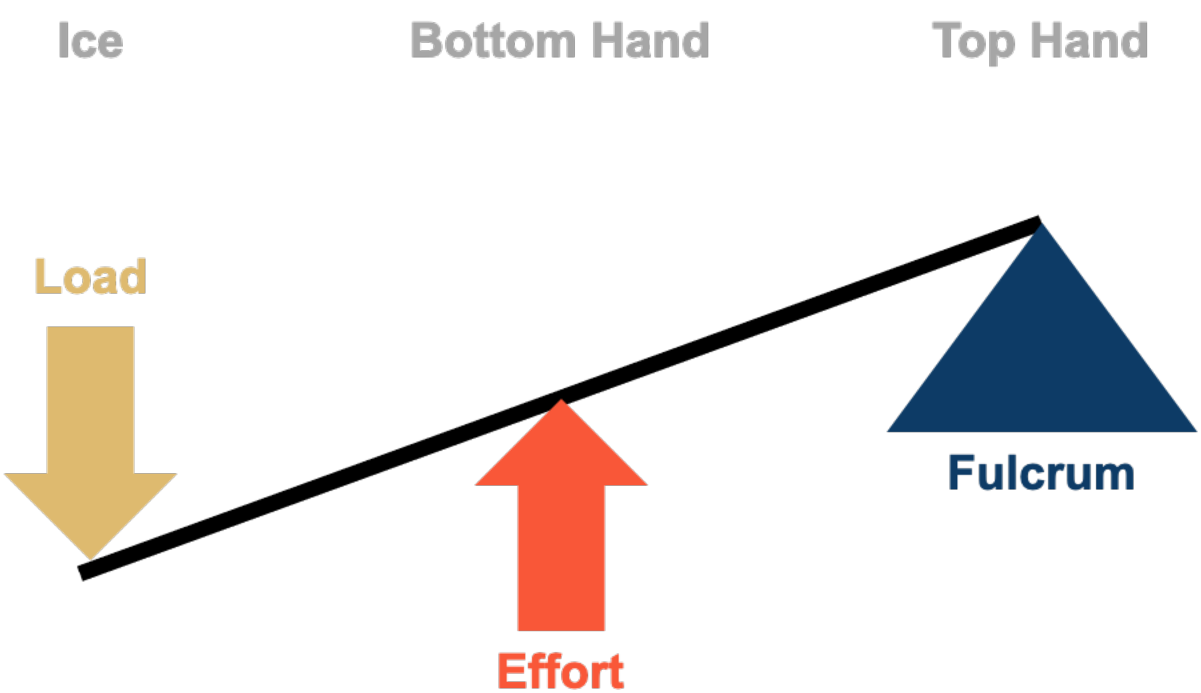

Figure 1. Top-down schematic displaying the hand-ice loading of the hockey stick shaft to create a third-class lever during a hockey shot.

Individuals across all skill levels display disparate spatiotemporal strategies of force application to the stick throughout the shooting movement (Flemming, 2014; Zane, 2012). Hence, tuning properties of the stick to individual shooting techniques may help players maximize shooting performance.

2.2 Effects of Hockey Stick Properties on Shooting Performance

Generally, shooting "performance" is measured as shot speed, accuracy, and quickness (Pearsall & Robbins, 2019). Shot speed is the puck's velocity between puck release and net entry. Shot accuracy is inversely related to the radial error of the shot from the target center. Quickness of release is inversely related to the elapsed time between puck contact and puck release.

In different game scenarios, the situation may call for one performance metric to be relied upon more than others may. For instance, a defenceman shooting from the top of the offensive zone would likely prioritize shot velocity to ensure the puck gets by opposing players between them and the net while a forward with time and space nearer to the net might prioritize the accuracy of their shot. Conversely, a player receiving a cross-zone pass needs to prioritize the speed of their release to score before the goalie can reposition themselves to cover the net opening. Hence, the effect of a single stick parameter on shooting "performance" does not affect all players equally. Instead, players must pick-and-choose the characteristics of their sticks—such as stiffness, dynamic flex profile, and blade pattern—based on their individual styles of play.

2.2.1 Shaft Stiffness ("Flex")

The shafts of hockey sticks are hollow and rectangular. Shaft stiffness in the plane of the shot (i.e. about the major axis of the shaft) is reported for hockey sticks using a "flex rating", with higher flexes representing stiffer sticks and vice versa. The stiffness about the minor axis of the stick is generally around double the stiffness about the major axis. Flex ratings are not exactly equal across brands; however, the ratings represent notable changes in bending stiffness for sticks of a specific type.

Sticks are sold in three different shaft sizes: junior, intermediate, and senior. Each size has a different cross-sectional area, with senior being the largest. Mechanically, this increases the bending stiffness of the axis, thus making senior sticks stiffer before considering the addition of any extra material. In addition to shaft cross-sectional geometry, the types of materials used in the shaft, the orientation of the material layers to one another, and the number of material layers all influence stick flex. Retail senior hockey sticks generally range from 70 to 100 flex. However, most senior sticks are only offered in lower flex ranges, such as between 70 and 90 flex. This represents a general trend of players preferring to play with more flexible sticks (Pearsall & Robbins, 2019).

Research on the influence of stick flex on shooting performance to date has been conflicted; however, it appears that players should select their flex based on the way they load the hockey stick. Three possible stick “loading styles” have been reported in the literature. These are Constant Displacement, Constant Force, and Constant Energy (Kays & Smith, 2017; Worobets et al., 2006). In each loading style, a player affects a constant maximal deformation of the shaft, applies an identical level of force, or stores the same maximal amount of energy in the stick regardless of changes in shaft stiffness.

During the shooting motion, the hockey stick functionally acts as a spring by releasing energy at a faster rate than it was previously stored, amplifying shot power. Hooke’s Law (Equation 1), which applies to springs, states that the amount of force (F) required to deform a spring (Δx) is proportional to that spring’s linear stiffness (k). Further, the amount of force applied to, the linear stiffness of, and the deformation of a spring all influence the strain potential energy (SPE) stored in the spring during the static equilibrium achieved at maximum stick bend (Equation 2).

Equation 1. Hooke's Law formula.

$$F = k\Delta x \rightarrow k = \frac{F}{\Delta x}$$

Equation 2. Strain potential energy formula.

$$SPE = \frac{1}{2} k \Delta x^2 = \frac{1}{2} F\Delta x$$

Due to these physical laws, a "Constant Displacement" shooter—who always maximally deforms their stick the same amount—will achieve greater peak strain potential energy in the stick as stick stiffness increases (i.e. k increases, Δx is held constant), and thus achieve higher shot velocities with sticks of increasing stiffness. On the other hand, a Constant Force shooter—who always apply the same peak force to the stick—will achieve higher peak shaft deformation, higher peak stored strain potential energy, and consequently higher shot velocities with sticks of decreasing stiffness. Players who exhibit a Constant Energy loading style will always store the same amount of strain energy in the stick at maximal deflection and are thus unaffected by changes in shaft stiffness.

These scenarios assume that deformation of the stick occurs primarily about the major axis during the shooting motion, that the player applies force to the stick along the same vector, that bending is purely about the stick's major axis, that bending stiffness about the stick's major and minor axes both increase with stiffness rating, and that the energy stored in the stick at the moment of maximum bend is permitted to be converted to blade kinetic energy which can be transferred to the puck. Further research is warranted to better understand the individual contributions of hockey stick transverse and axial bending stiffnesses towards these dynamic player-stick interaction profiles in human subjects (Behrmann et al., 2014).

At present, the exact origins of these disparate stick loading styles remain unknown, however, there is evidence that such differences may arise due to differences in anthropometrics, kinematics, and levels of experience. For example, it is believed that larger, stronger players may be able to use a Constant Displacement model while weaker players may follow a Constant Force model (Kays & Smith, 2017). Others have proposed that players have adopted new shooting techniques to take advantage of the spring-like properties of modern carbon composite hockey sticks (Pearsall & Robbins, 2019). In other words, today's players may be more inclined to use a Constant Force model having grown up with more compliant hockey sticks. These theories are consistent with previous findings that stick stiffness may negatively affect the shot velocities of younger (Roy & Doré, 1976) or female (Gilenstam et al., 2009) players by preventing them from realizing the full power-amplifying benefits of the stick. Regardless of the strategy employed, players must strive to maximize the strain energy stored in the stick during shooting to achieve maximal puck velocities.

Given the highly individualized nature of such dynamic interactions between players and their sticks, it is challenging to conclude that the use of a more (or less) flexible stick benefits all players at all levels in the same way. Historically, this has led to disagreement amongst scientific authors as to the effect of stick stiffness on shooting performance (Pearsall & Robbins, 2019). Instead, these findings suggest that players should be provided tailored recommendations of shaft stiffness based on their specific loading style.

2.2.2 Shaft Dynamic Flex Profile ("Kick Point")

While rods with uniform bending properties would have consistent, "static" stiffnesses at every point along the shaft, modern carbon composite ice hockey sticks are designed with intentionally asymmetric, "dynamic" flex profiles along the shaft (Figure 2). These dynamic flex profiles are commonly referred to by the location of the most flexible shaft portion, called the stick's "kick point". For example, a low kick point stick is most flexible at the bottom and increases in stiffness moving up the shaft while a high kick point stick is stiffest at the bottom. Alternatively, sticks with mid kick points are stiffest in the middle of the shaft (Figure 2). The mid kick point derives its name from the fact that it allows players to easily store energy in the shaft at any point in the upper or lower portion of the shaft. In other words, it is referred to as a "mid" kick point because it possesses a hybrid of low and high kick point dynamic flex profiles, not because it is most easy to bend in the middle. Sticks are designed to have these specific kick points to maximize specific shot performance parameters, such as speed, accuracy, and quickness.

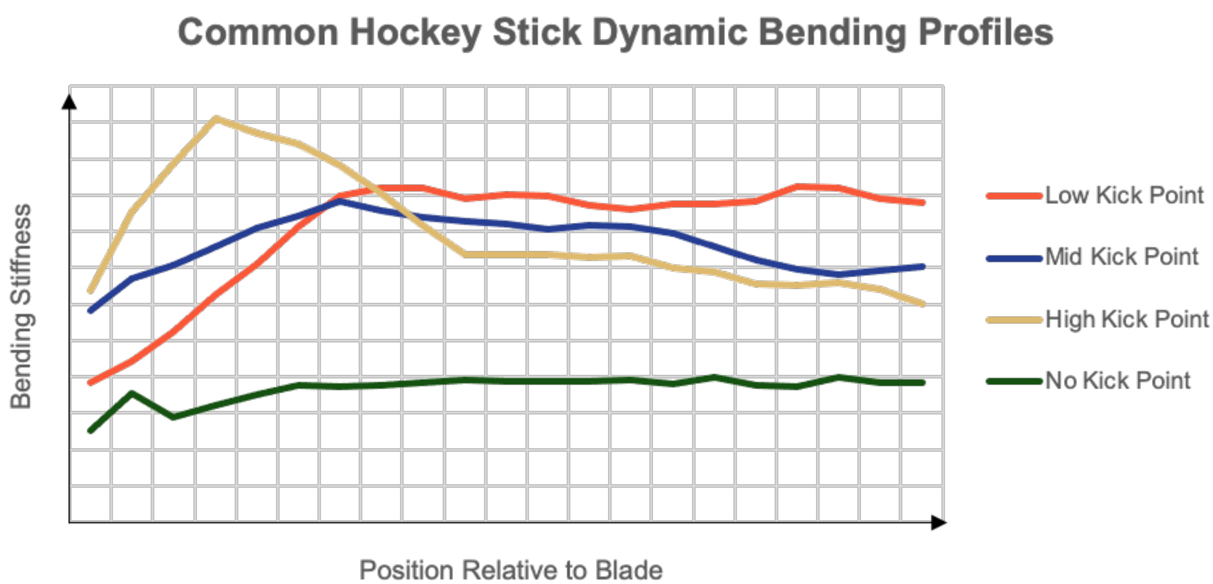

Figure 2. Theoretical depiction of common dynamic flex profiles used in the design of modern carbon composite hockey sticks.

Published academic research on the effect of stick dynamic flex profiles is scarce. However, it is generally believed that low kick point sticks assist with release quickness while high kick point sticks are best for maximizing stick bend and puck velocity (Legault, 2012).

Traditionally, these dynamic flex profiles have been achieved through material means with stick developers using stiffer materials, different lay-up orientations or simply more layers of materials in different portions of the stick. Given the prominence of stick weight as a driving factor of hockey stick selection (Hove et al., 2006), stick developers have begun turning to geometric strategies for tuning shaft bending stiffness in key portions of the hockey stick shaft (Rouzier & Chambert, 2020). For example, Bauer's high kick point *Ultrasonic* stick released in 2020 features a 7-sided shaft taper in the lower portion of the shaft (Figure 3A) to achieve increased bending stiffness in the lower portion of the stick without added material. Similarly, Bauer's mid kick point *Geo* stick features a "spine" along the mid-section of the shaft, tapering back to a rectangular cross section toward the top and bottom of the shaft (Figure 3B). These approaches allow stick designers to manipulate stick stiffness without adding material layers. Hence, dynamic flex profiles can be maintained while weight is reduced.

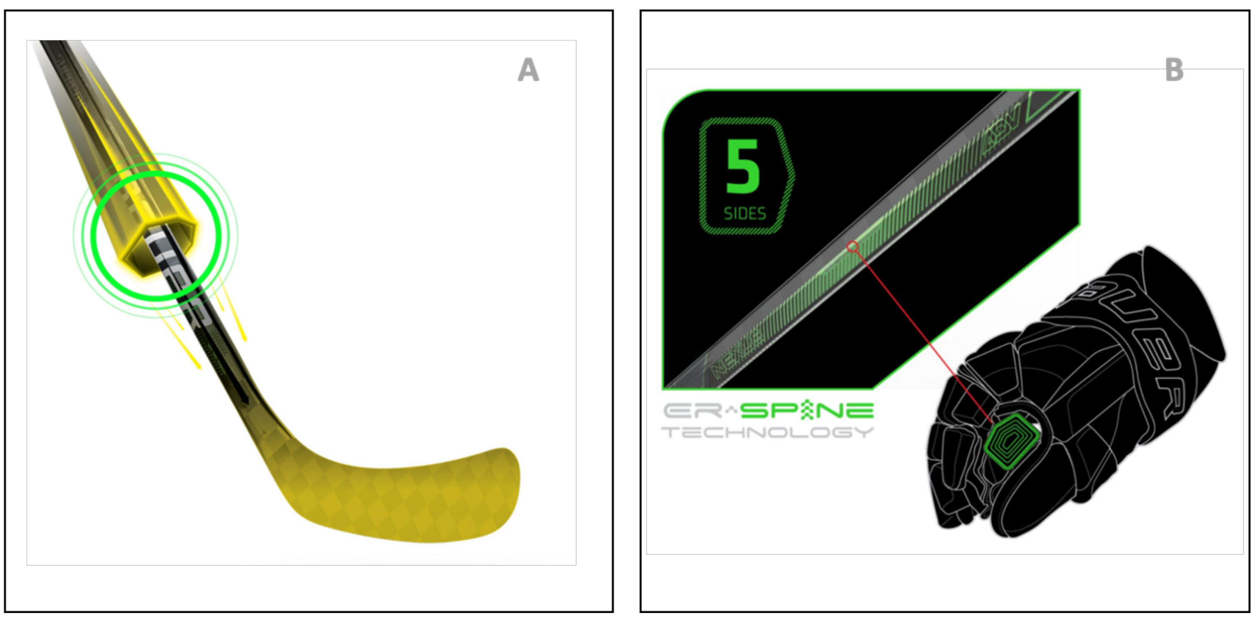

Figure 3. Depiction of the geometric approaches to achieving stick dynamic flex profiles in Bauer's Ultrasonic (A) and Geo (B) sticks (Bauer Hockey Ltd., n.d.-b).

2.2.3 Blade Pattern ("Curve" & "Lie")

Blade pattern is the mold that the blade is made from. Characterized by the curve of the blade (i.e. how deep it is, how open it is, and where the curve originates along the blade) and the lie (i.e. the angle between the blade and the shaft). Higher lie angles represent a more upright shaft position when the blade sits flat on the ice. The magnitude and degree of blade curvature are limited by regulations which state that the curvature of the blade cannot exceed three-quarters of an inch beyond a perpendicular line between any point of the heel and toe of the blade (NHL, 2020a; Rule 10.1). These rules from the NHL have been adapted to apply to players at every level (USA Hockey, 2021; Rule 301).

Research on the effect of blade patterns has shown that flatter curves may enhance shot speed by affecting the spatiotemporal characteristics of blade and stick loading during the slap shot (Gerbé, 2016). This may occur due to systematically decreased lag between blade-toe and blade-heel ice contact similar to how advanced hockey players achieve higher puck speeds by "pinning" the stick blade earlier and storing more strain potential energy in the stick (Lomond et al., 2007).

In contrast, the very origin of blade curves was to provide players with added levels of puck control (Anderson, 2008). Mechanically, more "open" curves—those with a more negative pitch (Figure 4)—make it easier to apply lift to the puck and consequently reach the upper net on forehand shots while a more pronounced curve and proper lie aid with puck control. Michaud-Paquette *et al.* (2009) found blade yaw angle, pitch angle, and change in pitch angle to be significant predictors of accuracy in lower net targets while blade roll, change in blade pitch and yaw, and maximum shaft bend were all found to be significant predictors of accuracy for upper net targets (Michaud-Paquette et al., 2009). Making these adjustments through mechanical adaptations of the blade may assist players in achieving these specific release parameters during shooting.

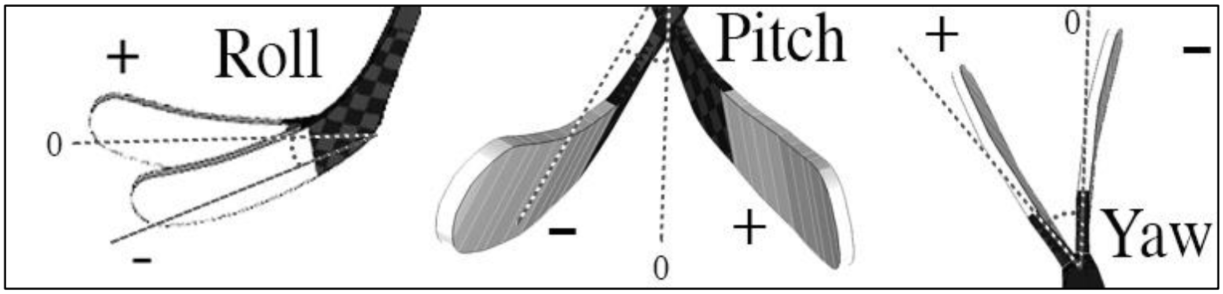

Figure 4. Hockey stick blade roll, pitch, and yaw reference frames (Paveck, 2015).

2.3 Ice Hockey Stick Selection & "Fitting"

Despite the substantial body of research on the systematic effects of ice hockey stick parameters on shooting performance, most players today do not utilize scientific means to determine which stick they use.

Marino and Cort (2004) identified five factors that influence the selection of ice hockey sticks. These factors are stick cost, appearance, feel, performance, and durability (Marino & Cort, 2004). Cost may prove prohibitive or not depending on a player's level of play and financial assets while appearance depends on the graphics, colours, and use of lettering on the stick. Feel, performance, and durability depend on the dynamic response of the stick's mechanical design and materials. Research suggests that the correct matching of mechanical characteristics of the stick to the physical attributes of the player—such as strength, size, kinematics, and perceptions—can improve shooting performance (Marino & Cort, 2004).

Factors such as feel, performance, and durability are challenging to assess for the consumer without testing the product. Thus, companies and retailers have attempted to offer stick "fitting" services: sessions with trained professionals to find the optimal stick for a player based on their individual technique and playing habits (Radia, 2010). The concept of stick fitting began in golf, where many players are able to pay for club recommendations based on their personal, static, and dynamic characteristics (Mauger, 2002).

2.3.1 Important Concepts and Trends in Golf Club Fitting

Since the early 2000s, club fitting practices in golf have grown at a rapid pace (Bertram & Guadagnoli, 2008; Harper et al., 2005; Mauger, 2002). There is much variety in the exact process between "fitters", however, the general methods used in golf club fitting are personal, static, and dynamic measures (Mauger, 2002). Personal fitting measures include items that could be extracted from a self-reported questionnaire like age, height, weight, and current club properties. Static fitting measures are those captured by a fitter but not in the dynamic sporting action, such as hand to floor distance, grip strength. Dynamic fitting measures are data points captured during the sporting action itself, such as club head speed, shaft deflection, and launch angle. The inherent challenge of using static measures in the implement fitting process is that they are not able to account for the nuanced interaction between the athlete and their club during the swing.

Mauger (2002) found dynamic fitting procedures were the most valuable data to fitters when helping athletes find their best implement fit. Mauger also provided two recommendations for future fitting systems. First, biomechanics motion capture systems should be integrated to the dynamic measurement process to capture data about the club head, shaft, and ball without interfering with the golfer's swing. Second, a big data approach to building recommendations should be taken by using AI-driven "expert systems" to match the many channels of data gathered from a player against patterns within a larger set of golfer data and their corresponding club recommendations.

2.3.2 Important Concepts and Trends in Hockey Equipment Fitting

Hockey gear is still sold mainly in physical retail stores. Intuitive, as players need to try equipment to ensure good fit before buying it. In the sport of hockey, skates are one such piece of equipment where fit is paramount (Pearsall & Robbins, 2019). Skates are also the most expensive piece of hockey equipment, with top end skates selling for over $1100 (Bauer Hockey Ltd., n.d.-a).

The shopping experience with skates is similar to that of shoes, whereby a consumer looks at a wall of available skate models in a store, has their feet measured by a sales associate, and then tries on one or more pairs of skates to see how they fit and feel. From a retailer's perspective, this makes skates a "full service" product category where consumers require a designated salesperson to guide them through their purchasing experience.

Recently, hockey companies have invested heavily in automating skate fitting processes. Traditional analog measurement tools such as the Brannock device, which was first introduced in 1927, are being replaced by in-store scanning kiosks that can capture the three-dimensional measurements of the foot and compare that with the space available within a specific company's skates to suggest a size. Bauer's 3D Skate Lab is one such example (Figure 5).

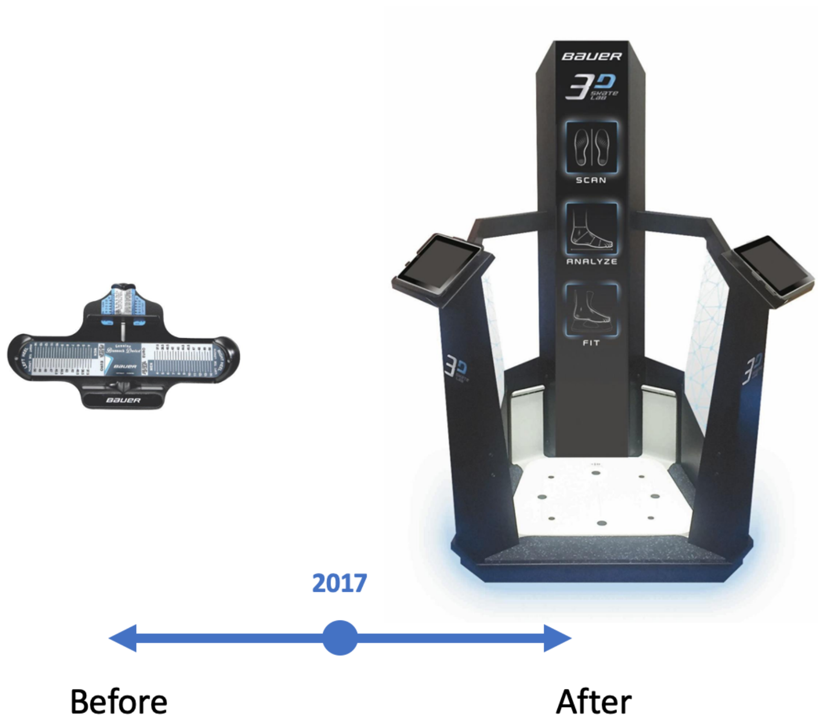

Figure 5. Bauer Hockey's introduction of the 3D Skate Lab kiosk in 2017 replaced time-consuming, traditional two-dimensional foot data collection with three-dimensional foot data available in matter of seconds, drastically changing the process of skate fitting.

The introduction of this technology exponentially improves hockey equipment fitting processes, taking up little floor space and automating detailed anthropometric foot shape measures with greater accuracy and minimal time commitment of retail store personnel. This places higher consumer expectations for similar accurate and rapid stick fitting practices in retail environments.

2.3.3 Important Concepts and Trends in Ice Hockey Stick Fitting

The hockey stick is thought to account for as much as 50% of shooting performance (Wu et al., 2003). Further, as ice hockey sticks continue to adopt technological innovations, sticks will continue to become more expensive. Today, top end sticks retail for as much as $350 CAD (Bauer Hockey Ltd., n.d.-b). Thus, players want to determine the exact stick characteristics that they should be using for optimal performance. To bridge this gap, hockey stick companies have begun offering hockey stick fitting services.

One of the first companies to begin offering stick fitting services commercially was a start-up hockey stick company Base Hockey in 2010 (Radia, 2010). Over the past ten years, major players in the ice hockey stick industry, Bauer and CCM, have made substantial advances to consolidate their respective full fitting processes. These “full” stick fitting procedures require 45 to 90 minutes with a professional sports scientist and/or former professional player. Today, fitting procedures can be accomplished in 5-to-15-minutes using programmed tablets operated by a minimally trained salesperson in a retail environment. At present, both companies’ custom-made applications use a combination of personal (i.e. position, importance of shot speed/accuracy/quickness), static (i.e. height, weight), and dynamic (i.e. shooting technique, stick bend) measurement. Both companies’ applications also capture dynamic measures using high-quality, high-speed video of a slap and wrist shot to analyze a player’s shooting technique and provide recommendations of optimal stick flex and kick point.

After capturing video in Bauer’s *Stick Studio* app, the operator manually identifies key events throughout the slap shot and wrist shot (United Sport & Cycle, 2019). Then, they answer a series of questions based on the position of the puck at these various phases of each shot. When using the retail version of CCM’s *Stick Fitter* app, the operator overlays virtual markers on top of the top hand on the stick and the puck to calculate the maximum stick deflection achieved during slap and wrist shots respectively (CCM Hockey, n.d.). For both apps, these fitter-derived performance metrics are fed through back-end code that generates stick flex and kick point recommendations to the player.

Despite the advancement of these processes over their analog predecessors, there is still pushback from retailers who claim they take too long. The obvious extension of this work is to replace these human-operated systems with automated, computer vision systems, however, recent advancements in this approach have failed to address this problem (Mendhurwar et al., 2020). Mendhurwar et al (2020) reported building a computer vision algorithm capable of calculating 3D stick bend using two stereo camera inputs. The issue was that this took 111 seconds of processing time per frame, adding up to approximately 18 minutes of processing if focused solely on the frames during which a player is in contact with the puck. Thus, alternative technological approaches to dynamic hockey stick fitting are needed.

One potential solution lies in machine learning models driven by inertial measurement unit (IMU) signal characteristics. Inertial measurement units—which are typically comprised of an accelerometer, gyroscope, and magnetometer—have been used in a variety of contexts to classify non-cyclical human movements (Crema et al., 2017; Groh et al., 2015; McGrath et al., 2021). Thus, some sort of embedded sensor capable of measuring linear and angular motion could be well suited for the purposes of automatic stick fitting processes with minimal human processing.

2.4 Factors Influencing the Perceptions of Sporting Implements

All science aside, it is ultimately players who must decide which stick to use. Research of sporting implements has shown this to be most closely related to implement “feel” (Roberts et al., 2006).

Research of tennis rackets (Bauer et al., 2020), golf clubs (Roberts et al., 2006, 2001, 2005), ball bats (Noble, 1998; Noble & Walker, 1994), and field hockey sticks (Carré & McHutchon, 2006) suggest these perceptions of feel are driven by feedback gathered by the athlete around impact.

There are four main types of feedback streams: kinaesthetic, visual, acoustic, and haptic. Kinaesthetic and visual feedback are challenging to quantify and inseparable from the athlete while it is not feasible for the purposes of ameliorating stick fitting processes to measure acoustic and haptic feedback directly.

In-glove IMUs could be a simple, unobtrusive and indirect way to measure gross hand kinematics that may correspond to haptic feedback. If it could be understood what characteristics specifically drive perceptions of sticks, these measures could be monitored in real time and/or with little processing time to deliver players with prompt stick fitting insights (Desbiens, 2021).

3. Objectives and Hypotheses

The aims of this study were to 1) understand the relationship between subjective perceptions and objective performance metrics with ice hockey sticks and 2) evaluate the feasibility of using inertial measurement unit (IMU) sensors and machine learning algorithms for the rapid fitting of ice hockey sticks.

Based on the previous literature, it was hypothesized that participants would not be able to correctly discriminate differences in performance between the sticks and that some sort of bias towards a prominent source of performance feedback would influence stick perceptions. As for the relationship between stick properties and performance, it was hypothesized that there would not be significant differences between the reference stick (Stick A) and the low flex stick (Stick B), but that shot speed would be significantly higher with the flatter blade pattern (Stick C). It was also hypothesized Stick C would be associated with lower shot accuracy. No hypotheses regarding the effect of kick point on shooting performance were made.

This was an exploratory study on the use of in-glove IMUs in a hockey shooting context, however, motivation and inspiration was derived from previous studies which have shown kinematic signals obtained using IMUs and machine learning algorithms to be capable of classifying athletic movement patterns (McGrath et al., 2021). It was hypothesized that differences in hand kinematics would be characteristic of different responses to stick flex, blade pattern and kick point.

4. Methods

4.1 Participants

Ten left and right-handed experienced male hockey players were recruited for this study. Two participants had experience at the Junior A level, five at the Canadian/American university level, and three at the professional level. All participants had played hockey in the past calendar year and were free of serious injuries at the time of data collection. Descriptive statistics of the participants are provided in Table 1. Testing procedures were explained in written and oral format to the participants, who then provided informed written consent in accordance with the Tri-Council Policy Statement on Ethical Conduct for Research Involving Humans (McGill REB II, File #: 375-0216) prior to data collection.

Table 1. Descriptive statistics of participants.

Measure	**Mean ± SD**	
Age (yrs)	25.9	± 4.9
Height (m)	1.81	± 0.07
Weight (kg)	88.5	± 7.7
Hockey Playing Experience (yrs)	20.3	± 3.7
Grip Strength (N): Top Hand	400.7	± 31.6
Grip Strength (N): Bottom Hand	400.2	± 36.0

4.2 Testing Instrumentation

Testing instrumentation was similar to that used by Denroche (2020), with Denroche's inertial sensor motion capture system (MVN Link, Xsens Technologies B.V., Enschede, Netherlands) replaced by custom-made in-glove inertial measurement unit (IMU) sensors (Motsai Research, Saint-Bruno-de-Montarville, QC, Canada) to more closely monitor the movement of the hands. The IMUs provided measures of linear acceleration and angular velocity and were placed in an opening along the glove thumb. This instrumentation configuration was chosen to ensure the IMU placement would not affect players' shooting technique during data collection and could be easily replicated in a real-world fitting context.

4.2.1 Vicon System

A Vicon optoelectronic system (Vicon, Oxford, UK) was used to capture three-dimensional kinematics of the body, stick, and puck. Such measures are important for the calculation of performance variables (i.e. shot speed, shot accuracy, quickness of release) and monitor changes in shooting technique across the different experimental conditions. The Vicon system consisted of 18 cameras: Eight T10S, two T40S, four Vantage V5 and four Vero 2.2 cameras recording at a sampling rate of 240 Hz. The cameras were mounted on tripods at various heights surrounding the capture area and were connected to an MX Giganet connection Hub and desktop computer. Camera positions remained consistent throughout the entire data collection. Fifty-two spherical retroreflective markers with a diameter of 14 mm were placed on the participant in accordance with an adapted version of the Plug-in Gait full body model (Nexus 2.6, Vicon, Oxford, UK) (Figure 6). Notable adaptations included the use of four-marker clusters on the forearm to reduce lower-arm collinearity during shooting (in place of a single forearm marker). This included five-marker clusters placed on the outside of a standard set of hockey gloves to monitor hand kinematics without disrupting realistic tactile feedback (in place of hand markers), and a pair of markers located on the medial and lateral aspects of the forearm proximal to the wrist to approximate wrist position without interfering with wrist movement during the shot (in place of wrist markers). The same set of gloves were worn by all participants during data collection. Foot marker placement remained the same; however, these markers were placed on the exterior of the ice hockey skates worn by the participant.

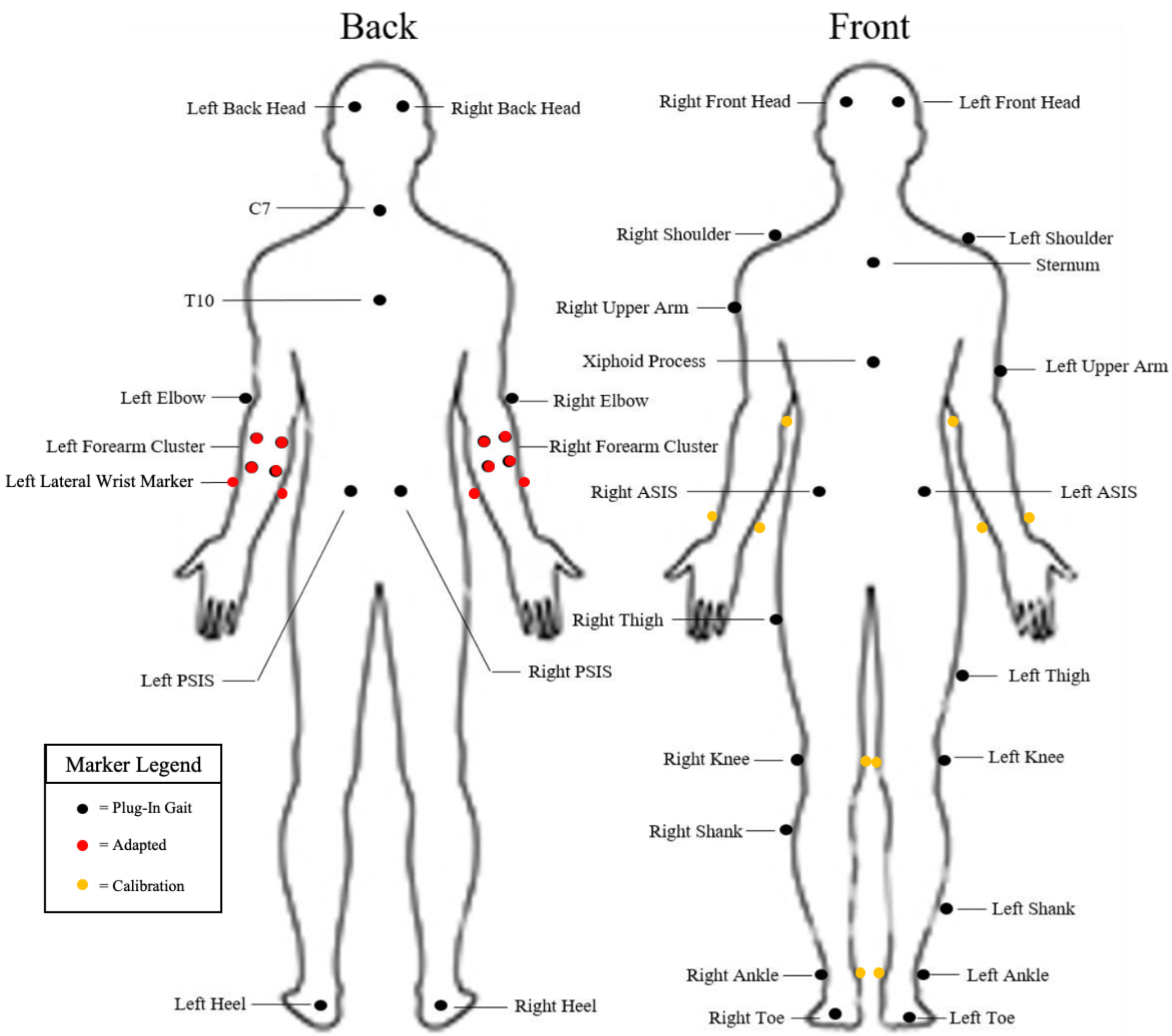

Figure 6. On-body reflective marker placements in the adapted Plug-in Gait model. Black markers are consistent with the standard model. Red markers represent adapted components.

Four markers were placed on the puck and ten along the stick's shaft and blade (Figure 7) to measure puck and stick kinematics, respectively. An additional eight markers were placed along the posts and crossbar of the net to compute puck-to-target accuracy measures. These three marker sets were important for the calculation of shot events.

Figure 7. Reflective marker placement on gloves, stick and puck. Markers on the stick are indicated by the red arrows (Denroche, 2020). IMU sensors were placed within an opening in the padding on each glove's thumb.

Prior to the start of testing, participants recorded a static calibration pose held by each participant for five seconds with the arms parallel with the floor and elbow bent to 90°. This calibration is required to determine the model of each participant's initial coordinate system reference frame.

4.2.2 IMU System

Bespoke IMUs capable of capturing linear acceleration in gravitational units and angular velocity in degrees per second (Motsai Research, Saint-Bruno-de-Montarville, QC, Canada) were inserted in an opening in the thumb segment of each glove during testing to capture concurrent kinematics of the hands. Data capture for the IMU system was initiated by a second researcher through the use of a custom-built tablet application (Bauer Hockey Ltd., Blainville, Canada) over Wi-Fi connection. The IMUs were comprised of an accelerometer capturing linear acceleration in gravitational units and a gyroscope capturing angular velocity in degrees per second at a rate of 200 Hz.

4.3 Testing Protocol

Testing took place in the Biomechanics and Performance Analysis Lab at McGill University's Currie Gymnasium in Montréal, Québec. The 18 Vicon cameras were placed around a synthetic ice surface (Viking, Toronto, Canada) (Figure 8), providing a capture volume approximately 8.0 m long x 3.4 m wide x 2.0 m high.

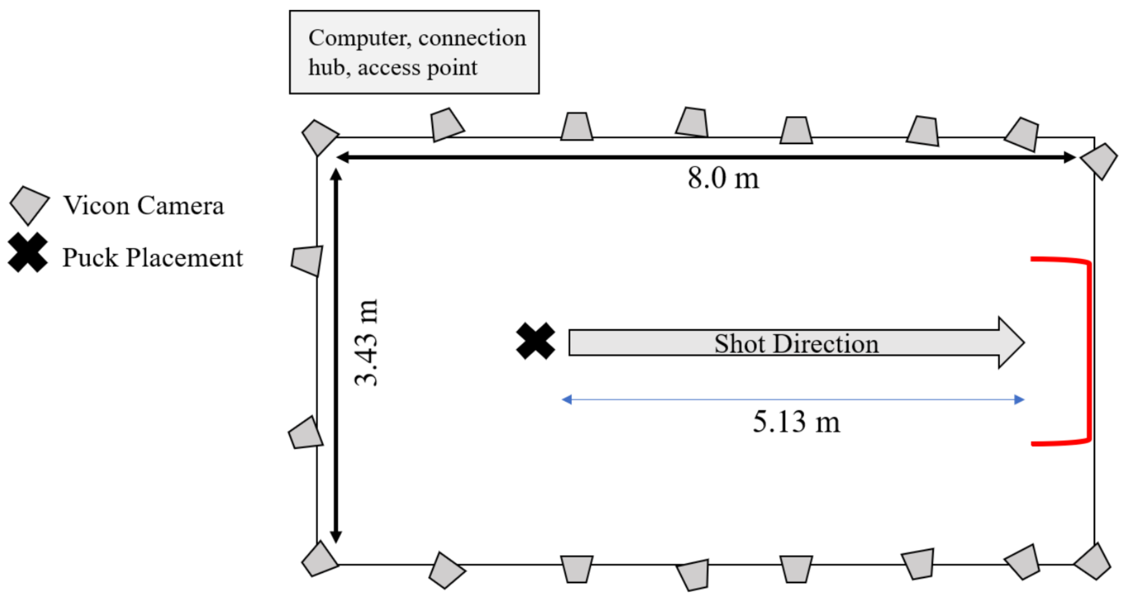

Figure 8. Top view layout of the motion capture area in the Biomechanics and Performance Analysis Lab during data collection.

After obtaining informed written consent, anthropometric measurements were taken as necessary for the Plug-In Gait model. These included height, weight, ankle width, knee width, leg length, hand thickness, wrist width, elbow width, shoulder offset (anterior-posterior thickness), and shoulder breadth. Participants were then fitted with a full-body, tight fitting Velcro suit (OptiTrack, Corvallis, OR, USA). Retro-reflective markers for the Vicon system were placed on the Velcro suit at anatomical locations in accordance with the adapted Plug-in Gait specifications. Participants also received a pair of skates (Bauer Vapor 1X) and a pair of gloves (Bauer Nexus) (Bauer Hockey Ltd., Blainville, Quebec) to be used during testing. After the static calibration trial was recorded, participants were given time to warm-up and get accustomed to the synthetic ice surface by taking practice shots on the net.

Testing consisted of 10 stationary wrist shots and 10 stationary slap shots with 4 sticks of uniform length but with different properties (Table 2), for a total of 80 shots. Stick A was the "baseline" stick and Sticks B-D varied from Stick A in bending stiffness, blade pattern, or dynamic bending profile respectively. Stick B had a lighter flex rating (70) than Stick A (95) and was thus easier to deform. Stick C had a less curved blade pattern (PM9) than Stick A (P92). Stick D had a higher kick point (high) than Stick A (low) due to differences in layup and geometry of the shaft taper. Bending stiffness, blade pattern, and dynamic bending profile were manipulated separately to understand the isolated influence of each on shooting kinematics, performance measures, and stick perceptions. The sticks were representative of those commonly used by players of similar caliber but absent of graphics to blind participants to differences between the sticks.

Table 2. Specifications of the four sticks used during testing. Stick A was used as a "baseline" implement. Values bolded show the property of difference for Sticks B-D.

	Flex	**Blade Pattern**	**Kick Point**
Stick A	95	P92	Low
Stick B	***70***	P92	Low
Stick C	95	***PM9***	Low
Stick D	95	P92	***High***

At the beginning of each trial, participants stood adjacent to the puck placed at a mark 5.13 m away from the net. Participants did not receive specific instructions with respect to their technique but were asked to shoot like they normally would in a game from a stationary position and to strive for maximum velocity and accuracy, aiming at a 0.3 m diameter circular target suspended from the center of the net crossbar (Figure 9).

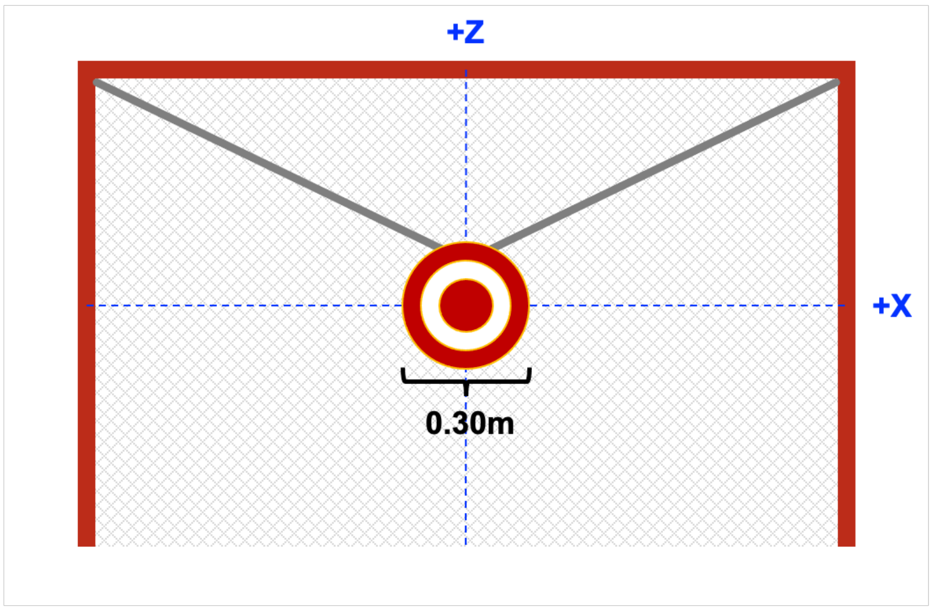

Figure 9. The 0.30m circular target—suspended in the center of the net using rope—which participants aimed for during each trial. Global Vicon X and Z axes are shown in blue.

Trials were performed in blocks of 10 shots. Between each block, participants received approximately 1 minute of rest and were asked to provide verbal ratings of the speed, accuracy, and feel with the stick and shot type they had just used on scales from 1 to 10. Perception data were captured as 10-point ratings to take advantage of participant familiarity with rating 'out of 10' and to provide greater granularity than 5- or 7-point scales (Dawes, 2008). Verbal end-point anchors were used to limit the burden and reliance on the respondents when evaluating the sticks subjectively (Dawes, 2008). At the end of testing, participants were asked to verbally rank the sticks in order of overall preference. Separate rankings of wrist and slap shot were recorded for each participant.

Each participant performed the first 20 trials with the reference stick (Stick A), with subsequent stick exposure orders assigned using the first ten orders from a permutation generator to approximate a crossover-balanced design. Shot exposure order (wrist-slap-wrist... or slap-wrist-slap...) alternated between participants.

Table 3. The four prompts used to acquire subjective ratings of stick speed (Q1), accuracy (Q2), and feel (Q3) and stick preference (Q4). * = the end of the scale associated with the most favorable rating.

	Prompt	**Scale**
Q1	*On a scale of one to ten how would you rate your shot speed with this stick?*	1-10*
Q2	*On a scale of one to ten how would you rate your accuracy with this stick?*	1-10*
Q3	*On a scale of one to ten how would you rate the overall feel of this stick?*	1-10*
Q4	*Rank the sticks, from your favourite to least favourite*	*1-4

Table 4. Subjective ratings and rankings of sticks across wrist and shot types using P02's responses as an example.

	Wrist Shots				**Slap Shots**			
	Q1	***Q2***	***Q3***	***Q4***	***Q1***	***Q2***	***Q3***	***Q4***
Stick A	8	10	8	1	10	7	8	2
Stick B	9	7	8	3	9	7	8	3
Stick C	8	8	7	2	9	6	6	4
Stick D	9	9	9	4	10	9	10	1

4.4 Data Analysis

4.4.1 Data Processing

Data captured using the Vicon cameras was processed using Vicon Nexus 2.6 software. Processing consisted of marker data identification (“labelling”) and gap filling (interpolating missing marker positions). This “processed” data from the Nexus software were then imported into Visual3D software (Ver 5.01.23, C-Motion, Germantown, USA) where data were filtered using a 4th order Butterworth filter with a cut-off frequency of 25 Hz and all 3D calculations and event detections were performed. Shot events were verified and data was organized and normalized using the MATLAB-based biomechZoo toolbox (Dixon, 2017).

IMU data for both the left and right sensor were combined in the same file for each trial. Acceleration and gyroscope data was filtered with 4th order lowpass Butterworth filter with a cut-off frequency of 20 Hz.

Subjective ratings of shot speed, accuracy, and feel were converted to 4-point rankings to 1) reduce the influence of between-participant variability on quantitative measures of stick perceptions, 2) preserve perceived differences between the sticks, and 3) perform non-parametric statistics to quantify the magnitude of perceived differences between the sticks (Roberts et al., 2008).

4.4.2 Calculating Objective Performance Measures

Objective measures of speed, accuracy, and contact time were calculated in MATLAB R2020a software (The Mathworks, Natick, MA, USA) after processing with biomechZoo was complete. Vicon kinematic data and shot events (

Table 5) were used to generate measures of speed, accuracy, and contact time for each trial.

Shot speed of each trial was measured as peak puck velocity in the Y (towards the net) between puck contact/forward movement (CON/FOR) and net entry (ENTRY) events for slap and wrist shots respectively in meters per second (m/s). Shot accuracy of each trial was measured as radial error (Equation 3), where x is distance from target centre to puck in X (the horizontal direction) at net entry and z is distance from target center to puck in the Z (vertical direction) at net entry in meters (m). Stick-puck contact time for each trial was measured as the time between puck contact and release (REL) for slap shots and between forward movement and release for wrist shots in milliseconds (ms).

Equation 3. Radial Error (Hancock et al., 1995).

$$RE = \sqrt{(x^2 + z^2}$$

The use of these specific performance measures was motivated by the performance metrics previously used in ice hockey performance research.

4.4.3 Joint Angle Calculations

Joint angles for the ankle, knee and hip were defined by XYZ rotation, consistent with the joint coordinate systems described by Wu et al. (2005) and Grood and Suntay (1983). X-rotation was defined as flexion (+) and extension (-), while Y-rotation was defined as adduction (+) and abduction (-) and Z-rotation was defined as internal rotation (+) and external rotation (-). Similarly, head angles were measured with respect to XYZ rotation around the thorax where X-rotation was defined as extension (+) and flexion (-), Y-rotation was defined as side flexion (right +/left -) and Z-rotation was defined as rotation (left +/right -). Trunk angles were defined by YXZ rotation with respect to the pelvis where X- rotation was defined as extension (+) and flexion (-), Y-rotation was defined as side flexion (right +/left -) and Z-rotation was defined as rotation (left +/right -). Finally, shoulder angle calculations used a Z-Y-Z rotation sequence, in accordance with the ISB recommendations and Wu et al. (2005). Consistent with the C-Motion Plug-In Gait guidelines (C-motion, Germantown, USA), the shoulder joint centre was inferior to the acromion marker by a distance combining the measured shoulder radius and the marker radius. X-rotation was defined as horizontal abduction where 0° was abduction and 90° was forward flexion. Y-rotation was defined as rotation about the humerus Y-axis where negative values represent elevation. Lastly, Z-rotation was defined as internal (+) and external (-) rotation.

Global blade angles in the X, Y and Z directions were defined as pitch, roll and yaw, respectively. Blade pitch was defined as the opening (+) and closing (-) of the blade face; roll as the toe up (+) and toe down (-) of the blade and yaw as the inward rotation (+) and outward rotation (-) of the blade (Figure 4).

For the IMU's, only the Z axis was systematically aligned in the glove due to technical challenges related to consistency. The +Z axis was aligned in the glove in the direction of thumb extension with the +X and +Y orthogonal to this axis (Figure 10). For this reason, only the resultant channels of the IMU's accelerometer (linear acceleration in gravitational units) and gyroscope (angular velocity in degrees per second) were used for analysis.

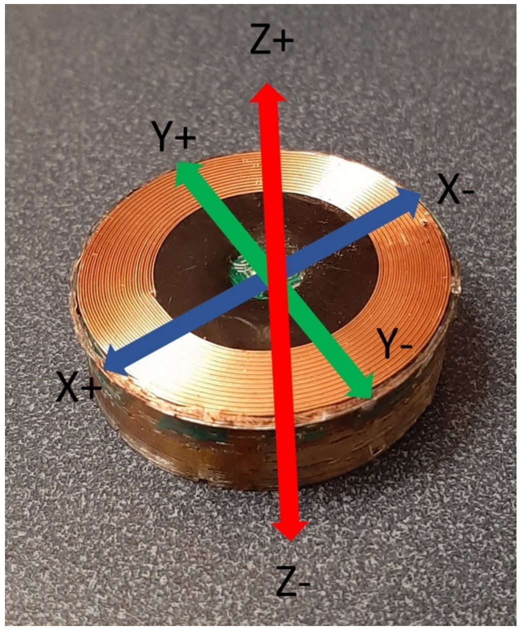

Figure 10. IMU axes. The +Z was systematically aligned in the “thumbs up” direction, however, the direction of X and Y were not held consistent across testing.

4.4.4 Event Detection

Signal events were defined from the Vicon data in Visual3D. Events were calculated using the stick and puck markers with respect to the global coordinate system:

> Z-axis in the vertical direction (i.e. perpendicular to the synthetic ice surface), +Z towards the ceiling of the lab space (Figure 9).
>
> X-axis perpendicular to the direction facing the net (i.e. parallel to the crossbar of the net), with +X towards the right post (Figure 9).
>
> Y-axis was the cross-product of the Z and X axes, with +Y towards the net and the Y-axis itself aligned with the middle of the net.

Five events in sequence order were defined for the slap shot, while four events were defined for the wrist shot (Table 5).

Table 5. Names and definitions of slap and wrist shot events.

Shot Type	Event Name	Description
Slap	TOP	The frame when the B1 blade marker was at its highest position in the global Z-axis (i.e. the start of the downswing).
	GRND	The frame of maximum blade acceleration in the +Z between the TOP and CON events (i.e. when the blade made contact with the ground).
	CON	One frame before puck velocity in the Y exceeded 5.0 m/s (i.e. when the blade made contact with the puck).
	REL	The frame when the distance between the B3 blade marker and the puck exceeded 0.075 m (i.e. when the puck had been "released" from the blade).
	ENTRY	The frame when the distance between the puck and the net was less than 0 m in the Y (i.e. when the puck "entered" the net).
Wrist	BACK	The final frame when blade velocity passed 0.05 m/s in the Y before the FOR event (i.e. the start of the shot).
	FOR	The frame when blade acceleration in the Y exceeded 150 m/s^2 (i.e. when the blade begins moving forward).
	REL	One frame before the distance between the B3 blade marker and the puck exceeded 0.090 m (i.e. when the puck had been "released" from the blade).
	ENTRY	The frame when the distance between the puck and the net was less than 0 m in the Y (i.e. when the puck "entered" the net).

All trials were inspected for completeness, data quality and event placement prior to the statistical analysis. Vicon trials were removed if certain events were unable to be detected in Visual3D; for example, if the trial ended prematurely or stick or puck markers had fallen off or went undetected by the Vicon system (n = 43). Since IMU trials did not have events, trials from this dataset were only omitted if they ended before the shooting motion had finished (n = 44). Due to differences in the causes of trial omission, the Vicon and IMU datasets were analyzed separately. Despite the fact they are of similar size, the datasets should not be confused as identical.

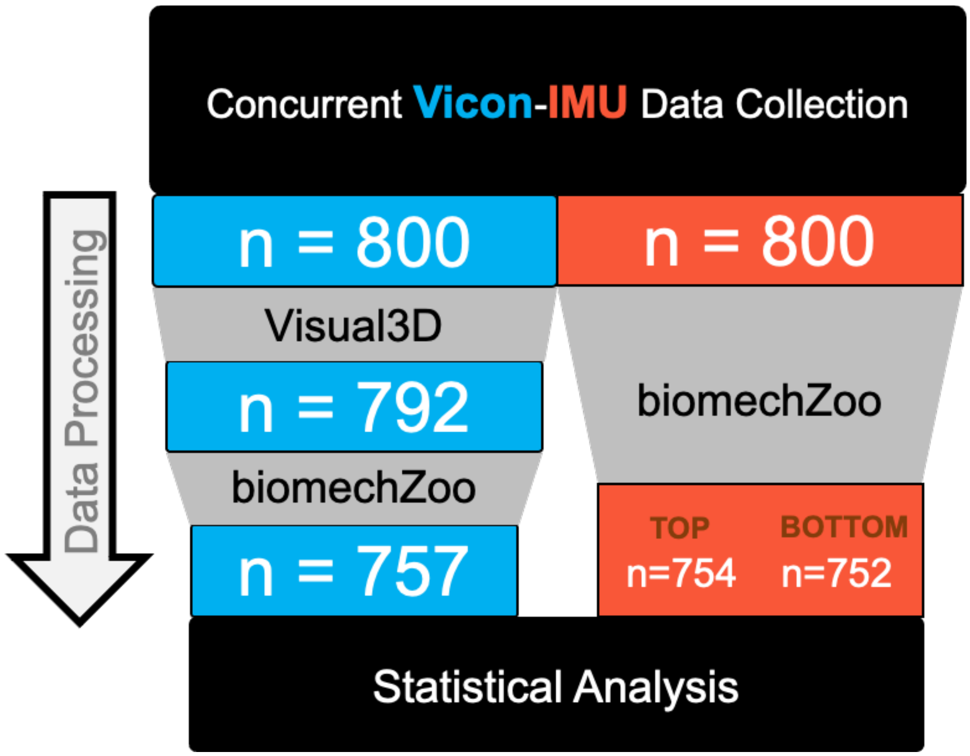

Figure 11. Schematic depicting data processing pipeline. Vicon data were passed through Visual3D and biomechZoo. IMU data were passed through biomechZoo only.

4.4.5 Data Normalization

All data were reflected to one body side to account for kinematic differences due to handedness. The terms “contralateral” and “ipsilateral” replaced “left” and “right” when identifying limb-specific kinematic signals. For example, a left-handed shooter’s bottom (i.e. left) hand on the stick was referred to as their ipsilateral hand, while their top (i.e. right) hand was referred to as their contralateral hand, and vice versa.

4.4.6 Machine Learning Model Validation

The prediction models of stick fit based on shot speed was done using k-Nearest Neighbors (KNN) classification with MATLAB R2020a’s Machine Learning Toolbox. The models were trained using a 5-fold cross validation and principal components explaining 95% of the data features to protect against overfitting with small sample sizes.

Three separate models were created for each channel to fit players for flex, blade pattern, and kick point. Slap and wrist shot data were analyzed separately.

Separate models were trained and tested on their ability to classify (i.e. fit) shooters using four different channels from the in-glove IMUs:

1. Top hand resultant linear acceleration (Top_A)
2. Top hand resultant angular velocity (Top_G)
3. Bottom hand resultant linear acceleration (Bottom_A)
4. Bottom hand resultant angular velocity (Bottom_G)

The true values of stick fit (for training the algorithms and evaluating model accuracy) were based on the stick with higher mean shot speed to the nearest whole meter per second (m/s). Thus, within each model, there were three possible responder conditions: Non-responder (Stick A = Stick X), Reference-responder (Stick A > X), and Other-responder (Stick X > A).

The inputs of each model were reduced from 199 data points to the 14 to 18 principal components that explained 95% of the variability within the waveform data (Table 6). In other words, principal components—rather than complete waveforms—were the features used to develop the algorithms.

Table 6. Number of trials (n) and features (PC) used for each algorithm.

		Top_A	Top_G	Bottom_A	Bottom_G
Slap	*n*	374	374	372	372
	PC	18	14	16	15
Wrist	*n*	380	380	380	380
	PC	15	15	16	15

For all models, standardized data, a Euclidean distance metric, equal distance weight, and a default misclassification cost matrix were used, and hyper parametrization was disabled.

4.5 Statistical Analysis

An array of statistical tests was conducted to analyze the quantitative subjective and objective data. All statistical tests were conducted using MATLAB R2020a (The Mathworks, Natick, MA, USA) with alpha set at 0.05.

4.5.1 Subjective Stick Perception Measures

Since perceptual ratings are not normally distributed, parametric statistics were not considered appropriate for analysis (Roberts et al., 2008). Additionally, it was unlikely that the differences between scale values obtained during testing represented an equal change in sensation across scales (i.e. speed, accuracy) or between participants. Therefore, stick ratings (1-10) were first transformed into a stick ranking (1-4) for each scale (speed, accuracy, feel, overall) for each shot type and participant. These ordinal data were then analyzed using non-parametric statistics.

Mean rank was calculated for the four sticks for each scale. These values were then used to identify perceived differences between the sticks using the Friedman two-way analysis of variance by ranks. Fisher's least significant difference (LSD) was calculated to identify where significant differences in stick perceptions emerged (Roberts et al., 2008).

At the 0.05 level of significance, the critical value for T is 7.8. Values greater than this indicate that participants perceived differences between the sticks. If projections of ½ Fisher's LSD from each stick's mean rank were not overlapping, this indicated significant differences between sticks.

4.5.2 Objective Stick Performance Measures

The experimental design included two independent variables: Shot Type (Sh_2) and Stick (St_4). The four stick levels were the reference stick (Stick A), the low flex stick (Stick B), the flat blade pattern stick (Stick C), and the high kick point stick (Stick D). Since the interaction between performance parameters and shot type was not a focus of this study and outcome variables were conceptually independent, data were analyzed using multiple one-way repeated measures analyses of variance (ANOVAs) for each of the three dependent variables (Huberty & Morris, 1989): puck velocity, shot radial error, and stick-puck contact time. If statistical significance was achieved (i.e. $p < 0.05$) post hoc analysis was performed using the Tukey-Kramer procedure.

4.5.3 Perception-Performance Relationships

Principal component analysis (PCA) was used to determine the relationship between sensory ratings and objective performance measures with each stick. PCA was performed on a 4×8 matrix with one score per stick per attribute for slap and wrist shots. The attributes were speed rating, accuracy rating, feel rating, overall ranking, measured speed, measured accuracy, and measured contact time.

4.5.4. Machine Learning Model Performance

Model performance was evaluated primarily on classification accuracy (high being preferable) and secondarily on computation time (low being preferable) after the fifth fold of cross-validation were used to compare performance between models. All of the most successful models were nearest neighbor algorithms (i.e. k = 1). Thus, in the interest of space, only the performances of these models were analyzed.

5. Results

The data collected were subjected to a battery of statistical tests. Sections 5.1 to 5.4 focused on the juxtaposition of stick perceptions and performance parameters and the investigation of how they appeared to be related. Perceptual scores of stick speed, accuracy and feel (10pt scales) were converted to rank order for each participant and compared between sticks, in conjunction with overall rank order, using Friedman analysis of variance tests (Roberts et al., 2008). Objective performance measures of average shot speed (maximum puck velocity), accuracy (mean radial error to net center at ENTRY), and release quickness (puck contact duration from CON/FOR to REL) obtained using the Vicon motion capture system were compared using multiple one-way ANOVAs. Finally, the variability within the perception ratings, overall rank order, and performance measures were analyzed using principal component factor analysis. For each test, slap and wrist shot data were analyzed separately.

Section 5.5 focused on the efficacy of machine learning models for shooter classification (aka performance fitting) using hand kinematic data captured with custom built in-glove IMU data (199 data points) and MATLAB's Machine Learning Toolbox. Of a handful of models, k-Nearest Neighbors (KNN) algorithms showed to be most accurate machine learning model based on the nature of the data being used. Thus, only the accuracy of KNN models using different IMU channels were evaluated in this thesis.

5.1 Stick Perceptions

Friedman's tests were performed on the mean rank order of stick speed, accuracy, feel, and overall perception scores to detect significant differences in the perceptions of the sticks. Significant differences in perceptual stick rankings were found within slap shots (speed, feel) and wrist shot (overall) (Table 9).

Table 7. Slap shot mean rank speed, accuracy, feel, and overall perception scores by stick ± ½ Fisher's LSD (n=10).

	Speed	***Accuracy***	***Feel***	***Overall***
Stick A	2.70 ± 0.38	2.95 ± 0.40	3.15 ± 0.39	2.30 ± 0.41
Stick B	2.95 ± 0.38	2.35 ± 0.40	2.10 ± 0.39	2.40 ± 0.41
Stick C	2.80 ± 0.38	2.85 ± 0.40	2.95 ± 0.39	3.10 ± 0.41
Stick D	1.55 ± 0.38	1.85 ± 0.40	1.80 ± 0.39	2.20 ± 0.41

Table 8. Wrist shot mean rank speed, accuracy, feel, and overall perception scores by stick ± ½ Fisher's LSD (n=10).

	Speed	***Accuracy***	***Feel***	***Overall***
Stick A	2.60 ± 0.37	2.30 ± 0.39	2.55 ± 0.38	1.50 ± 0.41
Stick B	2.30 ± 0.37	2.55 ± 0.39	2.20 ± 0.38	3.10 ± 0.41
Stick C	2.65 ± 0.37	2.60 ± 0.39	2.95 ± 0.38	2.60 ± 0.41
Stick D	2.60 ± 0.37	2.30 ± 0.39	2.55 ± 0.38	1.50 ± 0.41

Table 9. Friedman's test results for speed, accuracy, feel, and overall rankings by shot type (n=10).

	Slap Shots		**Wrist Shots**	
	Friedman's T	**p-value**	**Friedman's T**	**p-value**
Speed	***8.718***	***0.033***	0.556	0.907
Accuracy	4.915	0.178	0.367	0.947
Feel	***8.226***	***0.042***	2.310	0.511
Overall	3.00	0.392	***8.760***	***0.033***

Specifically, slap shots with Stick D were ranked significantly faster than those with sticks A, B, and C (Figure 12) and as having better feel than those with Sticks A and C (Figure 13). Conversely, within wrist shots, Stick A was ranked significantly better overall than Sticks B and D (Figure 14).

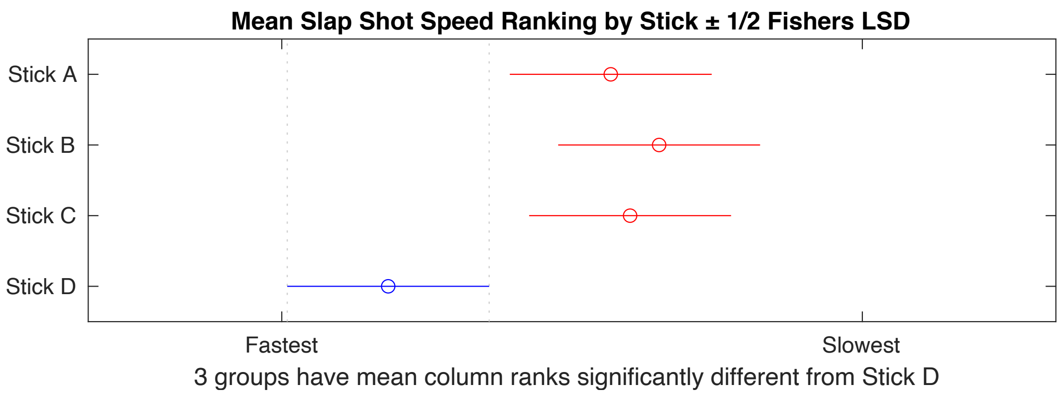

Figure 12. Mean slap shot perceived speed ranking by stick ± ½ Fisher's LSD.

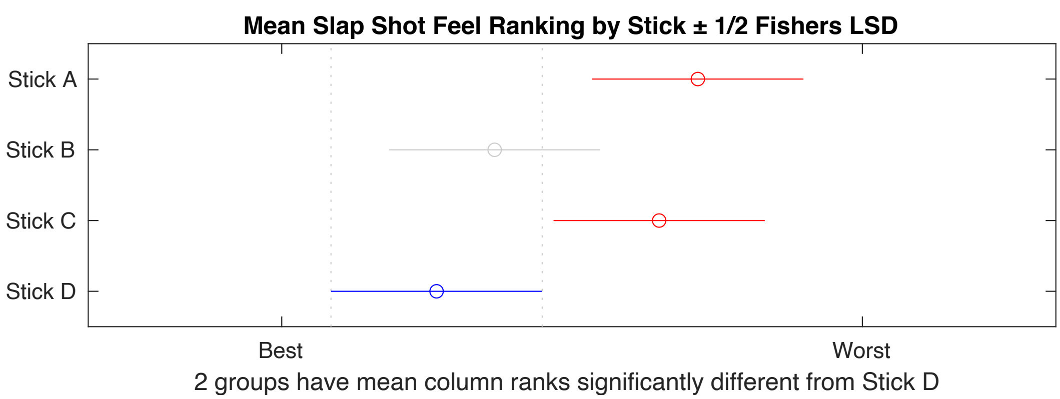

Figure 13. Mean slap shot perceived feel ranking by stick ± ½ Fisher's LSD.

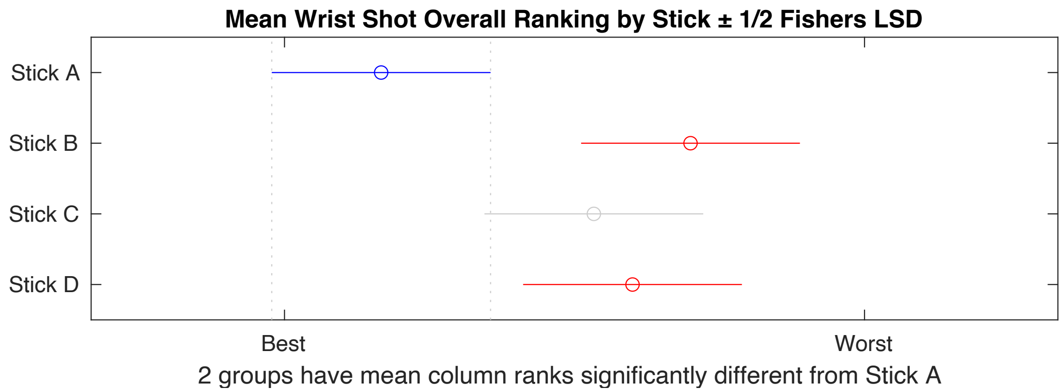

Figure 14. Mean wrist shot perceptual overall ranking by stick ± ½ Fisher's LSD.

5.2 Stick Performance

Statistical tests were conducted to elucidate differences in performance between the sticks. Multiple one-way ANOVAs were conducted to evaluate group-level performance differences in speed, accuracy, and quickness between the sticks. Separate analyses were conducted for slap and wrist shots since interaction effects between stick and shot type were not a focus of this study. Individual differences in stick performance are also presented in 5.2.2.

5.2.1 Group Level Performance Differences

Table 10. Ensemble average speed, accuracy, and quickness with each stick for slap and wrist shots ± SD (n=10).

	Slap Shots			**Wrist Shots**		
	Speed (m/s)	***Radial Error (m)***	***Quickness (ms)***	***Speed (m/s)***	***Radial Error (m)***	***Quickness (ms)***
Stick A	31.7 ± 2.2	0.296 ± 0.166	51 ± 4	27.7 ± 1.6	0.171 ± 0.089	103 ± 12
Stick B	31.8 ± 1.9	0.282 ± 0.138	53 ± 5	27.9 ± 1.4	0.177 ± 0.089	107 ± 13
Stick C	31.9 ± 1.7	0.321 ± 0.157	52 ± 4	27.6 ± 1.5	0.224 ± 0.138	104 ± 12
Stick D	32.0 ± 1.8	0.224 ± 0.129	50 ± 4	27.4 ± 1.4	0.159 ± 0.090	104 ± 13

One-way ANOVAs revealed significant differences in slap shot release duration between sticks ($F(3,36) = 3.66$, $p = 0.021$, $\eta_p^2 = 0.234$), but not for slap shot speed ($F(3,36) = 0.032$, $p = 0.992$, $\eta_p^2 = 0.002$) nor accuracy ($F(3,36) = 2.33$, $p = 0.091$, $\eta_p^2 = 0.162$). A Tukey-Kramer post hoc test showed release duration to be significantly shorter for Stick D compared to Stick B (Figure 15).

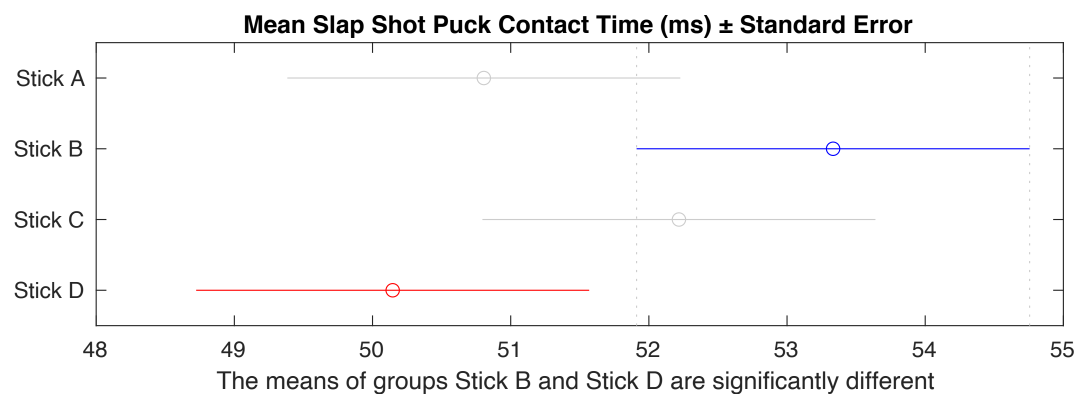

Figure 15. Mean slap shot puck contact duration ± standard error, by stick.

For wrist shots, one-way ANOVAs revealed significant differences in accuracy between sticks ($F(3,36) = 6.71$, $p = 0.001$, $\eta_p^2 = 0.359$). A Tukey-Kramer post hoc test showed wrist shot accuracy to be significantly lower for Stick C than the other three sticks (Figure 16).

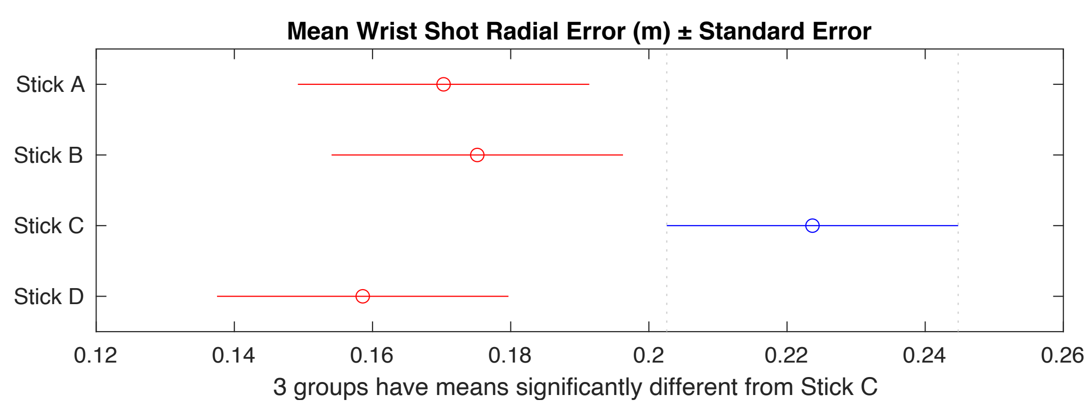

Figure 16. Mean wrist shot radial error from target center ± standard error, by stick.

5.2.2 Individual Level Performance Differences

Although significant differences were only observed in slap shot quickness and wrist shot accuracy at the group level, differences in performance arose in shot speed accuracy, and quickness between the sticks on an individual level.

5.2.2.1 Shot Speed

For slap shots, five participants reached their highest average shot speed with Stick C, two using Stick A, and two using Stick D. Only one participant reached their highest average slap shot speed with Stick B.

For wrist shots, six participants reached their highest average shot speed with Stick B, two using Stick A, and two using Stick C. No participants reached maximal wrist shot speeds with Stick D.

There were no consistent improvements in shot speed within sticks across shot types for participants, nor were there systematic trends linking maximal shot speeds with one stick for slap shots and a different stick type for wrist shots. For example, P01 and P10 both achieved maximal slap shot speeds with Stick C, however, P01 reached maximal wrist shot speeds with Stick B while P10 reached maximal wrist shot speeds with Stick A. Four participants reached maximal shot speed for both shots with the same stick (P03 & P08, C; P04, A; P09, B).

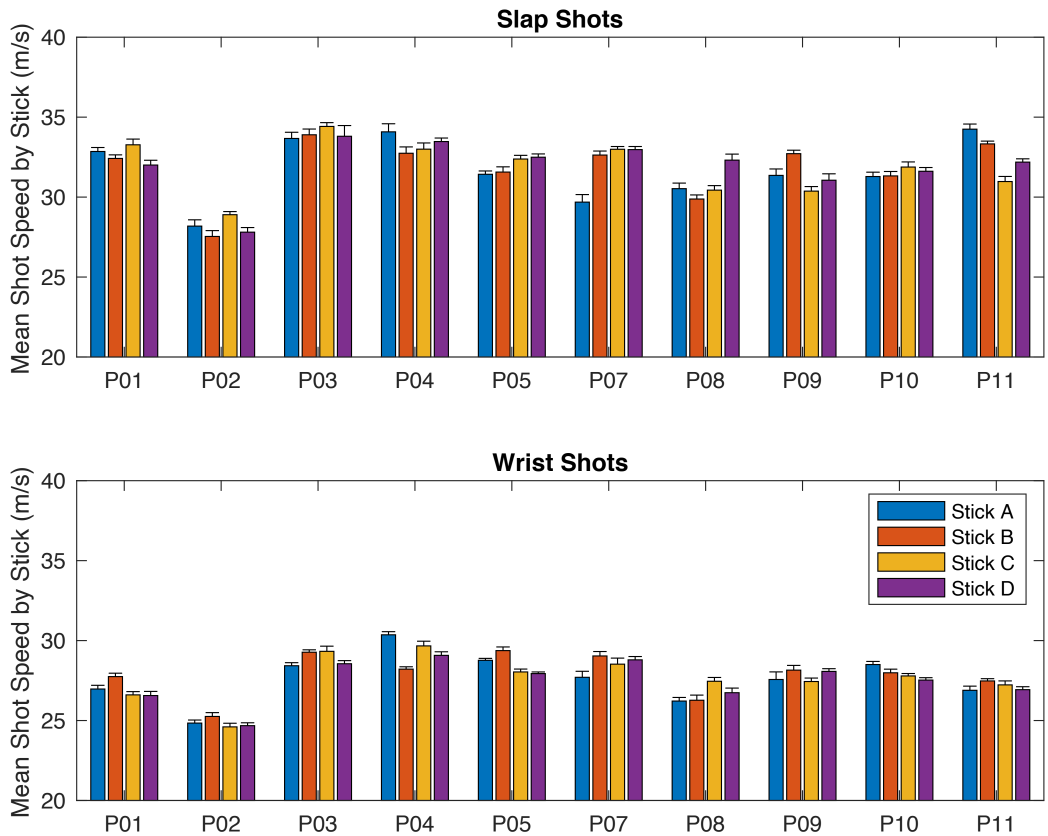

Figure 17. Mean slap (top) and wrist (bottom) shot speed (m/s) for each stick by participant ± standard error.

5.2.2.2 Shot Accuracy

For slap shots, eight participants reached minimal mean radial error with Stick D, two with Stick A. For wrist shots, five participants (including the two whose slap shots were most accurate with Stick A) shot most accurately with Stick D. Three participants shot most accurately with Stick A and two with Stick B. Eight participants were least accurate (highest mean radial error) with Stick C for wrist shots, compared to four for slap shots.

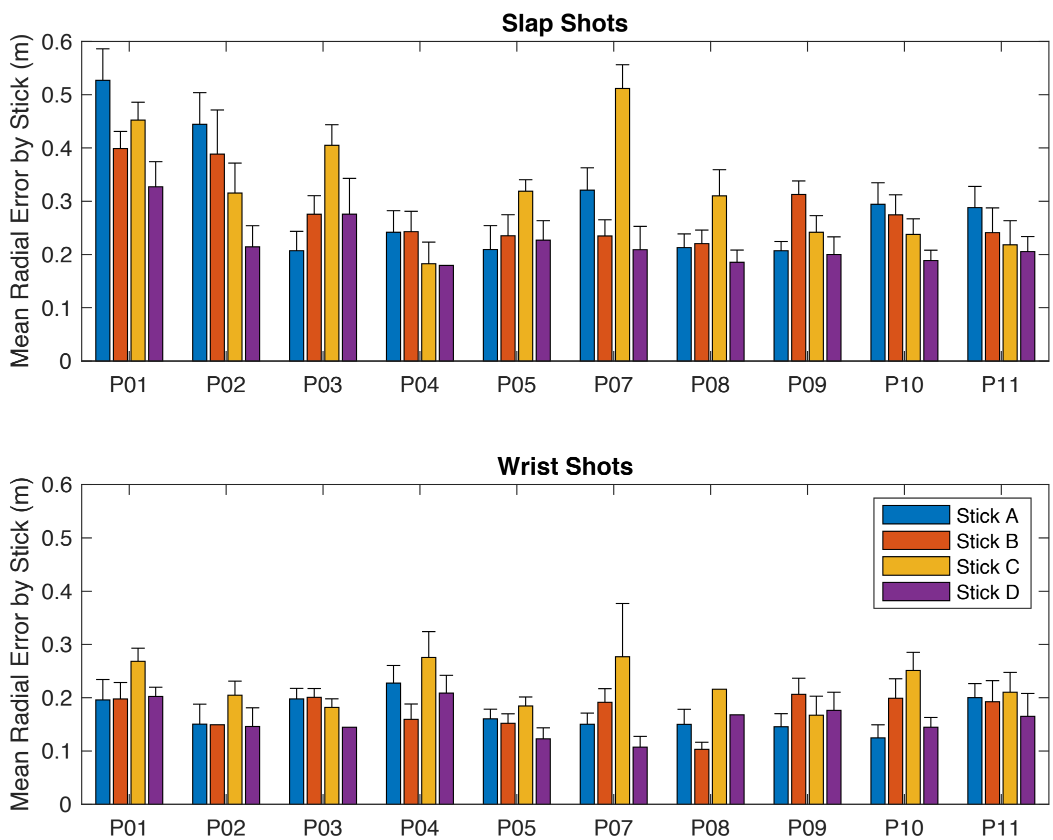

Figure 18. Mean slap (top) and wrist (bottom) shot radial error (m) from net center for each stick by participant ± standard error.

5.2.2.3 Shot Puck Contact Time

For slap shots, puck contact time was shortest with Stick D for five participants. Three participants had the shortest contact times with Stick A and one with Stick C. One participant (P09) had equally lowest contact times with Stick C and D. Six players experienced their longest contact times with Stick B. For wrist shots, puck contact time was shortest with Stick C for four participants, Stick D for three participants, Stick B for two participants, and Stick A for one participant.

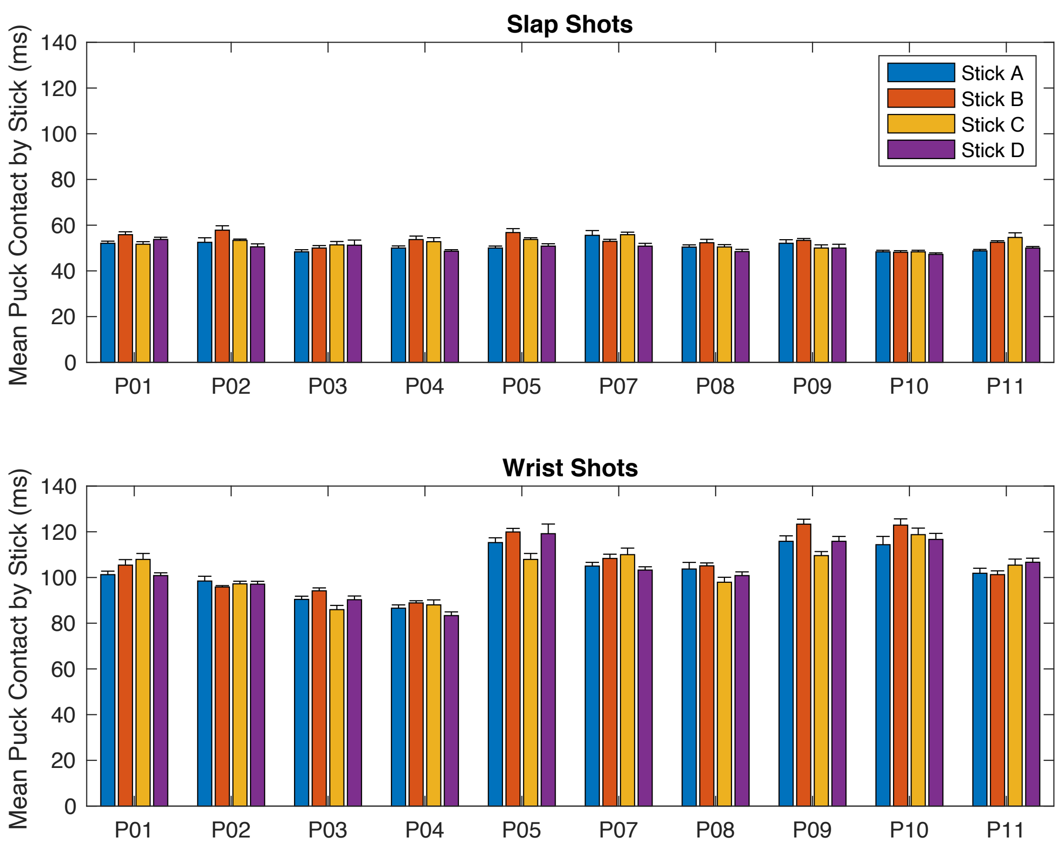

Figure 19. Mean slap (top) and wrist (bottom) shot puck contact duration for each stick by participant ± standard error.

5.4 Perception-Performance Relationships

Principal Component Analysis (PCA) was performed for slap and wrist shots separately (Table 11, Table 12) to understand the relationships between subjective perception scores of stick speed, accuracy, and feel; overall preference rank order; and objective measures of speed, accuracy, and quickness.

For slap shots, the first two principal components explained 86% of the total variance within the data. The first dimension (PC1) explained measured shot speed and accuracy and perceived shot speed, accuracy and feel ratings while the second dimension (PC2) explained overall stick rank order (Table 11).

Table 11. PCA Component Matrix for Slap Shot Objective and Subjective Data.

Variable	PC1 (69%)	PC2 (17%)
Measured_Speed	**0.783**	0.562
Measured_Accuracy	**-0.988**	0.148
Measured_Quickness	-0.540	0.452
Perceived_Speed	**0.963**	0.095
Perceived_Accuracy	**0.927**	0.316
Perceived_Feel	**0.881**	0.019
Overall_Rank	-0.630	**0.718**

Overall stick rank for slap shots was most closely related to measured slap shot speed while perceived speed, accuracy, and feel ratings were most closely related to measured accuracy. These relationships are presented in the form of variables factor map (Figure 20).

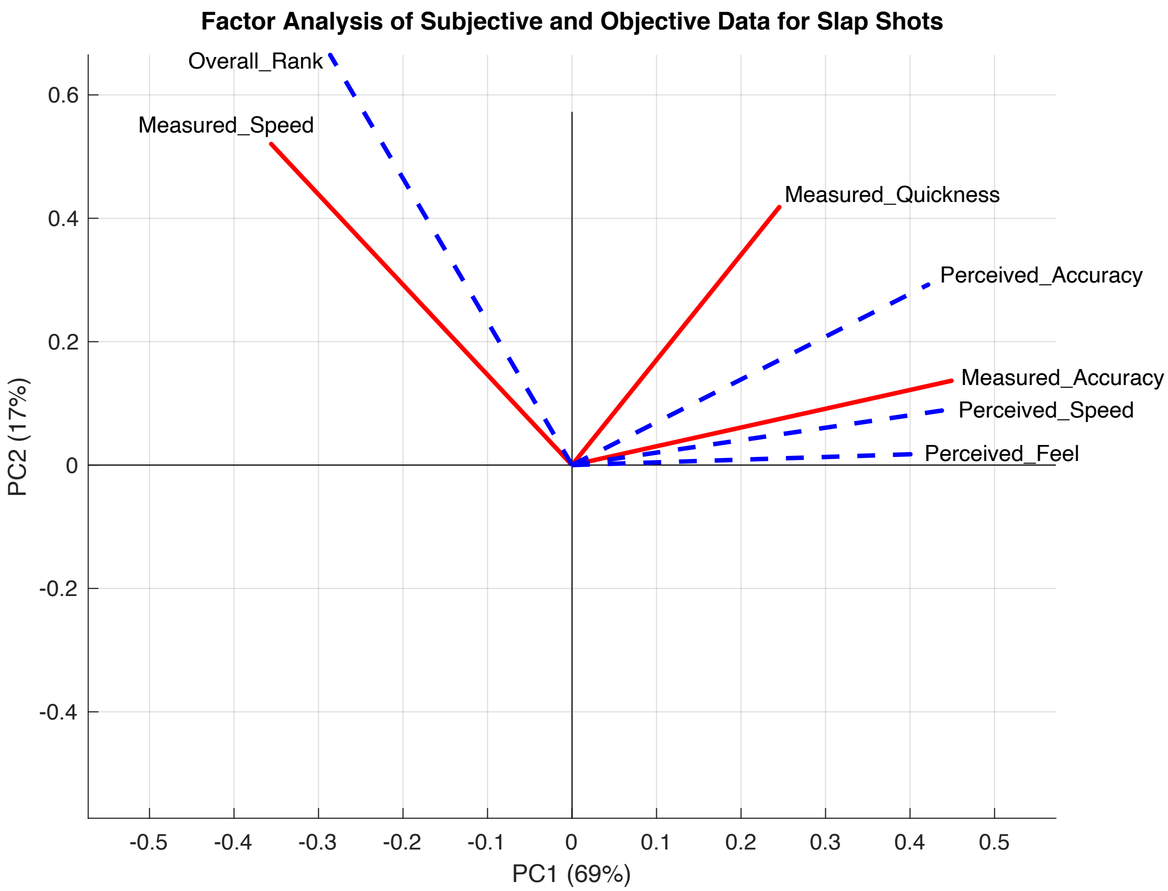

Figure 20. PCA variables factor map showing the relationship of the stick perceptions (blue dashed lines) with performance kinematics (red solid lines) in relation to the two principal components for slap shots.

For wrist shots, the first two principal components explained 90% of the total variance within the data. The first dimension (PC1) explained measured shot quickness and perceived shot speed, accuracy, and feel ratings while the second dimension (PC2) explained measured shot accuracy (Table 12).

Table 12. PCA Component Matrix for Wrist Shot Objective and Subjective Data.

Variable	PC1 (54%)	PC2 (36%)
Measured_Speed	0.671	0.537
Measured_Accuracy	-0.467	**0.870**
Measured_Quickness	**0.975**	0.165
Perceived_Speed	**0.877**	-0.480
Perceived_Accuracy	**-0.751**	-0.650
Perceived_Feel	**0.787**	-0.612
Overall_Rank	0.575	0.517

Perception ratings of stick accuracy for wrist shots were found to be most closely related to measured accuracy while perceived speed and feel were more closely related to measured speed. These relationships are presented in the form of variables factor map (Figure 21).

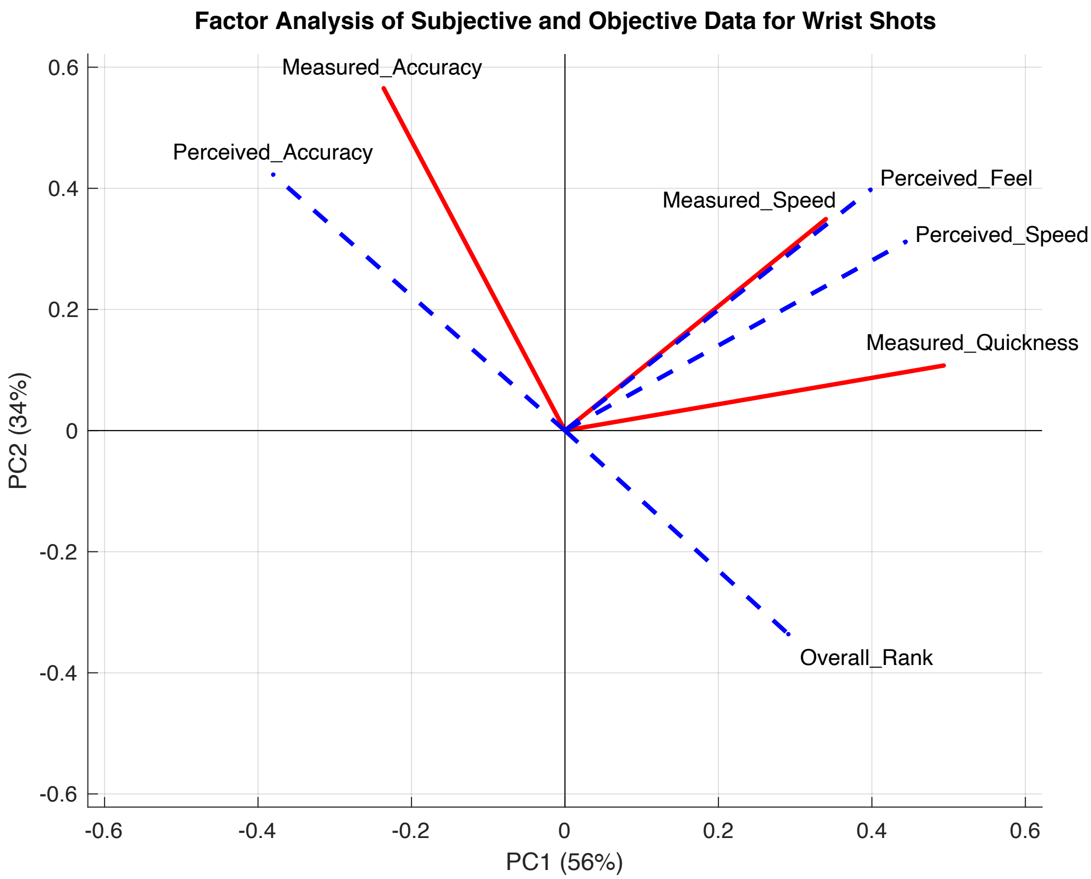

Figure 21. PCA variables factor map showing the relationship of the stick perceptions (blue dashed lines) with performance kinematics (red solid lines) in relation to the two principal components for wrist shots.

5.5 Stick Fit Prediction Models

Stick fit prediction models based on hand kinematics collected from inertial measurement unit (IMU) sensors and shot speed were built using Nearest Neighbors classification with MATLAB R2020a's Machine Learning Toolbox. The models were trained using a 5-fold cross validation and principal components explaining 95% of the data features to protect against overfitting with small sample sizes.

Three separate models were created for each channel to fit players for flex, blade pattern, and kick point. Slap and wrist shot data were analyzed separately.

Separate models were trained and tested on their ability to classify (i.e. fit) shooters using four different channels from the in-glove IMUs:

1. Top hand resultant linear acceleration (Top_A)
2. Top hand resultant angular velocity (Top_G)
3. Bottom hand resultant linear acceleration (Bottom_A)
4. Bottom hand resultant angular velocity (Bottom_G)

The true values of stick fit (for training the algorithms and evaluating model accuracy) were based on the stick with higher mean shot speed to the nearest whole meter per second (m/s). Thus, within each model, there were three possible responder conditions: Non-responder (Stick A = Stick X), Reference-responder (Stick A > X), and Other-responder (Stick X > A).

Model performance was evaluated primarily on classification accuracy (high being preferable) and secondarily on computation time (low being preferable) after the fifth fold of cross-validation were used to compare performance between models.

5.5.1 Model Accuracy

5.5.1.1 Slap Shots

Based on the models created, principal components of the bottom hand angular velocity (Bottom_G) data were able to recommend the optimal flex (96%), blade pattern (98%), and kick point (97%) for slap shot speed with the highest accuracy.

Table 13. Accuracy of various fine KNN models trained using Top and Bottom hand linear acceleration (_A) and angular velocity (_G) data for slap shot speed.

	Top_A	Top_G	Bottom_A	Bottom_G
Flex	95%	95%	93%	**96%**
Blade	95%	95%	90%	**98%**
Kick Point	93%	96%	94%	**97%**

5.5.1.2 Wrist Shots

Based on the models created, principal components of the top hand angular velocity (Top_G) data were able to recommend the optimal kick point (97%) for wrist shot speed with the greatest accuracy, while principal components of bottom hand linear acceleration (Bottom_A) best predicted optimal flex (97%), and blade pattern (96%).

Table 14. Accuracy of various fine KNN models trained using Top and Bottom hand linear acceleration (_A) and angular velocity (_G) data for wrist shot speed.

	Top_A	Top_G	Bottom_A	Bottom_G
Flex	93%	95%	**97%**	96%
Blade	93%	93%	**96%**	95%
Kick Point	94%	**97%**	96%	94%

5.5.2 Classification Confusion Matrices

In the interest of space, only the confusion matrices for the best models were analyzed. These were the Bottom_G models for fitting flex, blade, and kick point for slap shots and the Bottom_A, Bottom_A, and Top_G models for fitting wrist shot flex, blade, and kick point respectively.

5.5.2.1 Slap Shots

The most accurate flex fitting algorithm for slap shot speed used the first 15 principal components of the Bottom_G IMU channel. This model had an overall accuracy of 97.3%; correctly classifying 98.0% of non-responders, 99.3% of high flex responders, and 93.3% of low flex responders (Figure 22). This model never misclassified a high flex responder for a non-responder and had the greatest challenge with low flex responders, misclassifying 5.9% of them as high flex responders.

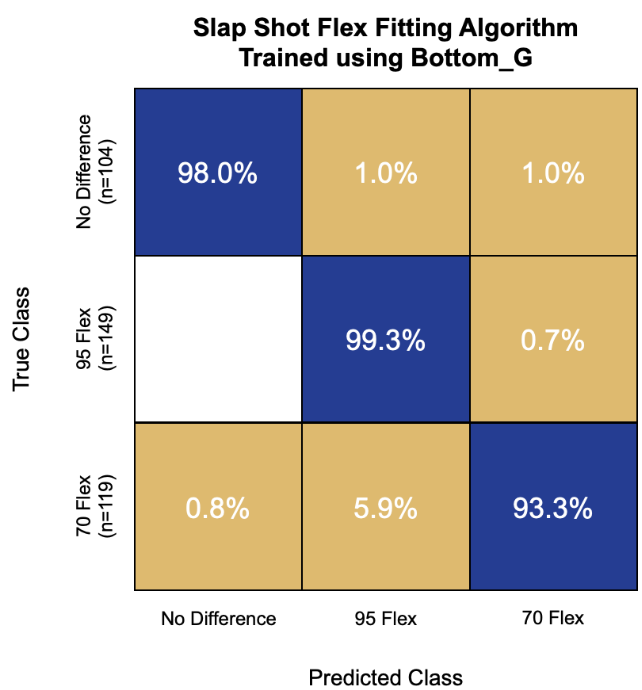

Figure 22. Confusion matrix of the flex fitting algorithm for slap shot speed trained using bottom hand resultant angular velocity (Bottom_G) signal features. Overall model accuracy was 97.3%.

The most accurate blade fitting algorithm for slap shot speed was trained using the first 15 principal components of the Bottom_G IMU channel. This model also had an overall accuracy of 97.3% and correctly classified 98.6% of non-responders, 98.1% of P92 responders, and 95.8% of PM9 responders (Figure 23). This model never misclassified a non-responder for a PM9 responder and had the greatest challenge with PM9 responders, misclassifying 3.5% of them as P92 responders.

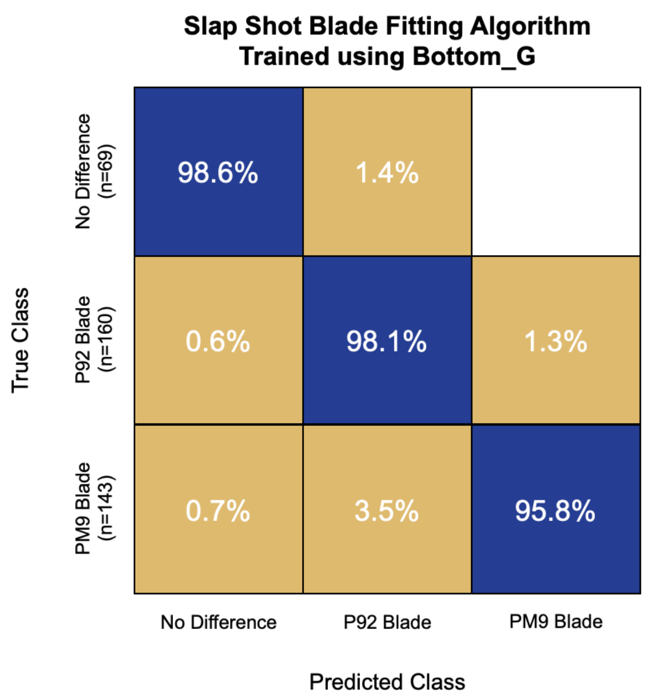

Figure 23. Confusion matrix of the blade fitting algorithm for slap shot speed trained using bottom hand resultant angular velocity (Bottom_G) signal features. Overall model accuracy was 97.3%.

The highest accuracy kick point fitting algorithm for slap shot speed was also trained using the first 15 principal components of the Bottom_G IMU channel. This model had an overall accuracy of 97.0% and correctly classified 95.2% of non-responders, 99.1% of low kick point responders, and 96.8% of high kick point responders (Figure 24). This model never misclassified a low kick point responder for a non-responder and had the greatest challenge with high kick point responders, misclassifying 2.5% of them as low kick point responders.

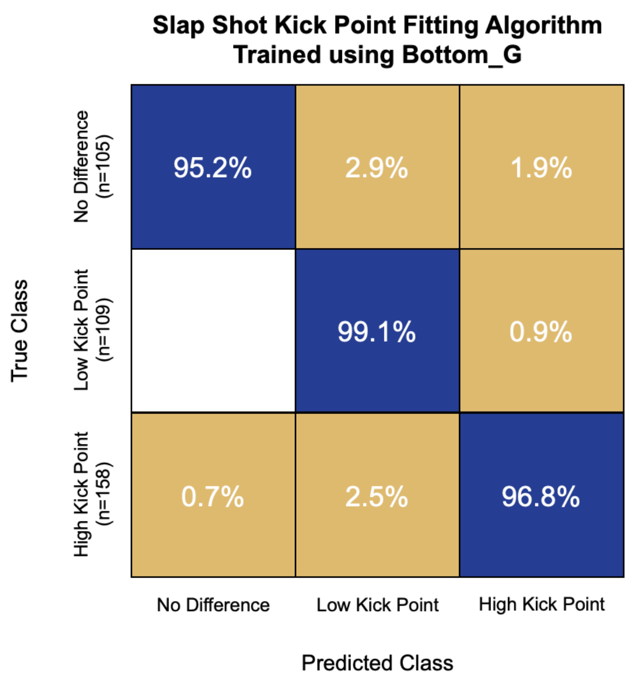

Figure 24. Confusion matrix of the kick point fitting algorithm for slap shot speed trained using bottom hand resultant angular velocity (Bottom_G) signal features. Overall model accuracy was 97.0%.

5.5.2.2 Wrist Shots

The highest accuracy flex fitting algorithm for wrist shot speed was trained using the first 16 principal components of the Bottom_A IMU channel. This model had an overall accuracy of 96.1% and correctly classified 97.9% of non-responders, 92.4% of high flex responders, and 95.6% of low flex responders (Figure 25).

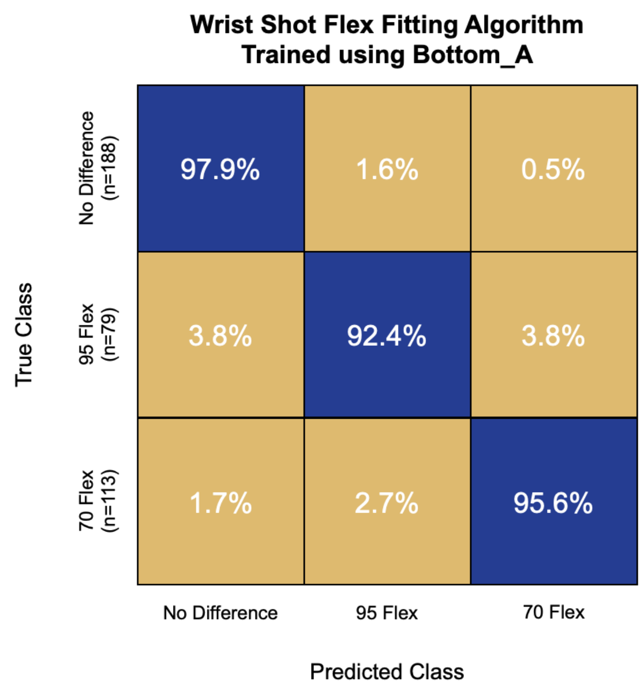

Figure 25. Confusion matrix of the flex fitting algorithm for wrist shot speed trained using bottom hand resultant linear acceleration (Bottom_A) signal features. Overall model accuracy was 96.1%.

In addition, the most accurate blade fitting algorithm for wrist shot speed was trained using the first 16 principal components of the Bottom_A IMU channel. This model had an overall accuracy of 95.3% and correctly classified 97.2% of non-responders, 95.8% of P92 responders, and 92.4% of PM9 responders. This model had the greatest challenge with PM9 responders, misclassifying 5.0% of them as P92 responders.

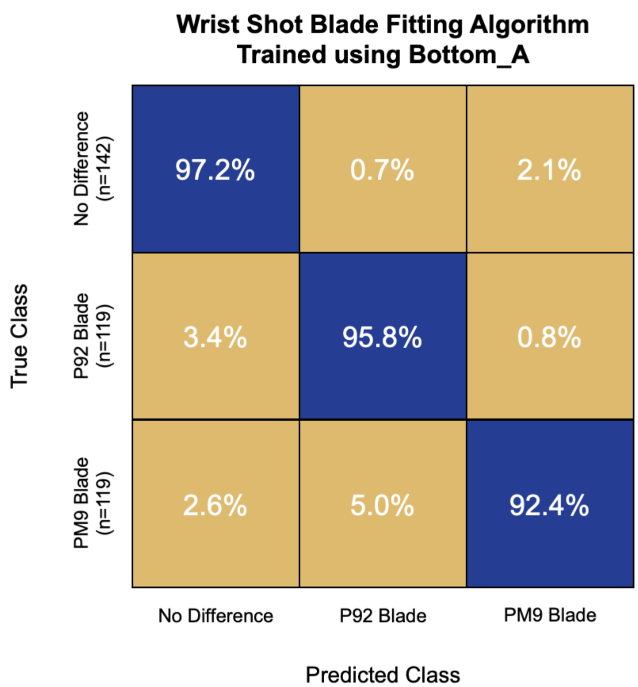

Figure 26. Confusion matrix of the blade fitting algorithm for wrist shot speed trained using bottom hand linear acceleration (Bottom_A) signal features. Overall model accuracy was 95.3%.

The highest accuracy kick point fitting algorithm for wrist shot speed was trained using the first 15 principal components of the Top_G IMU channel. This model had an accuracy of 94.5% and correctly classified 97.2% of non-responders, 93.3% of low kick point responders, and 92.4% of high kick point responders. This model had the greatest challenge with high kick point responders, misclassifying 5.1% of them as low kick point responders.

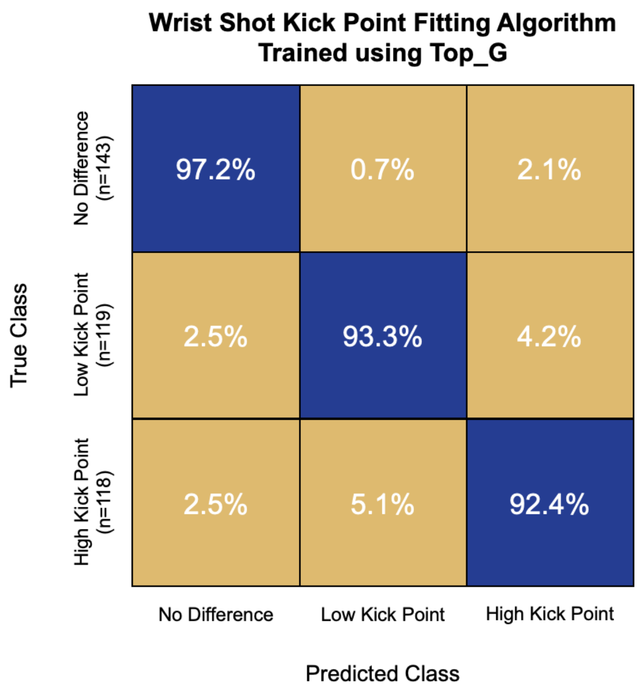

Figure 27. Confusion matrix of the kick point fitting algorithm for wrist shot speed trained using top hand resultant angular velocity (Top_G) signal features. Overall model accuracy was 94.5%.

5.5.3 Computation Time & Misclassification Costs

A key factor of interest in the evaluation of these machine learning algorithms was computational burden—aka computation time. The prediction speed of the best models, in addition to misclassification costs for each algorithm, are presented in Table 15. These include the Bottom_G models for fitting flex, blade, and kick point for slap shots and the Bottom_A, Bottom_A, and Top_G models for fitting wrist shot flex, blade, and kick point respectively. All computation times were less than one second.

Table 15. Total misclassification cost and prediction speed of each of the six most accurate models.

	Model	Total Misclassification Cost	Observations per Second
	Flex	10	~700
Slap	*Blade*	10	~1200
	Kick Point	11	~1700
	Flex	15	~1400
Wrist	*Blade*	18	~1400
	Kick Point	21	~1400

6. Discussion

The aims of this study were to 1) evaluate the inter-relationships between ice hockey shooters' perceptions and performance with sticks of different flex, blade, and kick point properties, and 2) evaluate the efficacy of inertial measurement unit (IMU) hand kinematic data and machine learning algorithms for the rapid fitting of ice hockey sticks.

6.1 Summary of Major Findings

The high kick point stick (Stick D) was perceived by shooters to be associated with better feel and higher speeds during slap shots while the low kick point reference stick (Stick A) was perceived to be the best stick overall for wrist shots.

However, the only significant differences in performance between the sticks were slap shot puck contact duration and wrist shot radial error. Slap shot mean puck contact duration was significantly shorter for the high kick point stick (Stick D) compared to the low flex stick (Stick B). Wrist shot mean radial error was significantly higher for the stick with the flatter blade pattern (Stick C) compared to the other three sticks. At an individual level, shooters exhibited different responses in maximal shot speed, accuracy, and puck contact duration between the stick models.

Factor analysis of subjective (perceived speed, accuracy, and feel ratings and overall stick rank) and objective (speed, accuracy, and quickness) measures revealed:

- For slap shots
    - **perceptions of shot speed, accuracy and feel were most closely related to measured shot accuracy**
    - **overall stick rank was most closely related to measured shot speed**.

and conversely

- For wrist shots
  - **perceptions of shot speed and feel were more closely related to measured speed**
  - **ratings of stick accuracy for shots were most closely related to measured accuracy.**

In addition to the above, using in-glove IMU data, fine KNN machine learning models were capable of fitting (or matching) players with their optimal flex, blade pattern, and kick point with 90-98% accuracy for slap shots and 93-97% accuracy for wrist shots. Perhaps more impressively, these algorithms were able to achieve these high levels of accuracy with a processing time of less than one second.

In summary, inter-stick differences were perceived by the participants in this study, however, these perceptions were not necessarily related to objective measures of shot performance. Instead, subjective stick ratings were influenced by a selected subset of performance measures specific to the type of shot being performed. Additionally, it appears possible—using embedded sensors and fine KNN machine learning algorithms—to rapidly fit players for stick flex, blade, and kick point with high levels of accuracy.

6.2 Comparison of Findings with Those of Other Relevant Publications

Slap and wrist shot speeds observed in this study were similar to those of high caliber male hockey players in previous stationary shooting studies (Alexander et al., 1963; Flemming, 2014; Hannon et al., 2011; Pearsall et al., 2001; Robbins et al., 2021; Roy & Doré, 1976; Zane, 2012). Wrist shot accuracy was slightly higher than that reported by Michaud-Paquette et al (2009) where university students (including varsity hockey players) shot at targets in the top and bottom corners of the net. Slap shot puck-blade contact time was longer than that previously reported for elite hockey players

(Villaseñor et al., 2006). This may be attributable to concurrent advances in the technologies and utilization of the hockey stick.

No significant differences in shot speed were found between the sticks—which varied in flex, blade pattern, and kick point—for wrist or slap shots. The finding that stick stiffness did not significantly affect slap or wrist shot speed of male hockey players is consistent with previous findings of Pearsall et al. (1999), Wu et al. (2003), Hannon et al (2011), and Flemming (2014). The findings contradict those of Worobets et al. (2006) for wrist shots but not slap shots. Further, the more flexible stick was not rated significantly better, as reported by Anderson (2008). This is justified given the larger sample of raters and sticks used in the present study. In fact, the stiffest sticks received the best ratings for slap (Stick D) and wrist shots (Stick A). This finding is similar to that of Overney and colleagues (2010), who found that tennis players preferred racket paddles with the stiffest material constructions, and in contrast to the findings of Fischer et al. (2007), who found that expert and advanced skiers preferred skis with low flexural rigidity.

Additionally, the stick with the flatter curve was not associated with higher slap shot velocities as reported by Lomond et al. (2007) and Gerbé (2016). This may have been due to the high variability in shot speed (Table 10) and experience level of the participants in the present study.

Individual differences in optimal stick for shot speed reported corroborate trends in previous hockey stick studies (Anderson, 2008) and those of other sporting implements (MacKenzie & Boucher, 2017). Anderson found three players using 6 different sticks of wood and composite constructions each shot fastest with a different stick.

Principal component analysis and machine learning algorithms were able to identify individual differences in hand kinematics that were predictive of optimal stick flex, blade pattern, and kick point. This is in agreement with previous findings of Zane (2012) and Flemming (2014), who reported player coordinative strategies (or “shooting styles”) that appeared in both high and low caliber groups. It has been established that no two players shoot exactly the same (Flemming, 2014), however, the methods used in this study were satisfactorily sensitive to the characteristics of hand kinematics that relate to fitting stick flex, blade pattern, and kick point in order to maximize shot speed. Thus, further research is warranted to better understand how features of these kinematic profiles relate to stick fit.

6.3 Possible Limitations of Present Study

The small sample size (n=10) may have limited the statistical power of the analysis. A larger sample size (e.g. n=40) of novel hockey players of differing ability levels would have permitted the comparison of different machine learning algorithms in predicting hockey stick preferences (Balsalobre-Fernández & Kipp, 2021; McGrath et al., 2021). Further, it is unknown how these trends and profiles will hold true within the larger population of hockey players since it is not certain how representative this sample is of all hockey players in terms of their responses to changes in stick properties.

For example, only experienced adult males participated in this study. Thus, the inclusion of female, youth, and less experienced athletes for the development of commercial hockey stick fitting applications is warranted since these groups represent large, growing segments of the global hockey stick market (Hockey Canada, 2020). However, the sample’s high level of experience in this study may have allowed them to better verbalize their perceptions of sporting implements (Roberts et al., 2006).

Another limitation of this study was that the IMU data were limited to the resultant magnitude of the accelerometer and gyroscope data due to the lack of systematic alignment of the IMUs' X and Y axes in the gloves. Nonetheless, the IMUs provided unencumbered, direct kinematic measurements of the hands which makes them practical for application in stick fitting in retail hockey stores. More work is required to investigate the repeatability of these findings when accounting for IMU alignment.

An additional limitation of this study was that the sticks were not subjected to a battery of mechanical tests to understand the physical properties of sticks (Behrmann et al., 2014). Having such information would be an interesting, particularly for understanding how such parameters relate to perceptions of shooting performance (Fischer et al., 2007; Overney et al., 2010). Further, understanding how perceptual and performance measures relate to dynamic player behaviours during shooting—such as grip width on the stick and stick bend—is of great interest.

6.4 Implications for Stick Fitting Practices & Research

The above results demonstrate the potential of using embedded IMU sensors tracking hand kinematics and machine learning algorithms to accurately fit individuals for stick flex, blade pattern, and kick point. Similar research to this study should be conducted with a greater number of sticks with more subtle differences in flex, blade patterns, and kick points and a larger pool of hockey players of differing backgrounds to further validate the findings of this study. This study could be further supplemented through the capture of shooting performance and stick perception data in retail and on-ice settings using simplified objective measurement instruments (i.e. a radar gun).

Although it appears that players don’t change their shooting style when using sticks of different flexes in short run, it is not known how stable these gross kinematic patterns are and whether they would yield consistent values under test-retest conditions. Additionally, it is not yet known how habitual exposure to sticks of different flex, blade, and kick point properties affect shooting technique. Studies aimed at the repeat exposure and measurement of kinematics in response to sticks with different properties should be conducted.

The results of this study also bring into question the reliability of athlete perceptions of stick performance parameters (i.e. speed and accuracy), particularly during slap shots. In the future, a common shooting performance vocabulary should be defined to prevent confusion and improve resolution of sensory testing in ice hockey stick perception research (Bauer et al., 2020; Desbiens, 2021).

7. Conclusion

The high kick point stick was perceived by shooters to be associated with better feel and higher speeds during slap shots while the low kick point reference stick was perceived to be the best stick overall for wrist shots. However, the only significant differences in performance between the sticks that arose were slap shot puck contact duration and wrist shot radial error. Specifically, the PM9 stick was associated with the lowest average wrist shot accuracy while the high kick point stick had a shorter average slap shot contact duration compared to the flexible stick. At the individual level, shooters exhibited different response patterns in maximal speed, accuracy, and puck contact duration to the sticks. Further, these response patterns were not always the same across shot types.

Factor analysis of subjective (perceived speed, accuracy, and feel ratings and overall stick rank) and objective (measured speed, accuracy, and quickness) measures revealed perceptions of slap shot speed, accuracy, and feel to be most closely related to measured shot accuracy while overall stick rank for slap shots was most closely related to measured shot speed. Interestingly, perception ratings of stick accuracy for wrist shots were found to be most closely related to measured accuracy while perceived speed and feel were more closely related to measured speed.

Fine k-Nearest Neighbors machine learning models were found to be capable of fitting players with their optimal flex, blade pattern, and kick point with 90-98% accuracy for slap shots and 93-97% accuracy for wrist shots using select principal components of in-glove IMU data. Perhaps more impressively, these algorithms were able to achieve these high levels of accuracy with a processing time of less than one second.

These findings suggest that 1) embedded sensors and machine learning algorithms can be used to dynamically fit ice hockey players for stick parameters (flex, blade pattern, kick point) with high levels of accuracy and quick computation times, 2) experienced players' subjective perceptions of ice hockey sticks are not based on corresponding objective performance criteria during slap shots, and 3) high kick point sticks are associated with shorter slap shot puck contact times, low flex sticks with longer slap shot puck contact times, and flatter blade patterns with lower wrist shot accuracy.

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