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Preface

LINHAC 2024 took place June 3-5, 2024, and was organized by Linköping University and Linköping Hockey Club. LINHAC brought together professionals and academics with an interest in hockey analytics. It featured the latest research in hockey analytics in academia and companies, discussions with analysts and coaches, industry sessions with the latest hockey analytics products, and an analytics competition for students.

In addition to the research track, the program included talks by Robin Schuermann (d-fine) on operationalizing analytics for clubs, by Anders Norén from Capacio with Staffan Olsson on cognitive assessment and profiling for increased understanding of game intelligence and performance, by Fredrik Sjöö from Onsite sport on using neuroscience to design a sport's fan-engagement platform, by Lars Skytte on visualizing play-by-play data, by Daniel Weinberger from Sportcontract on constructing a Wins Above Replacement model, by Erik Lignell from Frölunda HC about his experience of a decade as analyst in Swedish elite hockey, and by Craig Buntin from Sportlogiq about the history and goals of Sportlogiq. There were also mini-talks about AI and its possible use in ice hockey analytics. Patrick Lambrix gave a short overview of the field. Albin N Maelum from Stretch on Sense presented an industry perspective. Huanyi Li from Linköping University showed the use of knowledge representation for integration and search of data, and Marco Kuhlmann from Linköping University discussed the use of large language models for user interfaces to databases.

Further, there were panel discussions moderated by Mike Helber and Tim Brecht. A first panel was made up of analysts from different European teams (Miika Arponen from Ässät Pori, Adam Albelin from the Swedish Women's National Team, Zach Ellentahl from Rögle BK, Jan Morkes from Bílí Tygři Liberec and the Czech Men's National Team, and Simo Teperi from Rauman Lukko). The second panel discussed the state of the art and future of hockey analytics from the industry perspective (Thorsten Apel from Sportcontract, Lance Du'Lac from Hudl, Michael Elmer from KINEXON Sports, Andreas Hänni from 49ing, Albin N Maelum from Stretch on Sense, Jean-Sébastien Mérieux from Dartfish, and Morgan Zeba from Spiideo). The third panel discussed hockey analytics in the public sphere and how to get into the industry and teams. The participants were Petter Carnbro from Leksands IF, Lars Skytte (`https://hockey-statistics.com/`), Daniel Weinberger from Sportcontract, and Erik Wilderoth from Färjestad BK. Finally, the entertainment industry panel discussed their use of analytics (Almen Bibic from TV4, Meghan Chayka from Statlethes, Andreas Hänni from 49ing, and Henric Larsson from TV4/Hockeylabbet).

There were also three interviews with analysts from NHL teams about the state-of-the-art use of hockey analytics. The first interview was with Josh Pohlkamp-Hartt and Campbell Weaver from the Boston Bruins, the second with Katerina Wu from the Pittsburgh Penguins, and the third with Dave Radke from the Chicago Blackhawks.

Our industry collaborators presented their products: KINEXON Sports / Dartfish, Hudl, Stretch on Sense, 49ing, Spiideo and Sportcontract.

Finally, there was a student competition where the task was to provide insights based on sequences of events in a hockey game. Data was provided by the SHL and Sportlogiq.

LINHAC is the only conference of its kind in Europe, and as far as we know, it is the only hockey analytics conference that covers all aspects related to hockey analytics. These research track proceedings include an invited paper and the papers from the research track. A companion book includes additionally contributions from industry, the student competition papers, as well as insights from contributors to LINHAC regarding their experience with hockey analytics and thoughts about its future.

We thank our moderator Mike Helber, our conference service TM Event, and the members of our local organization committee Mina Abd Nikooie Pour, Huanyu Li, Ying Li, Gurjot Sing, Chunyan Wang, Jenny Rydén, Lene Rosell, Anders Cronstierna, and Daniel Jemander, for their excellent support.

Last, but not least, we thank our collaborators the Alliance of European Hockey Clubs, the City of Linköping, Sportlogiq, our sponsor the Swedish Research Council for Sport Science, and our gold (KINEXON Sports / Dartfish), silver (Hudl, Stretch on Sense) and bronze (49ing, Spiideo, Sportcontract) industry collaborators.

July 2024

Patrick Lambrix (chair),
Tim Brecht (co-chair),
Niklas Carlsson (co-chair),
Mikael Vernblom (co-chair)

Contents

Invited talk

Cognitive Assessment and Profiling for increased understanding of Individual and Team Game Intelligence and Performance in Ice hockey

Anders Norén

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Abstract. Game intelligence, the ability to be in the right place at the right time and make optimal decisions, is crucial for athletic performance. This whitepaper explores how neurocognitive testing and profiling can deepen our understanding of game intelligence, which includes elements such as situational awareness, decision-making, problem-solving, and flexibility.

The whitepaper targets sports professionals aiming to enhance their understanding of game intelligence through neurocognitive assessments. The assessments mentioned in the paper provide insights into athletes' cognitive strengths and weaknesses, aiding in talent identification, personalized coaching, strategic team composition, tactical adaptations, and injury prevention. Executive functions are crucial in both open sports (e.g., soccer, basketball) and closed sports (e.g., archery, golf). For example, in ice hockey, players must continuously adapt to dynamic environments, requiring quick decision-making, strategic thinking, and creativity.

Integrating neurocognitive assessments into sports practices has the potential to enhance the understanding of game intelligence, reduce subjectivity and bias, and improve individual and team performance, As well as ensure the wellbeing of athletes through tailored mental health support and coping strategies. Testing and profiling of individuals and teams can practically help enhance understanding of Game Intelligence. The process involves assessment, awareness, individual acceptance, strategic development, integration into coaching, and continuous follow-up to monitor progress and aid adjustments.

Game Intelligence in Sports

Game intelligence, the ability to be in the right place at the right time and make the right decisions, is a critical aspect of athletic performance. This whitepaper explores how neurocognitive testing and profiling can deepen our understanding of game intelligence, encompassing elements such as situational awareness, decision-making, problem solving and adaptability.

Understanding Game Intelligence

Game intelligence refers to the cognitive skills and processes that enable athletes to anticipate play developments, make strategic decisions, and execute actions effectively under varying conditions. Recent scientific studies indicate that distinct aspects of game intelligence can be predicted by examining specific executive functions (EFs) such as attention, working memory, cognitive flexibility, creativity, and impulse control.

Defining Game Intelligence and Executive Functioning

- **Game Intelligence**: The ability to understand and anticipate game situations, make strategic decisions, and execute appropriate actions. Or to be at the right place at the right time and do the right thing.
- **Executive Functioning** : The cognitive processes enabling individuals to focus on the right things and perform successfully in constantly changing environments. This ability varies between individual, and depend on a combined set of cognitive functions that interact.

These definitions highlight the executive functioning are central in forming game intelligence. Measuring and understanding executive functions can hence help understand distinct aspects of game intelligence, create insights, and aid us in how to coach and apply efficient strategies that support an athlete's performance and development.

Target Audience

This whitepaper is intended for sports professionals seeking to enhance their understanding of game intelligence, including scouts, sports directors, coaches, general managers, mental coaches, physiotherapists, and athletes. By integrating neurocognitive assessments into their talent identification, development and coaching processes, these professionals can gain a more comprehensive understanding of an athlete's potential and performance capabilities and integrate this knowledge to better support the development of individual athletes. As well of the optimal function of a team.

The Role of the Brain in Game Intelligence

The Brain and in particular Executive Functions in the frontal lobe are crucial for controlling and regulating information processing, thoughts, emotions, and performance. They include among others:

- **Attention**: Focusing on relevant information while ignoring distractions.
- **Short Term Memory**: Retaining and utilizing information over brief periods.
- **Working Memory**: Holding and manipulating information over short periods.
- **Impulse Control**: Suppressing inappropriate actions or responses.
- **Cognitive Flexibility**: Adjusting to changing situations and demands.
- **Creativity**: Generating novel ideas and solutions.

– **Conceptualization**: Forming and manipulating concepts.
– **Strategic Thinking**: Planning and executing strategies.

There are significant differences in cognitive functioning between individuals (and athletes). By assessing these differences, we can create cognitive profiles, where strengths and weaknesses of the individual can help us understand aspects of game intelligence and how to work with individual strengths and potential while finding efficient strategies to compensate for weaknesses. Based on the athletes' different cognitive profiles, it is possible to apply strategies that improve both individual and overall performance of teams. It is also possible to improve well-being among athletes by understanding and basing coaching and the athletes' roles of individuals cognitive profiles.

Measuring Cognition and Executive Functioning

Cognitive neuroscience has existed as a science for more than 80 years with the purpose of better understanding individuals based on their inherent abilities and help optimize function. The last couple of decades research has spread from focusing on function deficit to also study talent and top performance, particularly in sports.

Neurocognitive tests have been developed to measure these abilities and can be used to provide a detailed profile of an athlete's cognitive strengths and weaknesses. Cognitive capacities in executive functions are intricately linked to an individual's executive performance, which refers to their ability to function effectively in dynamic and demanding environments. Research constantly indicates that the validity of these measurements is high, ranging from 70-90% when it comes to measuring the capacity of these functions, on both general and athletic populations.

Application in Sports - Talent Identification and Development

By using neurocognitive profiling, sports organizations can better understand an athlete's cognitive capacities, which are crucial for game intelligence. These insights can facilitate better decisions related to scouting, team composition, and both personalized and situational tactics and coaching strategies for individuals and teams. An increased self-awareness and understanding of others can also improve team dynamics and collaboration.

Open and Closed Sports

Open sports are activities where the environment is unpredictable, and athletes must respond to changing conditions and the actions of opponents. Characteristics:

– **Unpredictable Environment**: Conditions change constantly, requiring quick adjustments.

- **Reactive**: Athletes must react to opponents, teammates, and environmental factors.
- **Examples**: Soccer, basketball, tennis, rugby, hockey.

Closed sports are activities performed in a stable, predictable environment where the athlete initiates the action. Characteristics:

- **Predictable Environment**: Conditions remain stable, allowing for consistent execution.
- **Self-Paced**: Athletes control the timing and pace of their actions.
- **Examples**: Archery, golf, bowling, gymnastics routines, diving, target shooting.

Key Differences between Open and Closed Sports:

- **Environment**: Open sports have dynamic and unpredictable environments, while closed sports have stable and predictable ones.
- **Action**: Open sports require reactive skills, while closed sports rely on preplanned, self-paced actions.

General examples of Executive Functions in Open Sports

- **Attention in High-Pressure Situations**: Studies show that high-level attention is critical in sports where multiple events occur simultaneously, such as basketball soccer, hockey etc. Enhanced situational awareness allows athletes to perceive and respond to dynamic play developments effectively.
- **Working Memory in Complex Play**: In sports like soccer, handball, football, basket, baseball etc, athletes need to hold information, such as instructions, online, and act on rapidly on them. Working memory facilitates the retention and application of these instructions during fast-paced games, for example adaption and integration of the instructions with the ongoing game.
- **Cognitive Flexibility and Creativity in Soccer**: Midfielders and forwards, especially in soccer and ice hockey, require elevated levels of creativity and cognitive flexibility to switch between offensive and defensive roles seamlessly and generate novel multi-step solutions to emerging challenges.
- **Speed vs. Accuracy in Decision-Making**: The balance between speed and accuracy varies across sports. For instance, in football and ice hockey, quick decision-making often takes precedence over precision due to the fast-paced nature of the games. Hence the focus on ball possession and retaking the ball. In contrast, handball emphasizes accuracy, as the sport involves more structured play, and the consequences of mistakes are magnified. Hence the focus on not losing the ball.
- **Impulse Control in Timing Actions**: An athlete's ability to regulate and time their actions precisely under pressure is vital. For example, a soccer player may need to control their impulse to shoot immediately and instead

wait for the optimal moment, ensuring a higher success rate. Especially defenders or goal keepers benefit from a strong impulse control not to be lured by an opponent, a process that requires behavioural inhibition. The timing is crucial and missing the action may result in a goal and a lost match.
- **Strategic Thinking in Pre-Planned Plays**: Sports like American football, basketball, and handball often involve complex, pre-planned plays. Athletes must learn and execute these plays accurately, which requires strong strategic thinking and memory skills combined.
- **Variability in Performance**: An athlete's executive functioning can fluctuate based on conditions such as fatigue and stress. For example, a player's impulse control might be high in calm situations but diminish under pressure, affecting their timing and emotional regulation. Understanding individual sensitivity to changes within and around may allow athletes to optimize in a decisive way to be at their best when it matters.

Importance of Executive Functions in Ice Hockey

Ice hockey is a fast-paced, high-stakes sport where players must continuously adapt to the dynamic environment. The role of executive functions in ice hockey is critical due to the need for quick decision-making, strategic thinking, and effective communication.

- **Focus and Attention**: During a power play, a player must maintain focus on the puck while being aware of the positions of teammates and opponents. This requires sustained attention and the ability to filter out irrelevant stimuli.
- **Cognitive Flexibility**: A defenseman might initially plan to pass the puck to a teammate on the left, but if an opponent intercepts that path, they need to quickly switch strategies and find an alternative passing route or decide to clear the puck.
- **Creativity**: Players must employ creative thinking to devise unexpected plays and manoeuvres, such as innovative passing sequences, deceptive shots, and creative dekes to outmanoeuvre opponents and create scoring opportunities.
- **Inhibition Control**: Controlling impulses is vital during face-offs and when checking opponents. A player must avoid unnecessary penalties by restraining from actions like high-sticking or tripping, which could harm the team.
- **Working Memory**: Players need to remember and execute complex play formations, such as a breakout strategy from the defensive zone. They must also recall the tendencies and strategies of the opposing team from pre-game analysis.
- **Planning and Strategic Thinking**: For a forward breaking into the offensive zone, planning involves deciding whether to pass, shoot, or deke based on the positions of the defenders and the goalie. They must anticipate the possible reactions of their opponents and teammates.

– **Team Dynamics and Communication**: Effective communication and understanding of team dynamics are crucial. Players must quickly interpret and respond to verbal and non-verbal cues from teammates to execute plays successfully, such as a quick pass during a fast break or coordinating a defensive strategy to counter an opponent's attack.

Examples of Executive Functions in Closed Sports

Closed sports, also known as self-paced sports, are activities where the athlete initiates the action and performs in a stable and predictable environment. Understanding and controlling executive functions in these sports is crucial due to the need for precision, concentration, and strategic planning. Here are some examples of closed sports along with the challenges where executive functions are essential:

Archery

– **Focus and Attention**: Archers need to maintain intense concentration for extended periods to aim and release the arrow accurately.
– **Inhibition Control**: The ability to suppress distracting thoughts and external noises is crucial to maintain a steady hand and precise aim.
– **Cognitive Flexibility**: Adjusting to varying wind conditions or slight changes in lighting without losing focus.

Golf

– **Planning and Strategy**: Golfers must plan their shots carefully, considering factors like wind, terrain, and distance.
– **Working Memory**: Remembering previous shots, course layout, and adjusting technique accordingly.
– **Inhibition Control**: Managing frustration and maintaining composure after a poor shot to avoid affecting subsequent shots.

Bowling

– **Attention to Detail**: Bowlers need to focus on their approach, timing, and release to ensure accuracy and consistency.
– **Cognitive Flexibility**: Adjusting technique based on lane conditions and performance of previous frames.
– **Inhibition Control**: Controlling emotions and staying calm under pressure, especially in competitive settings.

Gymnastics (certain routines)

– **Inhibition Control**: Suppressing nervousness and distractions to perform complex sequences accurately.

- **Focus and Attention**: Maintaining attention on precise execution of movements while ignoring external stimuli.

Target Shooting (e.g., rifle or pistol shooting)

- **Focus and Attention**: Shooters need to maintain elevated levels of concentration to aim and fire accurately.
- **Inhibition Control**: Suppressing physical and mental distractions, such as muscle tremors or anxiety.
- **Cognitive Flexibility**: Making minute adjustments to aim based on changing environmental conditions.

Diving

- **Planning and Strategy**: Divers need to plan their dives meticulously, considering the sequence of movements and entry into the water.
- **Working Memory**: Remembering and executing complex routines.
- **Inhibition Control**: Managing stress and maintaining composure before and during the dive to ensure precise execution.

Billiards/Pool

- **Strategic Thinking**: Planning shots several moves ahead to control the table.
- **Attention to Detail**: Precise control over cue ball and object balls requires intense focus.
- **Inhibition Control**: Maintaining calmness and control, especially in high-pressure situations.

Cycling

- **Focus and Attention**: Cyclists need to maintain focus on their pace, breathing, and positioning on the bike for extended periods. Any lapse in concentration can lead to decreased performance or accidents.
- **Cognitive Flexibility and quick decision making**: During a race, a cyclist may need to adjust their strategy based on changing weather conditions or the behaviour of other competitors. If a rider breaks away from the pack, the cyclist must quickly decide whether to follow or stick to their planned pace.
- **Inhibition Control**: Cyclists must manage their energy output and resist the urge to push too hard too early in the race, which could lead to burnout. They need to stick to their planned strategy and pacing.
- **Working Memory**: Remembering the course layout, including the locations of steep climbs, sharp turns, and aid stations, is crucial for effective race management. This allows for strategic energy conservation and optimal performance.
- **Planning and Strategic Thinking**: Effective race planning involves setting a pace strategy that considers the cyclist's strengths and the course profile. For example, knowing when to conserve energy on flats and when to push hard on climbs can make a significant difference in overall performance.

Importance of Executive Functions

In all sports, the ability to control executive functions directly impacts performance. To control we need to understand and therefore we need to measure. When measuring it is also important to examine and related capacity to awareness and existing coping strategies that might already be in place.

Based on enhanced awareness, effective adaption of training and coaching can help athletes enhance their performance by improving their mental control, decision-making, and overall strategic approach to their sport. As always in performance-intense environments slight changes may have a significant impact on the result.

Practical Implications

Integrating neurocognitive assessments into sports practices provides a robust basis for:

- **Enhanced Understanding of Game Intelligence**: Improving overall game intelligence by understanding how cognitive functions influence decision-making and situational awareness.
- **Reduce Subjectivity and Bias**: Providing objective data to minimize biases in talent identification, training, and team selection decisions.
- **Enhanced Understanding of Individual Functioning**: Gaining deeper insights into how each athlete's cognitive abilities impact their performance and tailoring support accordingly.
- **Enhanced Talent Identification**: Identifying athletes with high potential based on cognitive profiles.
- **Personalized Coaching**: Developing tailored training programs to, based on cognitive profile, strengths and weaknesses, support development of optimizing and compensating strategies as well as adapt physical, technical, tactical, and mental training.
- **Strategic Team Composition**: Forming teams with complementary cognitive strengths.
- **Tactical and Strategic Adaptations**: Adapting tactics and strategies to leverage cognitive strengths and address weaknesses, both at individual and team levels.
- **Matching Players**: Pairing or grouping players based on compatible cognitive profiles to enhance on-field synergy and effectiveness.
- **Co-Play and Team Dynamics**: Fostering better teamwork and communication by understanding and leveraging cognitive dynamics within the team.
- **Time Efficiency**: Saving time by quickly understanding athletes' cognitive profiles, allowing for faster and more effective training adaptations and decision-making processes.
- **Stress resilience and Well-being**: Enhancing athlete well-being by recognizing cognitive stressors, providing appropriate mental health support, and coping strategies.

– **Injury Prevention and Assessment**: Utilizing cognitive assessments to prevent injuries, including concussions, by identifying risk factors and monitoring cognitive health, and assessing cognitive impact post-injury to guide rehabilitation and return-to-play decisions.

Implementing Understanding of Executive Functioning

– **Assessment and Profiling**: In just 45 minutes, an athlete's cognitive profile can be assessed, providing a robust evidence base for their development. This quick yet comprehensive assessment ensures timely and accurate understanding of cognitive strengths and weaknesses. And can save weeks, months or even years of struggling to coaching and development. Thus supporting a quick transition from Good to Great.
– **Understanding and Awareness**: Fill the gap by understanding the "how" and "why" behind observed performance and behaviour. Engage all relevant stakeholders to ensure an integrated approach, enhancing cooperation and minimizing misunderstandings.
– **Acceptance and Commitment**: Ensure the individual athlete's acceptance of the test results and foster their commitment to working with the insights gained. This step is crucial for effective application and long-term success. Make sure all stakeholders are involved and have a sufficient level of understanding.
– **Optimizing and Compensating Strategies**: Leverage the cognitive profile to identify effective coping strategies not just cognitively, but also across the tactical, physical, technical, and mental domains. This multi-faceted approach ensures comprehensive development and performance optimization.
– **Integration into Existing Coaching and Training Schemes**: Seamlessly integrate the cognitive insights into daily coaching and training routines. This ensures that all involved actors, including coaches and support staff, are aligned and can work synergistically towards the athlete's development.
– **Follow-Up and Adjustment**: Establish a continuous follow-up mechanism to monitor progress and make necessary adjustments. This ensures sustained understanding, reinforcement of strategies, and ongoing development.

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Research papers

Evaluating Space Creation in the National Hockey League using Puck and Player Tracking Data

Hassaan Inayatali and Timothy Chan

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Abstract. Star ice hockey players are often described as having a magnetic pull, with the ability to draw out opponents and generate dangerous opportunities for their linemates in the space left vacant by defenders. Using spatiotemporal Puck and Player Tracking (PPT) data, we develop a quantitative approach to measure how players create space while in possession of the puck, termed On-Puck Space Generation (OPSG). The benefits of our model's approach include its decomposition into three components: 1) Rink Control, the probability of controlling the puck at a given location; 2) Rink Value, the probability of scoring from a given location; and 3) Transition Probability, the probability that the next on-puck event will occur at a given location. Preliminary results of our metric show that players who achieve high levels of OPSG are more likely to lead their team in goals, assists and points. Our model can be used to analyze which players are in positions of danger, identify instances in which an individual created valuable space for their teammates, and understand which teams are best at generating space.

1 Introduction

While much of the information used to construct ice hockey teams and evaluate players is limited to the contributions of an individual, success in ice hockey requires high degrees of coordination among teammates. A common point of discussion with regards to play-making is space creation, movement which enables fellow teammates to position themselves in areas of high value. The work in this paper aims to address the following research question: How can we quantify the value of player movement with respect to influencing defender actions and creating scoring opportunities? In this work, we develop a model to quantify space creation by players in possession of the puck.

In the past, ice hockey analytics have been limited to event and stint data, which includes actions on the puck, the players involved and which players were on the ice at the time of a given event. Building off of the work by Sam Green [5] in soccer, expected goals (xG) models were developed to better understand the quality of shot opportunities in ice hockey [7, 3]. More comprehensive models such as Regularized Adjusted Plus-Minus (RAPM) models [4] have been built to better understand an individual's offensive and defensive impact. However, these models were unable to include information on teammate and opponent positioning on the ice.

With the introduction of Puck and Player Tracking (PPT) Data during the 2019-2020 NHL Playoffs, we can obtain more context into the game state when an event occurs and answer more complex questions relating to space creation. With other sports like soccer having had access to spatiotemporal data for nearly a decade [6], researchers have developed methodologies which focus specifically on inter-player dynamics. Thus, we have the opportunity to adapt existing models to ice hockey while accounting for the differences in these sports.

From this literature, we develop a model to determine the probability of scoring on the next on-puck event given the state of the game conditioned on an instantaneous pass event. Our model consists of three components:

1. **Rink Control**: The probability of controlling the puck at a given location.
2. **Rink Value**: The probability of scoring from a given location.
3. **Transition Probability**: The probability the next on-puck event will occur at a given location.

We calculate the change in the probability of scoring from the start of the possession to the end and aggregate across all possessions. This yields our final metric, On-Puck Space Generation (OPSG). The results of our model can help in understanding specific instances of space creation, evaluate player movements, and discern which teams are able to generate space consistently against their opponents. The contributions of this work are as follows:

- We develop a novel transition probability model for ice hockey conditioned on the locations and movements of all players on the ice.
- We propose a model to measure space creation by players in possession of the puck. Our model is composed of three sub-models which increase interpretability of the model's predictions.
- We perform an evaluation over 35 NHL games from the 2023-2024 season. We aggregate OPSG for individual players and teams. Our results show that OPSG has the strongest correlations with forward assists, defensemen goals, and team shot attempt differential.

2 Related Work

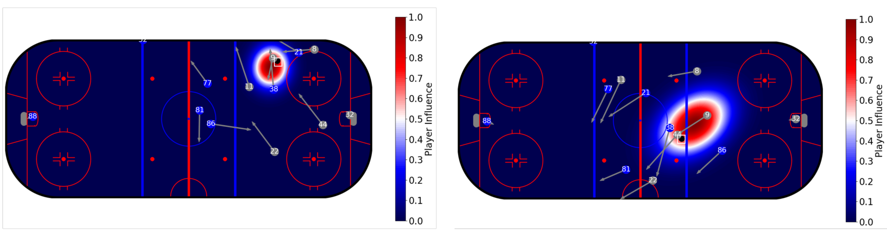
Pitch control refers to the "the probability that a player or team will be able to control the ball if it were at that location" [11]. Pitch control models have been developed in various forms, through the use of Voronoi Diagrams [12], Player Influence Models [1], and Poisson Point Processes [10]. While Pitch Control provides insight into spatial ownership, the value of this space is not considered. Pitch Value models aim to learn the value of space in different areas of a playing surface. These models can apply defensive positioning [1], distance from the net [10], or other models to decompose possession value into various actions [2]. These models are combined to better understand the quality of space controlled by each team [1, 10]. These can be used to create off-ball space creation metrics including Off-Ball Scoring Opportunity (OBSO) [10] and Space Generation Gain (SGG) [1]. In ice hockey, past research with PPT Data have focused on passing lanes [8] and passing value [9].

In this paper, we adapt Pitch Control and Pitch Value as well as expected pass speed from the aforementioned passing lane literature [8] to ice hockey to construct each of our Rink Control, Rink Value, and Transition Probability models. Our final result is a novel metric, entitled On-Puck Space Generation (OPSG), which examines a player's creation of space while in possession of the puck. We analyze how OPSG correlates with a player's cumulative production in terms of goals, assists, and points. Furthermore, we delve into a team's game-level space creation and how it relates to their performance in terms of shot attempts, shots on goal (SOG) and goals scored. Unlike previous work that focuses explicitly on puck transitions between players, our model provides insight into how players generate value when in possession of the puck. To the best of our knowledge, this is the first such model in the domain of ice hockey.

3 Methodology

3.1 Rink Control

We develop our Rink Control model using a bivariate normal distribution, in a similar fashion to Bornn and Fernandez [1]. To account for the speed of ice hockey, we increase the denominator in calculating a player's normalized speed ratio to 1500 ft/s. Additionally, we set the range of influence to be a minimum of 12 ft, which increases with distance from the puck up to a maximum of 30 ft. Distance from the puck affects the range of influence, aligning with the premise of Bornn and Fernandez, that "if the ball moves toward the player he would have more time to reach the ball within a larger space" [1]. Figure 1 shows two examples of player influence for a single player, both with the puck (Figure 1a) and without the puck (Figure 1b), ranging from 0 to 1. We focus on #9 in grey, where darker shades of red indicate higher levels of influence. For this and all future figures, the white square highlights the puck's location.



(a) Player Influence with the Puck (b) Player Influence without the Puck

Fig. 1. Visualizations for Continuous Player Influence

The influence of each player is aggregated and the home team's influence is subtracted from the visitor's at each location. The logistic function is applied to obtain a measure of Rink Control for each team, in the range of 0 to 1. A sample of this can be seen in Figure 2. Darker shades of red represent higher levels of influence for the team in gray, whereas darker shades of blue represent higher levels of influence for the blue team.

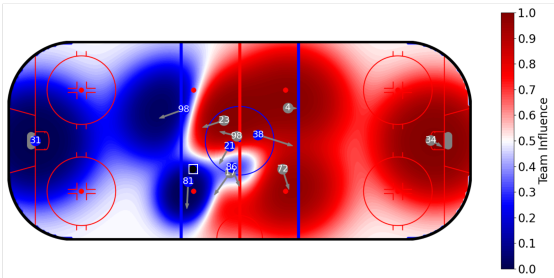


Fig. 2. Team Influence Model

3.2 Rink Value

To determine the value of a region on the ice, we develop an expected goals (xG) model to predict the probability a goal will be scored from a given location. This model is a logistic regression which predicts the probability of scoring based on the distance and angle of a shot. Our model is trained using NHL play-by-play (PBP) data from the 2015-2016 season, and achieves a cross-validated AUC of 0.731. This model can be seen in Figure 3. Darker shades of red represent a higher probability of scoring from the perspective of the team in grey, from 0 to 0.4.

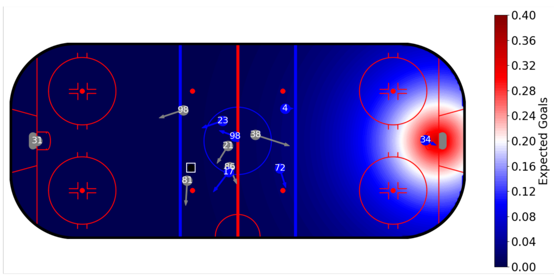


Fig. 3. Expected Goals (xG) Model

3.3 Transition Probability Model

With our Rink Control and Rink Value models, we determine the probability the next on-puck event occurs at a given location. using the following procedure:

1. Obtain a dataset of intended passes (successful and failed).
2. Model the probability a given pass will be successful.
3. Calculate the probability a pass will be successful to any location.
4. Normalize Pass Probability such that the sum over the rink is equal to 1

Thus, we assume Transition Probability is proportional to the probability a pass will be successful to a given location.

Possession Model Given that we do not have access to event data/passes, it is assumed that passes are transfers of possession between teammates. To obtain passing instances, we develop a possession model that produces a binary variable indicating the team in possession of the puck. The rule-based model is as follows:

1. The player is closest to the puck AND
2. The player is within six feet of the puck (one stick length) AND
3. The puck is traveling slower than 35 ft/s (max skater speed) AND
4. (a) The player was the previous player in possession of the puck OR
   (b) The player has an additional six feet between themselves, the puck, and the nearest defender

Pass Regression Using successful passes, we apply the linear regression methodology employed by Radke et al. [8] to predict the time until a pass will arrive at a receiver given their the distance from the passer. Transfers of possession were limited to less than two seconds to ensure only intended passes were analyzed as opposed to dump-ins or puck recoveries. This model was developed using 697 successful passes taken over the course of an NHL game, shown in Figure 4.

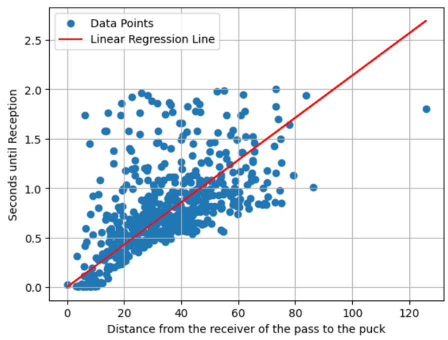


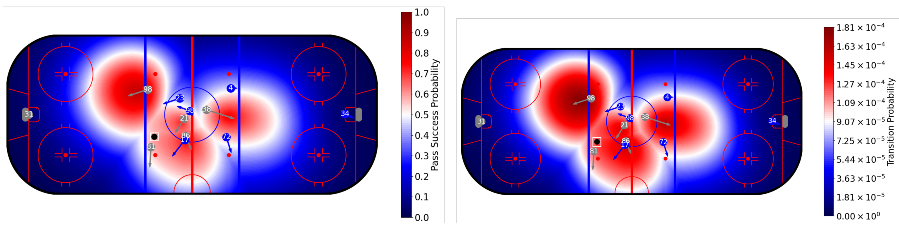
Fig. 4. Passing Linear Regression Model

The slope of this regression is 0.021 s/ft, meaning that for every additional foot a player is away from the puck carrier, it will take an additional 0.021 s for the puck to reach this player.

Pass Prediction To predict passes, we take the velocity vector of the puck at the moment the player no longer has possession, decided by our rule-based model presented in Section 3.3. For each teammate, the puck's velocity is projected according to how far they are from the puck carrier, using the linear regression in Figure 4. Each teammate's velocity is projected forward to estimate where they will be at the puck's arrival [8]. The distance between the puck's projection and teammate's projection is calculated. The player with the smallest distance is predicted to be the receiver of the pass. We exclude passes which hit the boards (dump-ins, bank passes, rims) as well as those which would be further from their intended receiver than 10 feet, to ensure we only analyze passes in which there was the direct intention to be received by a given player. A pass is successful if the following player in possession of the puck is the passer's intended target.

We fit a logistic regression model to predict pass success probability using five variables: defensive influence at the origin, midpoint and destination of the pass, projected distance between reception and receiver, and pass distance. The model was trained on 7000 passes and achieved a cross-validated AUC of 0.751.

Transition Probability We assume that a pass to a given location is intended for the player with the highest probability of receiving it. Because Transition Probability is proportional to the probability a pass would be successful to a given location, we normalize team pass probabilities across the rink surface to sum to 1. Team Pass Probability and Transition Probability can be seen in Figure 5. In Figure 5a, the right-defensemen of the grey team is in possession of the puck and the highest probability of a pass being successful is to his defensive partner. However, there are also passing lanes to each forward, and this can be seen by the darker shades of red in the direction each is travelling. Figure 5b takes the results from Figure 5a and normalizes across the rink surface by dividing the probability at each location by the sum of all probabilities.



(a) Team Pass Probability Model (b) Transition Probability Model

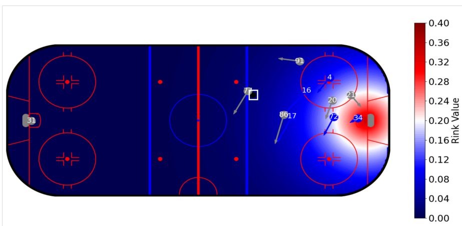
Fig. 5. Visualizations for Continuous Player Influence

3.4 Combined Model

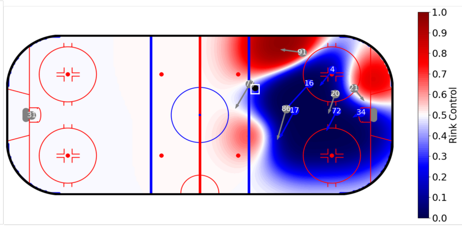
Using the framework presented by Spearman [10], we predict the probability of scoring on the next on-puck event for the attacking team conditioned on the puck possessor passing the puck. Let G_r denote the probability of scoring from location r, C_r represent the probability of controlling the puck at location r, and T_r signify the probability of passing the puck to location r. D and M represent the state of the game and a boolean representing an instantaneous passing event, respectively. Equation 1 shows how these models are combined to calculate the probability of scoring on the next on-puck event for the attacking team given the state of the game conditioned on an instantaneous pass event, $P(G|D,M)$.

$$P(G|D,M) = \sum_{r \in RXR} P(G_r|C_r,T_r,D,M)P(C_r|T_r,D,M)P(T_r|D,M) \tag{1}$$

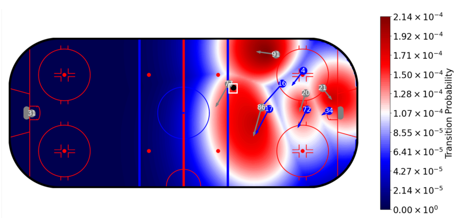
Figure 6 illustrates each component of the model, with Figure 6a showing Rink Value, Figure 6b displaying Rink Control, Figure 6c demonstrates Transition Probability and Figure 6d presents the combined model, with darker shades of red representing higher values. The sum of the combined model across the rink surface is $P(G|D,M)$. In Figure 6d, the probability of scoring is concentrated on the top right of the rink surface, driven by there being a player who is in a position of high value (Figure 6a), able to control the puck if it were to reach them (Figure 6b) and receive a pass at that location (Figure 6c).



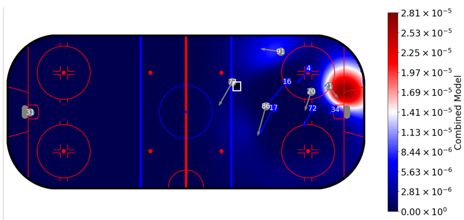
(a) Rink Value Model



(b) Rink Control Model



(c) Transition Probability Model



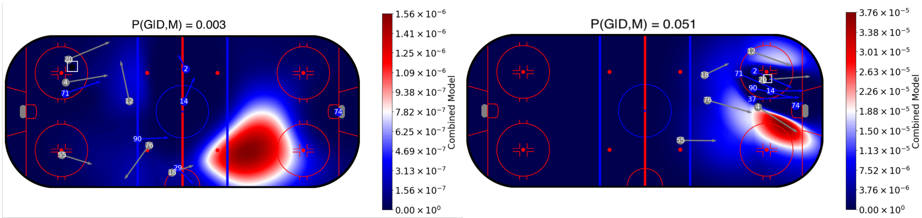
(d) Combined Model

Fig. 6. Visualizations for Continuous Player Influence

4 Results

4.1 Tactical Analysis

Using our model presented in Section 3, we measure how players create valuable space for their teammates. Figure 7 represents one of these situations, when the puck carrier starts with the puck in their own zone and proceeds to carry the puck from end-to-end and creates a direct passing lane to their teammate on a 2-on-1. At the beginning of the possession (Figure 7a), the probability of scoring on the next on-puck event is concentrated for #18 (bottom), which would depend on his being able to beat his defender to receive the pass from #20 (top left). By the end of the possession (Figure 7b), the teammate closest to the puck carrier (#4) on the 2-on-1 is occupying a high value area with a passing lane to receive the puck. This process can support coaches in identifying moments where an individual creates valuable space for their teammates in opposition scouting as well as better understanding how their players create space for one another.



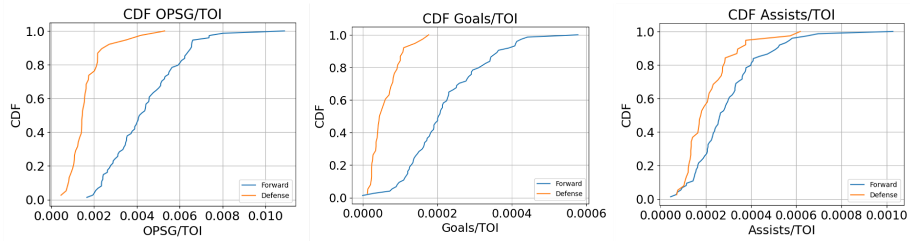
(a) Start of Possession

(b) End of Possession

Fig. 7. Visualizations for Continuous Player Influence

4.2 Player Evaluation

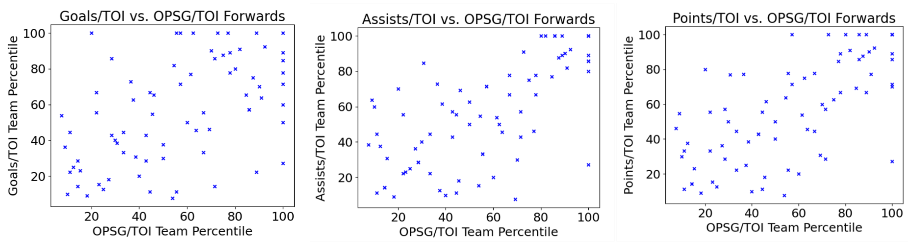
We aggregate the change in probability of scoring on the next on-puck event over a player's possessions to measure their On-Puck Space Generation (OPSG). We complete this process across 35 NHL games from the 2023-2024 season. Matchups were selected to maximize games played (GP) by a subset of teams to gather a representative sample for each player given compute constraints. Our evaluation examines players with five or more GP. This includes 74 forwards and 38 defensemen, with their mean time on ice (TOI) being 16.2 and 20.7 minutes per game, respectively. We normalize metrics using TOI to ensure usage does not affect player comparisons. In Figure 8 we plot CDF's for OPSG/TOI, Goals/TOI and Assists/TOI. Forwards generate more OPSG/TOI than defensemen (Figure 8a), with the 80^{th} percentile forward generating three times more than the 80^{th} percentile defensemen. This is comparable for Goals/TOI (Figure 8b); however the difference for Assists/TOI is considerably smaller (Figure 8c).



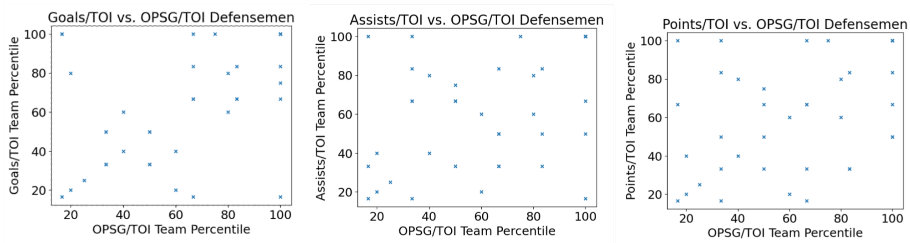
(a) OPSG/TOI (b) Goals/TOI (c) Assists/TOI

Fig. 8. CDF Plots by Position Category

Figure 9 demonstrates the relationship between OPSG/TOI and Goals/TOI, Assists/TOI and Points/TOI using their team percentile within their position category. Figures 9a, 9b and 9c show forward results and Figures 9d, 9e and 9f show defensemen results. While these scoring metrics generally increase as OPSG/TOI rises, the results are more pronounced for forwards compared to defensemen. Team percentiles are presented to maintain player/team anonymity. It should be noted OPSG focuses on player movements while the puck is possessed; it does not evaluate a player's eventual decision with the puck.



(a) Forward Goals (b) Forward Assists (c) Forward Points



(d) Defensemen Goals (e) Defensemen Assists (f) Defensemen Points

Fig. 9. Relationship between OPSG/TOI and Scoring Statistics by Position Category

Table 1. Average OPSG/TOI and Correlation with OPSG/TOI by Position Category

Position Category	**Avg. OPSG/TOI**	**Goals/TOI**	**Assists/TOI**	**Points/TOI**
Forwards	0.0048	0.504	0.654	0.660
Defensemen	0.0017	0.419	0.344	0.363

Table 1 shows the average OPSG/TOI and the correlation between OPSG/TOI and each of the aforementioned scoring metrics by position category. OPSG/TOI's correlation with Goals/TOI, Assists/TOI, and Points/TOI is higher for forwards compared to defensemen. Because defensemen are usually last to lead the rush and position themselves from the point in the offensive zone, we hypothesize they are less likely to move the puck into a space that will generate dangerous opportunities for their teammates relative to forwards. As seen in Table 1, defensemen generate nearly three times less valuable space for their teammates compared to forwards. Thus, the relationship between OPSG/TOI and Assists/TOI is weaker than forwards with a correlation of 0.344 compared to 0.654. This follows intuition given that this metric is designed to measure how well players create space for others, as opposed to themselves, and forwards are consistently moving the puck within the offensive zone to create scoring opportunities for their teammates.

Additionally, the correlation for defensemen is higher in goals compared to assists. One reason this might occur is that offensive defensemen that generate goals are more likely to carry the puck in more valuable areas in the offensive zone. Considering there are two assists for each goal, defensemen do not need to be in these areas to generate assists. Deeper analysis is required to confirm the underlying cause for these relationships. We leave this for future work.

We can also analyze the OPSG/TOI breakdown by position, shown in Table 2. While left-wingers and centers seem to generate more OPSG/TOI compared to right-wingers, these are subject to the composition of the rosters analyzed, and thus, a more comprehensive analysis of this area is needed. A similar statement could be made on left and right defensemen.

Table 2. OPSG by Position

Position	**OPSG/TOI**
Right Wing	0.0044
Center	0.0048
Left Wing	0.0050
Left Defensemen	0.0018
Right Defensemen	0.0016

4.3 Team Evaluation

We calculate the OPSG Differential between the Home and Away team, along with their shot attempts, SOG, and goal differential for each game in the dataset. The correlations between these measures are shown in Table 3. OPSG has a stronger relationship with shot attempts and SOG compared to Goal Differential. As various pieces on expected goals have noted, goals occur more randomly in comparison to shot attempts and SOG [3, 5]. Exploring the slightly negative correlation between OPSG and Goal Differential is left for future work with a larger set of games.

Table 3. OPSG Differential Correlation

Metric (H)	Correlation
Shot Attempt Differential	0.647
SOG Differential	0.603
Goal Differential	-0.055

5 Limitations and Future Work

While the model we propose in this work helps characterize space creation, it has several limitations. A limitation of our Rink Control Model is that it is a descriptive model and is not calibrated to event outcomes e.g. passes/puck recoveries; thus the model may not be indicative of actual values of control beyond player orientation to a specified location. Additionally, our Rink Value Model assumes the receiver of a pass is able to shoot. In reality, the value of possession in different areas on the ice should incorporate all possible decisions available to a player and their expected outcome. With regards to our Transition Probability Model, we have not incorporated the NHL offside rule into our models; thus receivers may not be in positions to receive a pass despite having a high transition probability. Finally, our combined model does not value passing lanes differently from one another. While low-high and seam passes increase the probability of a shot being scored relative to other shots at the same location, our current model does not incorporate features to differentiate these types of plays. Each of these limitations is left for future work.

Furthermore, given OPSG results are limited to a 35-game sample, an immediate direction of future work is to run this process across a full season to better understand the consistency in a player's ability to create space with the puck and our metrics repeatability.

A puck carrier's teammates also have the responsibility of moving into positions where they can receive the puck and create scoring opportunities. To understand a player's off-puck space creation for teammates, we could follow the framework presented by Bornn and Fernandez [1] for Space Generation Gain (SGG). To understand a player's off-puck space creation for themselves, we could isolate a player's contribution to Transition Probability through their Pass Probability Fabric, their contribution to Rink Control through their individual influence as seen in Figure 1, and Rink Value which does not require any adjustments. We could then measure the changes in their probability of scoring on the next on-puck event assuming the possessor of the puck were to pass it to them. This could then be aggregated across all possessions.

Another direction of future work is to measure how well teams perform in blocking passing lanes using our pass probability model. Given a set of intended passes, we can calculate the probability of the pass being successful, and measure how teams block opponent passes compared to the probability of the pass being successful. This would require an accurate dataset of incomplete and blocked passes, and thus, we leave this study for future work.

An additional area of future work would be to better understand which types of players play best together, known as team formation problems in the broader artificial intelligence (AI) literature. Teams may not want to have three players who excel at on-puck space creation but are poor in off-puck space creation on the same line. These types of traits could be applied further into team formation algorithms to better predict team success.

6 Conclusion

The presence of spatiotemporal data in ice hockey shifts the types of questions that can be addressed through analytics and the methodologies employed to approach them. Research developed in other sports, most specifically soccer, lends itself well to ice hockey and allows for more complex approaches to these problems. In this paper, we present a new metric for ice hockey, On-Puck Space Generation (OPSG). This metric can be used to better understand play-making through a quantitative approach to space creation using Puck and Player Tracking Data. Our models can be applied at the game-level to understand which players are creating space and where it is most often being generated. Furthermore, we can learn which teams are best at collaborating to generate space for one another, and how this relates to collective success. We believe this framework represents the first step toward better understanding how players create space in valuable areas in ice hockey.

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Examining the Role of Hockey Leadership to Foster Inclusive Coaching Practices: Discussions from Atlantic Canada

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Abstract. Coaching has been widely examined in the sport of ice hockey. Technical skill development, player management, and the ability to improve performance have been very notable areas of inquiry. As the critical roles of coaching leadership and communication become clearer, there is limited research available which explores the context of inclusive hockey coaching leadership to support more equitable practices. This paper will focus on specific data extracted from a previous study completed by the authors in which general hockey leadership skills and professional development were explored. This paper will present the outcomes of fostering inclusion and diversity from a coaching lens. Thirteen minor hockey coaches from Atlantic Canada (i.e., who are members of the Atlantic Hockey Group) participated in this qualitative study. Semi structured interviews were conducted online or in-person. A thematic analysis was used to explore data obtained from the interviews. Results revealed that coaches had limited communication training experience when working with diverse abilities, age groups, languages, genders, or cultures. Limited professional development specific to inclusive training was noted by participants. Our results demonstrated that various self-led leadership strategies were utilized to promote inclusive practices such as informal community-peer mentorship opportunities, and small group instructional sessions. Overall, the results give us insights into coaches' experiences with inclusive leadership and highlight current gaps. During the conclusion, future recommendations for continued study, specifically within leadership training for diversity within ice hockey, are offered.

Keywords: Communication, Ice Hockey, Coaching Leadership, Cultural Diversity, Inclusion, Performance, Player Engagement

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1 Introduction

1.1 Inclusivity in Sports

Sports are an integral part of an active and healthy lifestyle (Statistics Canada 2023). According to Statistics Canada (2023), Canada is a leading sport nation. There are several factors which contribute to participation, such as the season and the geographic and social diversity in the area. Hockey, our national winter sport, was invented in Canada in the 1800s, and basketball was invented by Canadian Dr. James Naismith in 1891 to condition young athletes during the winter. Other sports, such as soccer and basketball, are also popular. According to Gough (2023), hockey is the most popular sport in Canada, followed by soccer and basketball.

The influence of coaching behaviors on athlete performance has been one of the most investigated topics in coaching science (Gilbert & Trudel, 2004). Coaches are engaged with providing and assessing the development of various technical skills and monitoring training at various levels. Performance assessment has become a field of expertise that is crucial for researchers and practitioners (e.g., coaches, strength and conditioning coaches, scouts, program directors), who need to be aware of the mechanisms that predispose hockey players to perform in key situations (Bournival et al., 2023).

The National Hockey League (NHL) is the leader for many directives within ice hockey. Understanding communication, coaching leadership and cultural diversity has been examined recently. NHL commissioner Gary Bettman has stated that, "we are working to better understand and accelerate our engagement across all layers of diversity, including nationality, race, gender identify, sexual orientation, disability and religion," (Wyshnyski, 2022). We know very little about hockey coaching communication within the realms of inclusion and diversity. More research is needed to better understand perceptions, best practices, and inclusive practices to employ within ice hockey coaching specifically to improve coach engagement, player experiences, and hockey performances. Supporting this development, NHL commissioner Bettman stated that "Each day, we are committed to ensuring inclusion becomes more of 'who we are' than 'what we do" (Wyshynski, 2022).

According to Oldham (2022), society must break down the interlocking forms of discrimination and social injustices at the junior, college, and professional levels of ice hockey. Furthering a notion of "Why does this happen? "and "How can we fix it?" Leadership in sport is an emergent field which has been gaining attention on a national level (Jones & Khan 2017). More specifically, understanding the optimal leadership training for more inclusive hockey coaching is intriguing. The objective of this paper is to document and examine the communication experiences of minor hockey coaches in Canada who support youth with diverse needs and determining what resources are required to improve coaching experiences. According to Matthews and Erickson (2023), youth sport is a context that can promote positive youth development (PYD), with coaches being a key agent for positive development. Furthermore, transformational leaders employ four strategies, colloquially referred to as idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration (Matthews & Erickson, 2023, p.1). Lara-Bercial & Mallett, (2016) investigated characteristics of coaches and their relationship to leadership. The findings of this study revealed that coaches had a common set of personal characteristics, which included an exceptional work ethic, strong communication skills, a quest for continuous improvement, and effective leadership behaviors that inspired their athletes. This research study will explore coaching leadership through an inclusive lens. As described by Liew and McTigue (2010), educating the "whole child" became more prominent and thus enhanced the teaching and coaching skills of professionals who work directly with youth. Leadership and training are imperative to properly address the expansive growth and popularity of Canadian hockey.

1.2 Hockey and Canada

As the IIHF reported, there are currently 513,684 Canadian hockey players registered (IIHF, 2024). The total number of players registered with the IIHF is 1,563,749, meaning that Canadian players account for 1/3 of the total membership of an organization that governs 81 countries. Hockey is considered a cultural truism and a way of life among Canadians, with a connection so powerful and strong that it has united a vast nation from coast to coast (Cairnie, 2019). In fact, the sport is often considered a Canadian national treasure for its ability to build kinship bonds between ethnicities, classes, and cultural groups. While such perceptions of inclusivity have remained prevalent in the sport, recent critical events, such as abuse scandals and racism, have negatively impacted the sport and its leaders (Burke, 2022).

1.3 Inclusive Hockey Leadership & Coaching

From an understanding of the early vision that guided Canadian sport history, its is readily observable that promoting inclusivity in Canadian sport has been recognized as critically important and can be best described as follows:

> "Sport is welcoming and inclusive, offering an opportunity to participate without regard to age, gender, race, language, sexual orientation, disability, geography, or economic circumstances" (Canadian Sport Policy, 2002, p.13).

In December 2021, the Prime Minister of Canada released a mandate letter, providing clear direction on the importance of incorporating the views of Canadians when considering society, inclusivity, diversity, and our historically marginalized communities. As he noted:

> "We must continue to address the profound systemic inequities and disparities that remain present in the core fabric of our society, including our core institutions... I expect you to include and collaborate with various communities, and actively seek out and incorporate in your work,

> the diverse views of Canadians. This includes women, Indigenous Peoples, Black and racialized Canadians, newcomers, faith-based communities, persons with disabilities, LGBTQ2 Canadians, and, in both official languages." (Kay et al., 2022).

Providing equal opportunity and accessibility is an imperative need within Canadian sport communities. As noted by Kay et al. (2023), sport research findings suggest that research participants felt efforts should be made to increase the participation of under-represented groups in sport. Particularly, these groups included indigenous people, racialized people, women and girls, persons with disabilities, children and youth, new Canadians, and economically disadvantaged people. Hockey Canada, the governing body of amateur hockey in Canada addressed this need recently. In October 2020, the Equity, Diversity and Inclusion (EDI) task team provided a report to the Hockey Canada Board of Directors that included a framework for the strategic plan on EDI. Additionally, organizations require strategies to support the successful engagement of hockey players from these underrepresented groups (Hockey Canada, 2023). Hockey Canada has published its first Equity, Diversity, and Inclusion (EDI) Path Forward, which includes a Commitment to Action statement that summarizes the organization's ongoing work to drive long-term, sustainable change within the hockey ecosystem in Canada, building an environment where people feel valued for their differences and have positive experiences with hockey (Hockey Canada, 2023).

According to Matthews and Erickson (2023), youth sports can promote positive youth development (PYD); coaches are a key agent for positive development. Furthermore, transformational leaders employ four strategies, known as idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration (Matthews & Erickson, 2023, p.1). Duguay et al. (2020) found that coaches who embody effective leadership qualities not only impart essential athletic skills but also instill crucial life lessons, such as teamwork, discipline, and resilience. Additionally, inspirational leaders serve as role models, encouraging young athletes to strive for excellence while maintaining a positive attitude, sportspersonship, and respect for others (Davis, 2018). Conversely, poor leadership can have detrimental effects, leading to a toxic atmosphere, demotivation, and even dropout rates among youth participants (Fouraki et al., 2020). Fostering an environment of belonging and inclusivity is essential for all youth hockey players and may be difficult for coaches. Jedwab & Holly (2021), researched immigration and diversity in ice hockey and concluded that despite the many challenges hockey faces as the country's most watched and played sport, it still creates a strong sense of community belonging amongst those who choose to play (p.164). Providing coaches with appropriate training and leadership skills to support diversity is critical (Saotome, 2013). Additional research concludes that personality, character, and communication skills are essential (Erickson, 2023). In addition to coaching leadership research, evidence suggests that youth with strong leadership skills are more likely to have positive work and family relationships, enter and graduate college, succeed in their careers, and have better mental and physical health outcomes (Greenberg et al., 2017). Previous research has determined that when enhancing learning, one important factor is the ability and experiences educators and coaches possess to engage and support learners (Jones & Kahn, 2017).

2 Methodology

This qualitative research study utilized open-ended, semi structured interview questions to collect data specific to the training and coaching experiences of hockey coaches from Atlantic Canada. Data were collected for this study from November 2022-May 2023. Participants were recruited by email from the project partner, The Atlantic Hockey Group (AHG). The participant sample (n=13) comprised of minor hockey coaches who volunteered with the AHG and instructed youth aged 4-18 years. The sample for this research was purposive, as ice hockey coaches, both male and female, were invited to participate. Recruitment also involved notices through social media and direct email from the Atlantic Hockey Group. There were small inducements of Tim Horton coffee cards offered for study participation.

Participation was voluntary, and coaches were invited to complete a short interview with a member from the research team. The interviews took place in-person and/or online, via Zoom TM depending upon location and availability of each participant. All participants self-identified as male (i.e., n=13) who ranged in age from 23 to 52 years. The average span of coaching experience was 9 years.

The qualitative interviews were composed of five open-ended questions. For this paper, three questions served as focal points of analysis. Interview questions analyzed specifically for this paper included:

1. Social-Emotional Learning includes aspects of enhanced leadership, empathy, understanding, self-regulation, behavior support, trust, honesty, inclusivity, etc. What is your experience with these specific components? Were they taught explicitly or included within your coaching training? If yes, what types or when?
2. In your coaching career, how often are you provided with leadership training? What types of training did you receive as professional development?
3. When coaching young ice hockey players, what is the most challenging aspect in terms of connections and relationship building with your players and/or families? Are there other barriers or challenges with your players? What types of training do you feel would be beneficial for coaches?

Researchers took field notes at the end of sessions to ensure key messages were highlighted. Sessions were also recorded with permission for transcription. Ethics approval was obtained from Cape Breton University prior to engaging in our interview process.

Research Question: What are the hockey leadership experiences of coaches in Atlantic Canada?

2.1 Theoretical Framework

This study was framed upon aspects of Social Emotional Learning (SEL). Encompassing approaches where youth and children learn to recognize and manage emotions, develop positive relationships, behave ethically, care about others responsibly, make good decisions, and avoid negative behaviors (Gould et al., 2022). It involves "... teaching children to be self-aware, socially cognizant, able to make responsible decisions, and competent in self-management and relationship skills..." (Zins et al., 2007, p. 195). Social Emotional Learning (SEL) is critical for children and youth's long-term success in and out of school (Weissburg et al., 2015). Examining the intrapersonal characteristics for success, in-depth personal reflection, emotional intelligence, and a quest for continuous improvement have been instrumental within SEL research (Domitrovich et al., 2017).

SEL can be used to promote character development among athletes (Elias, 2016). The term "Educational Athletics" is used by the Massachusetts Interscholastic Athletic Association to express how athletics and competition can be used as an extension of the classroom and an educational activity to teach life lessons and prepare young people with values for lifelong learning (Elias, 2016).

3 Findings

In this section, one major, overarching theme will be presented through the analysis of three questions posed to hockey coaches, reflecting experiences within a leadership and inclusive lens. These semi-structured interviews were transcribed verbatim and filed within a MicrosoftTM Office Teams account. The first author and researcher read and reviewed the raw data transcripts sets several times and listened to audio files during the analysis to assist with the conceptualization of ideas presented. Data were organized and analyzed using a coding process that led to the construction of themes (Saldana, 2014). Inductive content analysis was employed as this project included non-complex research and the sample size (n=13) was small (Vears & Gillam, 2022). An inclusive theme among the research team emerged during our iterative, co-constructed analysis processes. As noted by Williams and Moser (2019), coding in qualitative research comprises processes that enable collected data to be assembled, categorized, and thematically sorted, providing an organized platform for the construction and development of meaning. In this article, one main theme is presented, highlighting inclusive practices for hockey leadership.

3.1 Theme 1: Development for Inclusive Leadership Practice

A key theme of inclusive leadership emerged as a result of data analysis from interviews with 13 minor hockey coaches. Participants in this study expressed the need for leadership training and development specific to coaching youth with varying hockey skills, cultural backgrounds, gender, and language capabilities. While participants attempted to recall types of professional development training they had received, many found this task very difficult.

Gender. In some cases, participants described challenges when coaching self-identified males and females on the same team. They felt a disconnect in team cohesion due to having separate dressing rooms for males and females, which left the female ice hockey players feeling isolated. Participant 2 illustrated this complexity in stating,

> ... I have a female hockey group, I am a male coach and its different than coaching males... we work on lots of skills and I need to know what is happening in their lives because if they are having a bad day at school or failed a math test they will show it... I have to be careful not to push them to far, right? ... I do that on my own; it's important to build relationships...

Participant 10 also addressed gender in hockey and the complexities regarding leadership training in this quotation,

> ... there's no behavioral, you know, teaching classes or any kind of courses like that let's put it that way. So that's really not at all. It's a very, you know, male dominated industry, I would say... push to have, you know, girls involved in coaching positions, things like that so like the diversity aspect... and you know welcoming everyone has changed...

Relationship and Leadership Building. Participant 1 highlighted the importance of building relationships with parents,

> To get to know the parents off the ice. Because everyone's schedules are so busy and hockey practices/ games are at weird times. Getting to know them more is the most challenging part. The hockey tournaments are beneficial because at a hotel the parents get can meet each other. During the weekday everyone's got to get home and get ready for the next day. As a coach you're the first one there and the last one out so mostly everyone is gone by the time you're out...

Informal community peer mentorship was identified as crucial for understanding and learning about leadership. Participant 8 also noted that the positive and welcomed impact of community mentors. He stated that,

> "... the hockey code mentor was pretty good. I had a guy, who is at Dalhousie, hockey team, so he gave me some drill ideas if I asked, and we walked a couple of our practices, and he came out a couple times..."

Participants often shared how they created relationships with community partners and other coaches. Peer mentoring was described as informative and useful, providing an informal opportunity for less experienced coaches to learn from more experienced or diversified coaches. Participant 3 shared his personal experience with local coaches. He stated that,

> ... the Atlantic Hockey Group team that I did, I was basically the head coach and manager of. I didn't really, I did everything myself. Basically,

> I took a couple of my buddies on to help me out when it came to like the on- ice stuff, just to be around and push some pucks. And if they had any drills, I made sure that the guys that I had on the bench were hockey guys too…

Further, participant 2 explained that communicating expectations is vital for success:

> "I think one thing is coaches need to be exposed to understanding team dynamics and how those things happen. So, there's, yes, you have expectations of the team. There are overarching expectations".

Participant 1 explained that,

> …There's been a whole new level of respect and peer coaching that we didn't have before. So, this year I got another player new to my team whose brother is actually the captain of the same major bantam team. What do we need to work on? And plan practices around their feedback and then really have the kids learn from their peers. They may have more talent on the ice, but they're kids that will not socialize. They sit in the corner in the dressing room. They won't talk to anybody else. They you know, you go away for a tournament, they won't go out to supper. They'll stay in their room. It is imperative to appreciate the need and desire for minor hockey coaches to identify existing gaps within leadership training. It is from this identification that professional development can be employed where and when necessary…

Participant 3 summarize his thoughts on mentorship and its value:

> "My first year that I got involved, I actually was handed head coach of the skills group, didn't even get to assistant, didn't even get to help out for a year. I was handed it the first year basically. Very good. I'll call it Mentor ahead of me that handed over all his notes and took the coaching clinics from hockey."

In alignment with the other participants, participant 2 reported:

> …this is the gap right now within our hockey communities. Is that there's a lack of understanding that we're building leaders…so what we say is all we're focused on the kids, and we forget that we're also developing coaching staff and future leaders in that… but the aspect of those other pieces of growth and leadership is where we could really improve, and we could build on…

Supporting Players with Disabilities. Describing some of the most challenging aspects of coaching a player with diversity and disabilities, participant 1 noted that,

> . . . some of those Hockey Canada modules, we did a lot on diversity for sure. Biggest training would be working with kids who have like ADHD and stuff like that it kind of it kind of misses that number of years we've had 4-5 maybe six kids that if levels of ADHD and I wish I was more training I guess on that part of things sure like diversity they cover very well yeah but I find kids with ADHD there needs to be more training. . .

The additional need for training to support successful coaching was also highlighted by participant 1 as noted here,

> ". . . I received . . . not a whole lot other than what's covered in hockey Canada that's mandatory. We would have to volunteer to take on others on our own time. I wish there was a lot more. . . "

Conversely, participant 4 recalled discrimination in sport and fair play course trainings that were offered through Hockey Canada and this training was augmented with additional courses added by Atlantic Hockey Group.

> "That is one thing I can say, like to list couldn't possibly remember the courses, but they are great to make sure the coaches have what they need". Participant 9 expressed the need for additional and frequent training: "I'd say professional development. I haven't really seen any other than the requirement, which is every three years to do the courses."

Language and Cultural Diversity. During the interviews, participants discussed important experiences coaching culturally diverse teams. For example, participant 3 revealed the following:

> . . . but I think when it comes to like the inclusivity part, I think like we've had over the years, we've had a lot of kids from Indigenous communities and ask us only playing on our team. . . compared to kids who are from Non Indigenous communities, who are not really around that much unless they're playing against them. . . to bring them in on a team and have them playing together, it was kind of like a different thing for the kids out in the Bay where there's not many First Nations people out there. . .

Communicating with youth and parents/caregivers who have language or cultural diversities can be challenging for coaches. The participants agreed that when coaching a player with language barriers, this can be difficult to engage the player within the team game plans and practices or it can also hinder the team bonding. As participant 4 revealed,

> Uh, sometimes it can be just a simple thing like language. Like, I coach quite a few kids from all over the province. Yeah, you know, so like, a lot of times you do, you have like, your Francophones and your French speaking stuff. This can be difficult, right ?...but, nothing... Can't be overcome.

The training gap was identified again by participant 8 who explained,

> “. . . and, I believe there’s one coaching... development at the beginning of the year, um, but other than throughout the year, it’s, if there’s no complaints, then nobody really says anything to you.”

Participant 10 shared a valuable case, specific to cultural diversity where he stated that,

> I would like to see maybe more education along the way on how to treat people. Times have changed, you know diversity and inclusion is a big part of you know the sport that really there’s not a lot of training about, you know, so I would like to see some stuff like that had, how did you come from Ukraine? We’ve got, you know, roles and different ethnicities

In conclusion, some participants noted that they felt unprepared to coach players with diverse cultural backgrounds and language.

4 Discussion

The findings of this study emphasize the importance of current professional development training required for the changing landscape of ice hockey in Canada. Coaches are essential to hockey at every level. A caring, enthusiastic, well-trained coach can positively influence the experiences of players, parents, and other coaches (Hockey Canada, 2024). Provincial hockey coaches receive certification from the National Coaching Certification Program (NCPP). Hockey Canada works with local hockey associations across Canada to provide effective education, certification, and registration for thousands of hockey coaches annually. The Hockey Canada Learning Lab has also been recently launched to provide additional coaching training resources (Hockey Canada, 2024). To remain active within the NCCP program, hockey coaches must maintain their status by obtaining professional development (PD) points. Activities such as e-learning hockey modules workshops, judging, facilitation, committee work, and active are all accepted PD points (Hockey Canada, 2024).

Communication, inclusive practices, and the need for additional training and professional development were focal points addressed by participants. This study suggests that many coaches had received technical training in ice hockey coaching; however, there is a need for additional training that addresses parent communication and coaching for diverse populations and cultures. Coaches also described the distinct difference between community and formal mentorship training and mandated technical development training. Previous reports have suggested that professional development training in these aspects can be beneficial in sport coaching (Shen, Rose & Dyson, 2022). This research may inform coaches, hockey administrators, players, and parents about inclusive hockey practices that can support gender diversity, players with disabilities, and cultural awareness.

Important findings emerged from discussions surrounding the need for accurate and frequent development training that included gender, cultural diversity, and communication best practices. Implications from this study support the ongoing need for training and professional development, addressing existing gaps in current training, and the changing culture within ice hockey from a male-dominated sport to one more welcoming for all abilities and all players.

Suggestions for future study include additional research in the area of ice hockey coaching, particularly focusing on diversity and inclusive application. Limitations and research directions for qualitative inquiry noted in the study included sampling from only one hockey organization. While the present study explored coaching leadership in ice hockey and the aspects of inclusivity, cultural diversity, and gender, the findings and discussion focused on the participant's experiences in coaching. All participants had coached hockey for the AHG in Atlantic Canada. Additional and continued research is also needed to explore training delivery modalities and specific content for leadership and professional development. Future qualitative studies may also focus specifically on these inclusive sub themes to cultivate an in-depth understanding of coaching leadership.

Replicating the study within other regions of Canada would also be important to allow for a larger sample and broader base of study. Based on the findings of this research, the authors recommend a streamlined access point or tab system that directly outlines PD links from the Hockey Canada website, as accessing the e-training modules was difficult. Data from this study revealed several challenges in coaching players with disabilities or language barriers. Offering PD training such as Inclusive Coaching Practices for Players with Intellectual Disabilities may be helpful. New courses supporting effective communication practice with adolescents may also be beneficial. Community coaching mentorships with experienced junior-level coaches could be recommended to support successful leadership. Engaging local minor hockey associations with local Junior level coaches could potentially provide practical and experiential learning opportunities.

5 Conclusion

This study explored leadership and professional development training experiences among hockey coaches in Atlantic Canada. Specific findings examined inclusive practices within hockey coaching. These emerged as topic areas of gender, relationship, and leadership building, supporting players with disabilities, and players with cultural or language diversities. The results suggest that most coaching training is done by Hockey Canada and provincial associations, and informal training was provided through local community hockey teams or via peer coaches. Additional training that focuses on inclusion, diversity, adolescent development, and communication within hockey realm is necessary. Hockey culture is evolving, and coaching needs to support a much more diverse population.

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Characterizing Playing Styles for Ice Hockey Players

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Abstract. Although analytics is being used in, e.g., the evaluation of players and scouting, it is still challenging to quantify skills and playing styles of players. Such information is important for roster creation and scouting, where teams want to find players that have a playing style that fits within the team, as well as for game preparation to understand the playing style of opponents. In this paper we use player vectors to characterize a player's playing style. The player vectors contain representations of skills that are computed from game event data. Further, we use fuzzy clustering on the vectors to generate five types of defender playing styles and five types of forward playing styles. For these types, we show the typical skill levels and players with similar styles.[1]

1 Introduction

In ice hockey, the general manager and scouts are responsible for identifying the most skilled players to build a high-performing team within their budget limits. Historically, the teams relied on the manual analysis conducted by scouts and general managers. The introduction of data analytics transformed the process for scouting hockey players [18]. By leveraging data-based metrics, teams were able to adopt a more objective approach to decision-making, particularly in evaluating player performance. However, despite the growing influence of analytics in areas such as scouting and player performance evaluation, quantifying the nuanced skills and playing styles of individual players remains a challenge. Such information is important for roster creation, where teams want to find players that have a playing style that fits within the team.

In the complex and dynamic game of hockey, characterizing playing styles is challenging due to multiple aspects. One such aspect is that certain features are difficult to quantify, making it a challenge to identify appropriate variables for model building. Moreover, skills are typically not explicitly encoded and stored in the available event data, but rather must be derived from player actions or performance across various event types. For instance, a certain kind of defensive skill may depend on how well the defender performs in different aspects such as blocked shots, hits, and dump outs.

[1] Equal contribution for the first two authors.

In this paper, we characterize the playing style of a player in a data-driven manner. We use event data from hockey games of three leagues and 2.5 seasons (Sect. 3) to define different kinds of skills for defenders and forwards (Sect. 4). A player's playing style is then represented by how the player performs for these different skills. Formally, the player's playing style is represented by a skill vector. Further, we use fuzzy clustering to define five distinct playing styles for both defenders and forwards (Sect. 5). We show the typical skill levels for prototypical players in the clusters and give examples. Information about the clusters can be used for scouting, e.g., for finding players with similar playing style, as well as for game preparation, as understanding the playing style of the opponent can offer certain tactical advantages.

2 Related Work

There has been research on different topics that relate to trying to characterize and compare players in ice hockey.

One approach has been to define performance metrics. Many performance metrics assign values based on particular types of actions in the game. For instance, goals, assists, and Corsi attribute a value to goal-scoring actions, to passes that lead to goals and to different types of shots, respectively. Variants of traditional metrics have been proposed such as regression models replacing the +/- measure (e.g., [16,17,7]). In [8] principal component analysis was performed based on 18 traditional metrics and a performance metric based on the four most important components was proposed. More recent work takes the context in which actions are performed into account. For instance, [20] attributes value to goals, but the value of the goal depends on the situation in which it is scored. Event impacts for different kinds of actions in [26] are based on the probability that the event leads to a goal (for or against) in the next 20 seconds. Several works model the dynamics of an ice hockey game using Markov games (e.g., [29,9]). In [21,27,28,13,24,15] action-value Q-functions are learned with respect to different targets. Different goal-based performance metrics taking the importance of goals into account are defined in [10,22]. Player rankings are presented in [25,14,11].

Another approach uses a probabilistic method for quantifying player roles in ice hockey. Earlier work allowed for a player to only belong to one role [30,2], while more recent work allows for a player to belong to different roles with some probability [23]. In the latter case, players can be compared based on their membership in different roles.

In other sports player vectors have been used to try to characterize a player's playing style. In [6], a basketball player's defensive play is characterized by shot taker, shot location, and expected outcome of the shot. In [3], a football player's playing style vector represents the areas on the field where the player tends to be and which actions in terms of passes, dribbles, crosses, and shots, the player performs in these areas. Movement patterns in shot situations in football were predicted in [12].

3 Data

The data we used is a proprietary dataset produced by Sportlogiq [2]. The dataset consists of event data from the following leagues: Swedish Hockey League (SHL), Hockeyallsvenskan (HA) and the American Hockey League (AHL). The choice of these three leagues originates from the fact that many transfers happen between these leagues. For instance, traditionally, many imports to the SHL come from the AHL, and many drafted SHL players start out in the AHL. As HA is the league one step down from SHL, SHL is a natural next step for many HA players. The data includes complete seasons for the three leagues for 2021/2022 and 2022/2023, as well as data from the 2023/2024 season up until January 28th, 2024. In total the dataset contains 7,532 games, 4,014 unique players, 68 unique teams and 28.5 million events. An event is described by more than 50 different parameters. The dataset comprises 2,553 forwards, 1,393 defenders, and 452 goaltenders, totaling 4,398 players. This figure exceeds the number of unique players, capturing that some individuals have played both forward and defender.

4 Player Vectors

4.1 Feature selection

Based on domain expert knowledge, we decided to use the skill sets as shown in Tables 1 and 2, for defenders and forwards respectively. For each skill, we utilized dataset features that influence it. Examples are given in the tables.Features can belong to different skills. For defenders there are 13 different skills that are described by five to seven features/actions and for forwards there are 18 different skills that are described by two to seven features/actions.

Table 1: Skills and example actions for defenders.

Skills	**Actions**
Passing	e.g., different types of passes
Skating	e.g., exits, entries, dumps
Shooting	e.g., different types of shots
Defensive Stickwork	e.g., blocked passes, loose puck recoveries
Puck Moving	e.g, some types of passes, dump-in recoveries
Point Producing	e.g., different offensive zone events
Powerplay Playmaking	e.g., powerplay playmaking events
Powerplay Scoring	e.g., powerplay shots and goals
Physical Play	e.g., body checks and defensive plays
Slot Defense	e.g., blocked shots and dump outs
Stay at Home	e.g., different defensive zone events
Penalty Killing	e.g., different penalty killing events related to puck recovery
Penalty Killing Slot Defense	e.g., different penalty killing defensive plays

[2] https://www.sportlogiq.com/hockey/

Table 2: Skills and example actions for forwards.

Skills	Actions
Passing	e.g., different types of passes
Skating	e.g., different types of controlled entries
Powerplay Playmaking	e.g., different types of controlled entries and passes in powerplay
Powerplay Slot Engagement	e.g., powerplay actions close to net
Powerplay Scoring	e.g., powerplay shots and goals
Defensive Puck Control	e.g., dump outs and loose puck recoveries
Defensive Zone Play	e.g., different defensive zone actions
Defensive Positioning	e.g., blocked shots and passes
Slot Defense	e.g., rebounds and dump outs
Penalty Killing	e.g., shorthanded defensive plays
Slot Engagement	e.g., offensive actions close to net
Heavy Game	e.g., body checks and defensive plays
Forechecking	e.g., offensive zone loose puck recoveries
Cycling the Puck	e.g., puck protections and receptions
Neutral Zone	e.g., different neutral zone actions
Puck Moving	e.g, some types of passes, entries
Offensive Zone Play	e.g., different offensive zone events
Shooting	e.g., different types of shots

4.2 Player vector construction

The player vectors are constructed based on the skills in Tables 1 and 2. First, all players who played less than 200 minutes were filtered out. Next, 13 feature vectors were created for each defender and 18 feature vectors for each forward. Each of these feature vectors quantifies a skill and contains the frequency of each action that describes that skill. For instance, for a particular defender, a defender skill with seven actions is represented by a vector of length seven where each element in the vector represents an action and its frequency for the defender in the dataset.

After constructing all feature vectors, we normalize them based on the player's ice time, i.e., the values are divided by the time on ice (TOI) of the player and multiplied by 60 (where 60 minutes is the length of a game in regulation time). This ice-time normalization was done to address potential differences in event frequency attributed to playing time disparities. Further, the values are standardized using MinMaxScaler in the scikit-learn library for Python [19]. This method transforms each feature by scaling it to a value between 0 and 1. This was done to take into account that some events are more frequent than others in a game and would otherwise have an undesired larger weight. For example, a pass happens much more often than a body check. In Fig. 1 we show the distribution of some events in the dataset. We note that passes, pass receptions, and loose puck recoveries account for the majority of events in the data with a total of 65.1% of all events.

Further, we apply non-negative matrix factorization (NMF) to each feature vector using the NMF in the scikit-learn library for python [19] to reduce its dimensionality to a single component. Thus, after this operation, every skill is

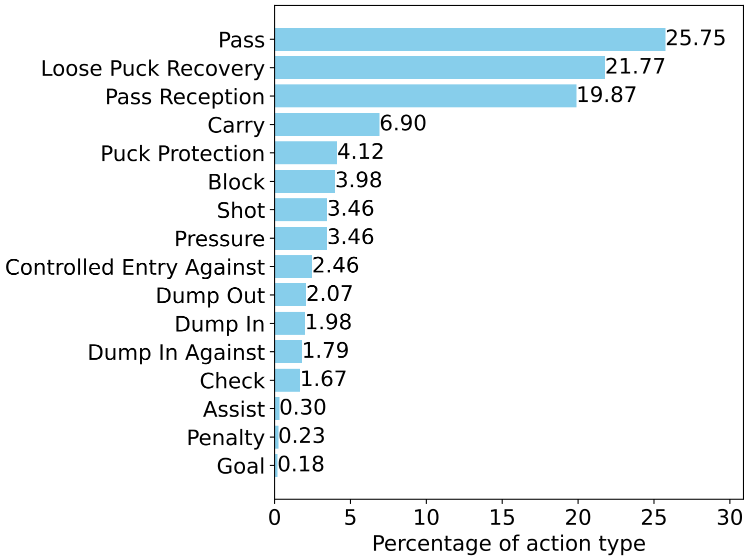


Fig. 1: Distribution on event frequency.

represented by one feature. Note that this operation leads to the fact that some values are higher than 1. Figs. 3a and 4a show the distributions of the values for the skills for defenders and forwards, respectively, using boxplots[3].

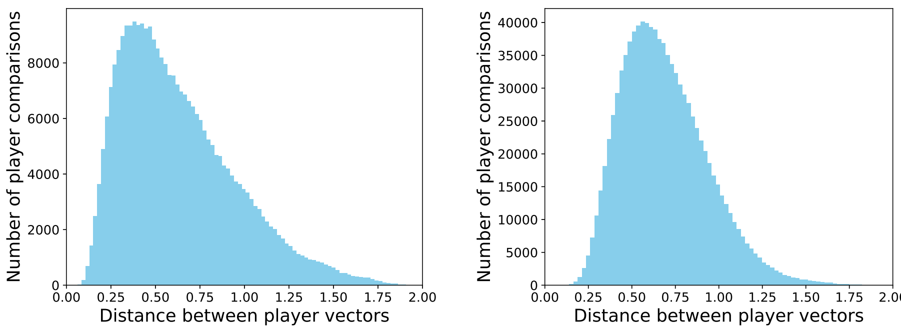
Finally, all features are concatenated together for each player, resulting in player vectors with 13 skill features for defenders and 18 skill features for forwards.

Figs. 2a and 2b display the distribution of the Euclidean distances between player vectors. As discussed before, defender vectors have length 13, while vectors for forwards have length 18. Each defender is compared to each other defender, and similarly for forwards. The distances between these vectors range from approximately 0.1 to 1.75 for both forwards and defenders. Most defenders fall within the range of 0.4 to 0.75, whereas forwards are typically found between 0.4 and 1.0.

5 Playing Style Classification

Given the skill vectors for players, our aim is to generate different categories of playing styles. As we wanted to model that players can take on different

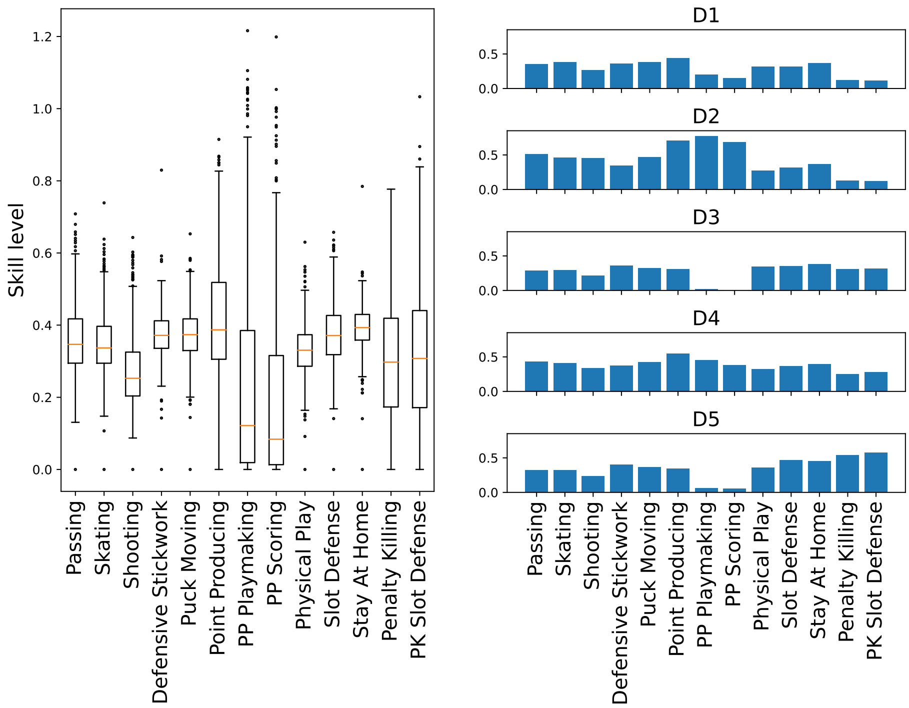
[3] The lower edge of the box represents the lower quartile value (25%) value, the (yellow) line in the box the median (50%) value, and the upper edge of the box the higher quartile (75%) value. The lower whisker shows the minimum value and the upper whisker the maximum value. Points below the lower whisker or above the upper whisker are outliers.



(a) Skill vectors for defenders.

(b) Skill vectors for forwards.

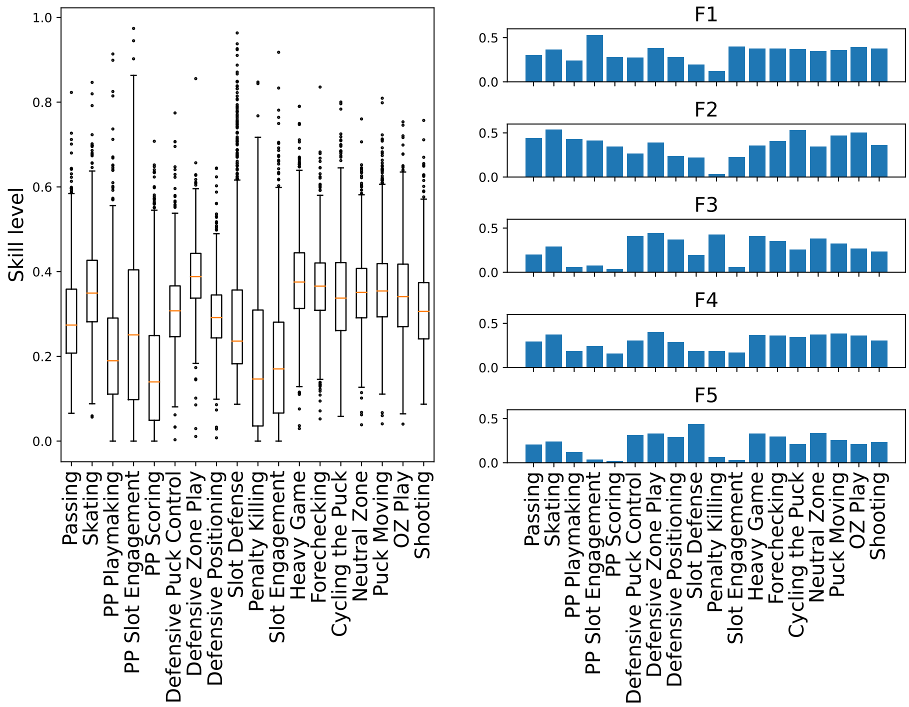
Fig. 2: Distribution of Euclidean distances between player vectors.



(a) Skill distribution (D).

(b) Cluster centroids (D).

Fig. 3: Skill distribution and centroid values (D).



(a) Skill distribution (F).

(b) Cluster centroids (F).

Fig. 4: Skill distribution and centroid values (F).

playing styles to certain degrees and that styles may have overlapping elements, we opted to use a fuzzy clustering approach. In this paper, we used the fuzzy c-means algorithm [5,1]. The objective in fuzzy c-means is to create k fuzzy partitions among a set of n objects from a data vector $\mathbf{x}$ by solving (1) until convergence.

$$\min_{\mathbf{U},\mathbf{C}} J_m = \sum_{i=1}^{n}\sum_{j=1}^{k} u_{ij}^m d^2(\mathbf{x}_i, \mathbf{c}_j) \;\; s.t. \;\; u_{ij} \in [0,1], \sum_{j=1}^{k} u_{ij} = 1 \tag{1}$$

In (1), d denotes the distance between object i and the j:th cluster centroid c_j. Further, u_{ij} is the degree of membership for object i to cluster j. The hyperparameter m controls the degree of fuzziness, where a higher m leads to a fuzzier solution. The fuzzy solution converges to the crisp solution when $m \to 1$. When $m \to \infty$ then $u_{ij} \to \frac{1}{k}$.

For the implementation of fuzzy c-means clustering the open source fuzzy-c-means package for Python was used [4]. We used the maximum possible number (1,000) of iterations. The hyperparameter m was set to 1.5, which was determined by calculating the Fuzzy Partition Coefficient (FPC) that indicates how well the model can divide the data points into clean clusters across different m-values. We investigated which value for k to use with different methods and decided to use 5.

The clustering resulted in five clusters for defenders and five clusters for forwards, where players have certain degrees of membership for each of the clusters of their role. In Tables 3 and 4 we show for each cluster the ten defenders and forwards, respectively, that have the highest degree of membership for that cluster. All of these degrees of membership for the top ten players are over 0.8.

Table 3: Clusters for defenders.

Cluster D1 (91 players)	Cluster D2 (229 players)	Cluster D3 (188 players)	Cluster D4 (128 players)	Cluster D5 (142 players)
S Forsmark (SHL)	R Murphy (AHL)	J Nyberg (SHL)	D Brickley (SHL/HA)	B Pachal (AHL)
H Skinner (AHL)	L Cormier (AHL)	A Söderberg (HA)	F Kral (AHL)	A Strand (AHL)
W Wallinder (SHL/AHL)	T Smith (AHL)	Y Kuznetsov (AHL)	E Sjöström (SHL/HA)	D Samorukov (AHL)
J Andersson (SHL)	L Mailloux (AHL)	K Lowe (SHL)	M Setkov (HA)	I Solovyov (AHL)
H Gabrielsson (HA)	C Carrick (AHL)	P Tischke (AHL)	S Åkerström (HA)	G Brisebois (AHL)
A Brandhammar (HA)	T Niemelä (AHL)	V Pulli (AHL)	M Björk (AHL/SHL)	M Kokkonen (AHL)
H Styf (HA)	A Lindelöf (HA)	J Lundegård (SHL)	K Johansson (HA)	W Aamodt (AHL)
C.J Lerby (SHL/HA)	J Laleggia (SHL)	L Jardeskog (HA)	J Jansson (HA)	M Karow (AHL)
Q Schmiemann (AHL)	A Kniazev (AHL)	H Falk (HA)	J McIsaac (AHL)	D Helleson (AHL)
J Brook (AHL)	J Pudas (SHL)	I Heens (SHL/HA)	O Nilsson (SHL)	S Santini (AHL)

To investigate which skills are important in the different clusters, we used the ten players with highest membership degree from each cluster to compute centroids for the clusters.

In Fig. 3b we show the values for the skills of the centroids in the defender clusters. As these values are based on the skill values of the players with top

Table 4: Clusters for forwards.

Cluster F1 (302 players)	Cluster F2 (359 players)	Cluster F3 (255 players)	Cluster F4 (243 players)	Cluster F5 (250 players)
T Barron (AHL)	L Larsson (SHL)	J Grönhagen (HA)	R Damiani (AHL)	M Strömwall (AHL/SHL)
M Westfält (SHL)	O Sillinger (AHL)	F Nilsson (SHL)	S Walker (AHL)	O Palve (SHL)
N Caamano (AHL)	R Elie (SHL)	F Barklund (HA)	N Todd (AHL)	M Ruohomaa (SHL)
N Jones (AHL)	A Räty (AHL)	J Devane (AHL)	R Marenis (HA)	D Holloway (AHL)
K MacLean (AHL)	J Kellman (SHL)	R Clune (AHL)	A Beckman (AHL)	D Tomasek (SHL)
M Marushev (AHL)	J Lauko (AHL)	R Muzik (SHL)	C Conacher (AHL)	J Looke (SHL/HA)
M O'Leary (AHL)	A Poganski (AHL)	O Pettersson (SHL)	A Andreoff (AHL)	A Petersson (SHL)
B Maxwell (SHL)	G Meireles(AHL)	J Joshua (AHL)	J Doan (AHL)	A Louis (AHL)
T Kaspick(AHL)	P Carlsson (SHL)	K Gabriel (AHL)	B McCartney (AHL)	M Modigs (HA)
J Labate (AHL)	E Desnoyers (AHL)	I McKinnon (AHL)	S Wright (AHL)	L Bristedt (SHL)

membership degrees, they can be seen as the skill levels representing the playing style for a prototypical player for that cluster.[4] Defenders in D1 do not excel in any particular skill, but they also do not rank the worst in any category. The skills with the highest values are those that facilitate point production and puck movement, which suggests a somewhat more offensive than defensive role in the team. D2 defenders are the most offensively skilled defenders that significantly outperform other defenders in point producing and powerplay skills. These defenders show lower values in the defensive skills such as physical play and penalty killing skills. D3 is comparable to D5 in terms of overall defensive capabilities, although D3 defenders demonstrate lower values in all skills than D5 defenders. This suggests that D3 players are more defensive-minded, but not necessarily the top defensive performers. Further, D4 shows high values overall in all skills but excel the most in passing, point producing and powerplay playmaking. This indicates that these defenders can play both in powerplay and boxplay as they excel both in the defense and offense. The strengths for D5 are penalty killing where they have the highest skill level of all playing styles. D1 also has high values in defensive skills such as defensive stickwork, physical play, slot defense and stay at home. D5 shows lower values in more offensive skills such as passing, skating, shooting, puck moving, and point producing. The powerplay skills are almost non-existent indicating that most of these players do not play in powerplay.

In Fig. 4b we show the values for the skills of the centroids in the forwards clusters. The F1 forwards show high values across all skills, with the highest skill level observed in powerplay slot engagement. This indicates that F1 forwards excel in both defensive and offensive skills. F2 forwards are the offensively skilled players with high values in skating, cycling the puck, and offensive zone play, as well as powerplay skills. F3 forwards demonstrate higher values in defensive skills and lower in the offensive skills. F3 also obtains the highest skill level in boxplay out of all playing styles. F4 shows similar skill values as F1 except a bit

[4] The histogram visualization for the values for the centroids for the clusters would show a similar shape if we would have taken the average values of all players in the clusters instead of the average values for the top 10 players in the clusters, although the peaks would be lower. This is also the case for the forward clusters.

lower powerplay skills exchanged for a bit higher boxplay skills. F4 shows decent skill levels in both the offense and the defense. F5 forwards demonstrate lower offensive values together with decent defensive skill levels. F5 has the highest value of all forwards in slot defense indicating a lot of ice time in the defensive zone.

6 Conclusion

In this paper we represented the playing styles for ice hockey defenders and forwards based on skill sets. The skills were computed based on event data. Further, we used fuzzy clustering to define five types of playing styles each for defenders and forwards and showed typical skill levels and example players for these playing styles. This information can be used for scouting and game preparation.

As future work, we will define a new similarity between players based on their membership values to the playing style clusters. This will not only allow for finding players with the same main playing style, but also where the secondary styles are similar. Further, we will investigate in other clustering methods such as Gaussian Mixture Models.

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Puck Possessions and Team Success in the NHL

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Abstract. This paper investigates the relationship between puck possession and team success in the NHL, focusing on the games played during the 2023-2024 regular season (up to the All-Star break). The analysis first reveals a moderate correlation (r = 0.56) between average team possession percentage and Average Goal Differential (Avg. GoalDiff). Next, we introduce Average Offensive Zone Possession Time Differential (Avg. OZPTD) as a key metric, defined as the difference between a team's offensive zone possession time and that of their opponents. We find a strong correlation (r = 0.77) between Avg. OZPTD and Avg. GoalDiff, thereby highlighting its relevance in assessing team performance. Our analysis confirms OZPTD's stability, discriminatory power, and independence from existing metrics like Shot Attempt Percentage (SAT%), also known as Corsi. Additionally, we detail a comprehensive methodology for processing and cleaning possession data sourced from the NHL. This methodology underpins our findings and facilitates future research involving player and team possession data.

1 Introduction

In the National Hockey League (NHL), where the margin for victory is small, teams are in constant pursuit of advantages to enhance their chance of success (i.e., winning). The unpredictable nature of hockey compounds the difficulty of identifying and quantifying metrics that genuinely influence outcomes. In this paper we analyze puck possession and its use as a potential indicator of success. This work is further motivated by the premise shared across sports that possessing the ball or puck for significantly more time than the opponent increases your chance of winning.

Research in other sports present mixed results regarding the correlation between possession and team success; some studies affirm a strong correlation [19] [16] [13] [5] [3], while others find no significant relationship [4] [6] [7] [9] [12] [10]. In the NHL, prior investigations into puck possession have mainly relied on manual tracking [17] or metrics approximating possession such as Shot Attempt Percentage (SAT%), also known as Corsi [20]. SAT% (Corsi) measures a team's share of the total shot attempts in a game. The rationale behind SAT% (Corsi) is that a higher number of shot attempts, which can only be credited during a possession, indicates superior puck control.

Despite these indirect methods for measuring possession, the strategic importance of puck possession in the NHL has notably increased, particularly during overtime since the introduction of 3-on-3 overtime in 2015. This growing emphasis is underscored by the NHL general managers convening this season to discuss potential regulatory changes, such as implementing a shot clock during overtime [22]. This consideration directly reflects concerns about extended possessions during overtime, highlighting the central role puck control has come to play in modern NHL strategies.

With the recent introduction of puck and player tracking (PPT) technologies in the 2021-22 NHL season and the significance of puck possession, this paper investigates whether teams with more puck possession have greater success. The contributions of this paper are:

– We provide a methodology for cleaning and processing the NHL's player possession data. This is required to support our analyses and also lays the groundwork for future studies.
– We examine correlations between several possession metrics and indicators of team success, providing insights into their predictive value.
– We introduce the Average Offensive Zone Possession Time Differential (Avg. OZPTD) metric, defined as the difference between a team's offensive zone possession time and that of their opponents. Avg. OZPTD is highly correlated ($r = 0.77$) with Average Goal Differential. This highlights its potential for enhancing our understanding of team success in the NHL.
– We show that Avg. OZPTD's is stable across two halves of our dataset (i.e., useful for prediction), is able to differentiate between teams and is independent from existing metrics which demonstrate its potential as a useful new metric.

2 Related Work

Previous studies on the importance of possession across sports provide context for this paper, particularly highlighting the research gap in hockey analytics.

In football (soccer), the relationship between ball possession and team success has been extensively studied using various research methods. Some of these studies find a positive relationship. For instance, researchers studied the 2016 UEFA Euro and found that the average possession time for a leading team was 20.3 minutes with a standard deviation (SD) of 16.0 minutes, compared to 18.2 minutes with a SD of 16.8 minutes for teams when the score was tied, and 13.7 minutes with a SD of 12.3 minutes for a trailing team [5]. The authors explained that the p-value, which assesses the likelihood that these differences occurred by chance, was less than 0.01, indicating a statistically significant difference. Additionally, researchers studying the 2006 FIFA World Cup found that the percentage of ball possession, analyzed using principal component analysis, had the greatest influence on match outcomes with a coefficient with an absolute value of 0.72. This indicates that it is an important variable for discriminating winning teams from those that lose or draw [19]. Another study found that ball possession had a positive effect on winning in the 2014 FIFA World Cup, with an 11% increase in the probability of winning for all matches and a 14% increase for close matches when ball possession increased by two standard deviations [16]. Also, a study covering the 2017-18 and 2018-19 season in the German Bundesliga showed a positive correlation ($r = 0.75$) between team possession and overall points earned [3].

However, other studies have found that possession may not correlate with or may even negatively impact team success. For example, researchers for the FIFA Training centre studied the 2022 FIFA World Cup and found that, for the men's tournament, teams with less possession than their opponents won slightly more games (26 wins versus 23) [10]. Additionally, a study of the 2010-11 season in the Portuguese Premier

League found that the amount of ball possession had a very weak negative correlation (r = -0.192) with the match result [12]. In a study analyzing elite leagues in Europe, researchers found that a significant difference in ball possession percentages between winning and losing teams only occurred in matches with wide result margins (3 or more goals). In the other, closely contested matches, the difference in possession between winning teams (51.48% with a SD of 13.05%) and losing teams (48.52% with a SD of 13.05%) was not statistically significant [9]. Similarly, researchers studying the World Cups of 2002, 2006 and 2010 found that ball possession was slightly higher for winning teams (51.6% with a SD of 6.8%) compared to those that drew (49.9% with a SD of 5.8%) or lost (48.5% with a SD of 6.8%), though the differences were not statistically significant [6]. In another study using data from five European leagues, UEFA, and FIFA tournaments, researchers found that possession time was a poor predictor of team success once team quality and home advantage were accounted for [7].

In basketball, intuition might lead one to believe that possession is less important due to the shot clock, which mandates a field goal attempt within 24 seconds in the NBA and most European leagues. Previous studies have shown a positive but insignificant correlation between longer possessions and success. Research on the Spanish Basketball Playoffs from the 2004-05 season investigated the possession durations of winning and losing teams against various defensive systems. They found that, when averaged across all defenses, winning teams had an average possession duration of 13.1 seconds with a SD of 6 seconds, compared to 12.32 seconds with a SD of 5.88 seconds for losing teams [13]. Although significant differences were observed depending on the defensive system faced, these differences did not translate into statistically significant overall differences in possession durations between winning and losing teams.

In American football, significant value is placed on time of possession, notably because it allows the defense to rest, enhancing both offensive and defensive performance. Time of possession refers to the amount of game time an NFL offense has the ball. Researchers studied the 2003-04, 2004-05, and 2005-06 NFL seasons and found that 67% of teams with greater time of possession than their opponents won their games [4]. However, the research recognized potential biases; leading teams often prolong their possessions near the end of the game to conserve their lead. To avoid this bias, the analysis was confined to first-half data. In this analysis, a logisitic regression model was applied to predict the halftime score. The model revealed a negative coefficient for time of possession (β = -0.126), indicating that for each additional minute of possession in the first half, the log-odds of winning at halftime decrease by 0.126. This indicates that more possession, with biases removed, does not contribute positively to winning.

Hockey's analysis of puck possession has comparatively been less robust as it relies on manual tracking [17] or metrics approximating possession such as SAT% (Corsi) [20]. Some studies using manual tracking or SAT% (Corsi) have found a positive correlation between possession and team success. For instance, a study of 243 NHL overtime periods from 2015 to 2021 in which possessions were manually tracked revealed that victorious teams in 3-on-3 overtime generally have a higher count of individual possessions (53 percent of the total number of individual possessions of both teams), a higher duration of individual possession (54 percent of the total duration of individual possession of both teams), and more offensive zone time (57 percent of the total offensive zone time of both teams) compared to teams that lost [17]. Additionally, a study of the 2007-08, 2008-09, and 2009-10 NHL regular seasons revealed that SAT% (Corsi) Tied (even strength SAT% (Corsi) with the score tied) is more predictive of how well a team will perform (r = 0.47) than goal ratio (r = 0.35) or winning percentage (r = 0.34) [20]. This correlation is relatively low compared to our findings, where higher correlations emerge from utilizing PPT data to measure various metrics of puck possession, most notably for Average Offensive Zone Possession Time Differential (Avg. OZPTD).

Although previous hockey analytics research shows a positive correlation between possession and team success, there are challenges to manually tracking possession. As well, SAT% (Corsi) has its limitations, as it does not account for possession in the defensive or neutral zones and may not reflect the strategy of teams that prioritize high-quality shots over quantity.

In recent years, expected goal (xG) models have gained popularity. Originating in football (soccer), xG represents the probability that a scoring opportunity will result in a goal. It addresses some issues with SAT% (Corsi) as it includes weighting shot attempts based on quality, recognizing that certain shots have a higher probability of resulting in a goal. In hockey, efforts to evaluate shot quality began in 2004 [23] [14] [15]. This foundational work led to the first explicit mention of xG in hockey in a 2012 study, which used ordinary least squares (OLS) regression and ridge regression to predict goals, incorporating variables such as goals, shots, missed shots, blocked shots, faceoffs, hits, turnovers, and zone starts [18]. Since 2012, numerous xG models have emerged, each aiming to capture the best set of predictive variables, often including more than ten variables weighted during model training [8] [24] [26] [25]. These models generally outperform SAT% (Corsi) and other metrics in predictive accuracy [8] [25].

However, there are drawbacks to xG models. First, there are many different xG models, which can have varying parameters, potentially leading to inconsistencies when advising a team on how to improve their xG to win more games. Additionally, to our knowledge, there has been limited work on testing the stability of these models, meaning the parameters and weights might not remain consistent from one season to the next. Lastly, because these models have several parameters, determining the specific actions a team can take to improve their xG may not be straightforward.

In this paper, we utilize PPT data to conduct a detailed investigation into measures of puck possession and their correlation with NHL team success. Our findings indicate that a single metric of possession can be as effective, if not more so, than existing, publicly available xG models in predicting team success.

3 Background

3.1 Definitions of Individual and Team Puck Possession

Before we delve into the dataset and analysis, we define the concepts of individual and team puck possessions as utilized in our study.

According to the NHL definition for the model that produces the individual possession data we employ, a player is considered to have possession and control of the puck, and thus in individual possession, when they make two or more consecutive touches with the puck. The start of the individual possession is marked by the first touch, which is confirmed upon a second touch. Individual possessions also includes brief moments during one-touch actions, like shots, passes, or area plays (e.g., dump-ins). An individual possession ends when the player is separated from the puck or when another player gains possession. We delineate these episodes to identify windows of time with “no individual possession”, representing segments of active gameplay where the puck is not under direct control by any player. This includes scenarios ranging from face-offs, puck battles, and loose pucks to passes, shots, and “area plays” (e.g., dump-ins and dump-outs). The top line in Figure 1 shows examples of individual possessions by members of different teams (red and blue lines) and “no possession” (orange dotted lines).

We define team puck possession as the aggregate of individual possessions with continuous possession by members of the same team, interrupted only by game stoppages or a change in possession to the opposing team. Consequently, “no team possession” intervals are distinct from “no individual possession” intervals. The bottom line in Figure 1 shows examples of team possession (red and blue lines) and “no team possession” (green dashed lines). As shown in the figure, team possessions end when the puck is last touched by one team, prior to the opposing team gaining possession. Our use of team possession differs slightly from the official NHL definition as the details required to implement the NHL’s definition aren’t available in the current dataset.

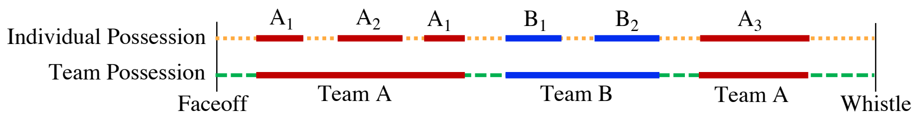

Fig. 1. Differentiating individual and team possessions

3.2 Dataset Overview

This paper utilizes the proprietary PPT dataset provided to us by the NHL. The PPT data, captured through devices in players’ sweaters and the puck, records x, y, and z coordinates at high frequencies: 60 times per second for the puck and 12 times per second for each player on the ice. An additional update is provided once per second for players on the bench, resulting in around 734,400 location points in a typical 60-minute game. Due to the varied frequencies of data collection across players and the puck, and the lack of synchronization between devices, all player and puck positions are interpolated to uniform timestamps every hundredth of a second.

In March 2023, a significant advancement was made with the introduction of an individual player possession model into the “DISH” data stream, which features Delayed, Interpolated, Smoothed and Hundred-Hertz enhancements. This dataset is considered unofficial by the NHL and may differ from other datasets that track possession information (e.g., a hand-labeled dataset). Our study uses the DISH data to compute team possessions, which form the basis of our analysis. Since this data only became available in March 2023, the dataset for the 2022-2023 season is limited. Consequently, our analysis focuses on the 2023-2024 NHL season, using data from 780 games played up to January 31, 2024 (the All-Star break). After excluding games with significant data issues, as detailed in Section 4.3, or those with no tracking data, such as the Heritage Classic and the games played in Europe, 708 games remained for analysis.

4 Dataset Cleaning and Filtering

The player possession data provided in the NHL's DISH data stream, indicating who held the puck and for how long, lacks broader game context such as powerplay situations and player locations. To address this, we merge it with data from a detailed game information file, enriching player possessions with relevant game context, and then compute team possessions based on this integrated data. Through this process, we encounter challenges that necessitate extensive cleaning and preprocessing to ensure data integrity. Cleaning refers to the process of correcting or removing inaccuracies within the data that can be rectified, such as adjusting timestamps or eliminating duplicates. Conversely, filtering is our strategy for dealing with more complex issues that cannot be directly corrected; it involves the exclusion of entire games from our dataset.

4.1 Dataset Cleaning

Possessions Occurring During Stoppages: One issue with the data is that some possessions occur either entirely during stoppages or span active and stopped intervals. These erroneous possessions are identified after merging the player possession file with the game information file and computing active gameplay intervals. To resolve this issue, we eliminate portions of the possession that occurred during stoppages, ensuring accuracy in active play representation.

Abnormal Timestamps and Non-chronological Data Entries: The game information file contains updates every hundredth of a second, but some of these updates display additional digits of precision and are out of sequence. These extraneous updates, found to be non-essential, are removed to maintain dataset integrity. After their removal, the data is re-sequenced to reflect the actual gameplay order.

Clock Resets: Another issue encountered in the dataset are unexpected time jumps, with the time remaining on the scoreboard clock suddenly increasing, leading to duplicated timestamps. These time jumps primarily occur after video reviews where time is added back to the clock, such as when a play is subsequently ruled as offside. Smaller adjustments may also result from false face-offs or if the clock inadvertantly continues running briefly after a whistle. The NHL addresses these situations by eliminating all recorded statistics and events that transpired during the time that is later nullified. Our approach mirrors this; upon identification of such a clock reset, we disregard stats and possessions recorded during the time frame subject to the reset.

Overlapping and Duplicate Player Possessions: The last challenge rectified through cleaning is the presence of duplicate or overlapping possessions. Duplicates are resolved by retaining a single entry. For overlapping possessions, we evenly distribute the overlapping time (i.e., the period during which the data indicates two players simultaneously possess the puck) among the involved players.

4.2 Dataset Filtering

There are cases where the above cleaning methods are insufficient to repair the data and preserve the integrity of the dataset. Consequently, we establish exclusion criteria based on the severity of data corruption: if the data is compromised for either more than 4% of a game's duration or more than 4% of a team's possession time, we exclude the game from our analysis. This filtering process results in the exclusion of 68 games, leaving 91% of the games for which we have data available for use in our analysis. The distribution of team appearances in the excluded games varied, with an average of 4.5 games per team, a standard deviation of 2.2 games, a minimum of 1 game for the Tampa Bay Lightning (TBL), and a maximum of 11 games for the Vancouver Canucks (VAN), constituting 22.4% of their total games. In Section 6.1, we show that robust analysis can be achieved with just 20% of a team's games in our dataset, as the correlation between early game data and the rest of the season stabilizes after this. Table 1 shows the number and percentage of games impacted by each filter; note that the sum of games exceeds 67 and the sum of percentages exceeds 9% since 20 games were subject to more than one filter criterion.

Filter Criteria	Games Impacted	Percent Impacted
Irregular Possession Lengths	34	4.4%
Clock Gaps	30	3.8%
Irregular Period Lengths	26	3.3%
Possessions with Missing Data	5	0.6%
Excessive Distance Between Puck and Possessor	2	0.3%

Table 1. Impact of various filters on game dataset

Irregular Possession Lengths: Games are flagged for exclusion when the duration without any possession or the length of specific possessions significantly exceeds normal expectations. For total "no possession" time, we apply the statistical outlier definition of mean plus three standard deviations. Given the mean of 62.8% and the standard deviation of 4.8%, this led to the exclusion of any game exceeding 77.2%. Additionally, games with a no possession duration longer than 144 seconds, or any individual possession lasting more than 48 seconds, are excluded, impacting 4.4% of the total games. The limit of 144 seconds corresponds to 4% of a 60-minute game and 48 seconds represents 4% of the average of the per game sums of individual possession times (20 minutes).

Clock Gaps: We identify games with significant windows of time missing in scoreboard data timestamps, indicating lost data segments affecting puck locations, player locations, or possession details. We set a 144-second threshold for these gaps, equivalent to 4% of a 60-minute game. Games exceeding this limit due to missing data are excluded, affecting 3.8% of the dataset.

Irregular Period Lengths: We identify games with periods deviating significantly from the standard 20-minute length in order to filter games with extensive data loss or situations where our data cleaning techniques may be ineffective. We exclude games with periods exceeding or falling short of the expected duration by more than 48 seconds, equivalent to 4% of a 20-minute period, impacting 3.3% of the total games.

Possessions with Missing Data: Games are flagged when they contain missing player data, or missing possession start or end times. This is likely due to tracking failures in the puck or jerseys, or instances where a player does not have a tracking device in their jersey. Games with more than two instances of missing data related to possessions are removed from the dataset; impacting 0.6% of our games.

Excessive Distance Between the Puck and Possessor: We considered possessions where the distance between the puck and its possessor is too large. We focus on possessions where the puck is over 16 feet from the possessor continuously for more than 2 seconds, indicating potential data inaccuracies. Games with a total "excessive distance duration" exceeding 48 seconds, equivalent to 4% of a team's average possession time of 20 minutes, are excluded, affecting 0.3% of the total games. In previous work, we adjusted the timestamps for events like shots and passes to try to more accurately capture the point of release [21]. We considered a similar approach in this work but the problem proved more difficult because we found instances where the distance between the puck and possessor is large in the middle of the possession. Adjusting such possessions would amount to building a new model, which is currently the domain of the NHL.

5 Analysis of Team Possessions

In this paper, we explore the relationship between team success and possession metrics, focusing on team possession percentage, aggregate individiual possession count differential, and offensive zone team possession time differential. Team success is measured primarily by goal differential because it is adaptable across game situations, unlike points per game, which is less flexible. Additionally, for the games in our dataset, average goal differential exhibits a strong correlation with average points per game (r = 0.95). Note that, unless stated otherwise, the analysis includes all strengths (i.e., even-strength and powerplays) and pertains exclusively to regulation time. This means that for our analysis, each team is awarded one point if a game goes to overtime.

5.1 Team Possession Percentage Versus Team Success

Team possession percentage is calculated by dividing the total duration of team A's possession by the combined possession duration of team A and the opposing team. Team possession percentage is calculated for each team in every game and subsequently averaged across all games played. We compute the correlation between average team possession percentage and average goal differential (Avg. GoalDiff), as well as average goals for (Avg. GF) and average goals against (Avg. GA), aiming to delineate the correlations of possession with offensive and defensive metrics.

As shown in Table 2, average team possession percentage is moderately correlated with Avg. GF, suggesting that teams with higher possession tend to score more goals. In contrast, the correlation between average team possession percentage and Avg. GA is weaker, implying that while possession might play a role in limiting opposition goals, its effect is not as strong.

Possession Metric	**Success Metric**	***r*-value**
Avg. Team Possession Percentage	Avg. GF	0.56
Avg. Team Possession Percentage	Avg. GA	-0.38
Avg. Team Possession Percentage	Avg. GoalDiff	0.56

Table 2. Correlations between average team possession percentage and team success metrics

Furthermore, our analysis reveals a nonlinear relationship among the correlations of average team possession percentage with Avg. GF, Avg. GA, and Avg. GoalDiff. Intuition might lead one to expect these correlations to sum linearly; for example, given the correlation between average team possession percentage and Avg. GF is +0.56, and between average team possession percentage and Avg. GA is -0.38, one might anticipate the correlation between average team possession percentage and Avg. GoalDiff to be the difference, equating to +0.94. This is not true and can be explained by understanding the correlation formula's normalization process. The Pearson correlation coefficient is:

$$r = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

where $\text{cov}(X,Y)$ is the covariance between X and Y, and σ_X and σ_Y are the standard deviations of X and Y, respectively. The denominator normalizes the covariance by dividing it by the product of the standard deviations of X and Y, ensuring the correlation values fall within the range of -1 to +1. Given the distinct standard deviations for Avg. GF (0.44), Avg. GA (0.39), and Avg. GoalDiff (0.70), this normalization introduces nonlinearity to the relationships.

5.2 Possession Count Differential Versus Team Success

Shifting our analysis from the percentage of team possession to the aggregate quantity of individual possession instances can potentially offer new insights by capturing both the totality of possessions gained through turnovers or puck battles and the extent of puck movement within team possessions. To assess which teams excel in managing aggregate individual possession quantity, we introduce a metric called average possession count differential.

For team A, the possession count differential is defined as the count of team A's individual possessions, minus the count of the opposing team's individual possessions. We compute this metric for each game and subsequently determine the average across all games played by each team. Utilizing this metric reveals a slightly enhanced correlation with Avg. GoalDiff (r = 0.63) compared to the correlation between average team possession percentage and Avg. GoalDiff (r = 0.56). This improved correlation may indicate the potential impact of frequent and dynamic possession changes to outscoring opponents, suggesting a strategy centered on maximizing possession instances correlates positively with achieving a better goal differential.

5.3 Offensive Zone Possession Time Differential Versus Team Success

We now examine the significance of possession within the offensive zone. The rationale for this approach is that possessions in the defensive or neutral zones can serve to facilitate transitions, whereas offensive zone possessions might contribute more directly to scoring goals and outscoring the opponent. In this refined analysis, we introduce a new metric, Offensive Zone Possession Time Differential (OZPTD), which is defined as the sum of the duration of team A's individual possessions in the offensive zone, minus the sum of the duration of the opposing team's individual possessions in their offensive zone (team A's defensive zone). For possessions that span multiple zones, the duration is allocated proportionally based on the time spent in each zone. Similar to the previously examined metrics, OZPTD is computed for each game and subsequently averaged across all games played by each team.

As shown in Figure 2, our analysis reveals a significant positive correlation of 0.77 between Avg. OZPTD and Avg. GoalDiff. This finding highlights the importance of not just possessing the puck more than the opponent, but doing so in the offensive zone where it more strongly correlates with outscoring the opponent. Teams such as the Colorado Avalanche (COL) and Florida Panthers (FLA) who, on average, maintain offensive zone possession longer than their opponents, typically see positive goal differentials. Interestingly, the Winnipeg Jets (WPG), Boston Bruins (BOS) and Vancouver Canucks (VAN) achieved the highest Avg. GoalDiff values despite having values of Avg. OZPTD near the league average of 0. In contrast, the San Jose Sharks (SJS) and Chicago Blackhawks (CHI) exhibit negative Avg. OZPTD values and, correspondingly, negative Avg. GoalDiff values. Recognizing that SJS and CHI may contribute significantly to the strong correlation, we compute the correlation coefficient without those two teams and observe an r-value of 0.63. In future work we plan to examine if offensive zone possession counts and differential are also correlated with success.

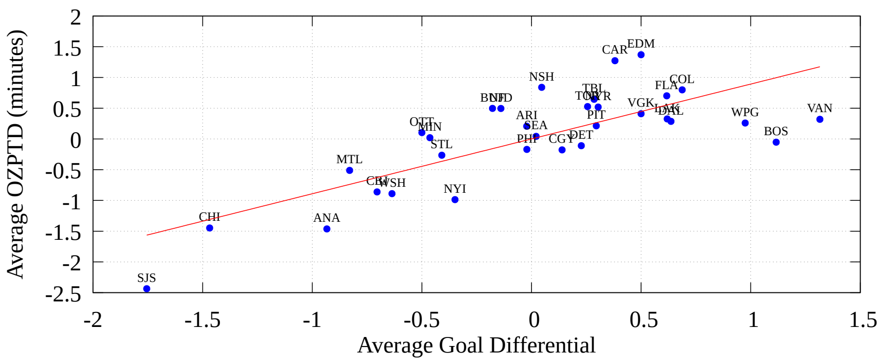

Fig. 2. Avg. OZPTD versus Avg. GoalDiff (r = 0.77)

As Avg. GoalDiff is highly correlated (r = 0.95) with average points per game for the games in our dataset, Figure 2, which arranges teams from left to right based on Avg. GoalDiff, provides a useful reference for readers to assess team standings, offering a more accurate perspective than actual standings that include games outside our analysis.

Recognizing the significance of the correlation, we conduct a deeper examination of its components, focusing exclusively on even-strength play. The correlation remains high at 0.73, indicating that the initial correlation is not simply a byproduct of power plays but is also prevalent during even-strength play, reinforcing the importance of offensive zone control throughout the game.

Given Avg. OZPTD's strong correlation with Avg. GoalDiff, we also analyzed it on a per-game basis, as depicted in Figure 3. This per-game analysis shows an r-value of 0.00, indicating no correlation. This finding suggests that, despite the correlation between Avg. OZPTD and Avg. GoalDiff across many games, individual games show high variability. Thus, while superior offensive zone possession doesn't guarantee game victories, teams with consistently higher offensive zone time may outscore their opponents over the course of a season.

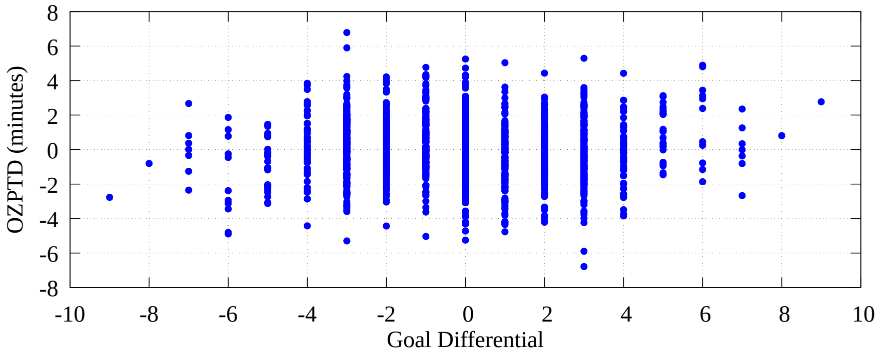

Fig. 3. OZPTD versus GoalDiff for all games (r = 0.00)

5.4 Possession Across Different Strengths

Building on our earlier findings, this section delves deeper into possession metrics across different strength scenarios, as shown in Figure 4. We observe that at even strength, possession is typically balanced between teams. However, with a plus-1 strength advantage, teams dominate possession. In contrast, a minus-1 strength differential leads to a substantial decrease in possession percentage for the disadvantaged team.

The variance in average team possession percentages is notably higher in even strength scenarios than in situations of plus-1 or minus-1. Specifically, the Chicago Blackhawks (CHI) and San Jose Sharks (SJS) show lower possession percentages at even strength, yet they are near the league average in plus-1 and minus-1 situations.

6 Meta Metrics: Evaluating Average OZPTD

Due to Avg. OZPTD's significant correlation with Avg. GoalDiff, and thus its potential to offer insights, it is imperative to evaluate this new metric. We utilize the notions introduced by Franks et al. [11], which emphasizes three key properties: stability, discrimination, and independence. While some of our tests of these properties differ slightly from those suggested in their paper, we maintain the spirit of each property. Stability measures the consistency of a metric across seasons or portions of a season (e.g., the

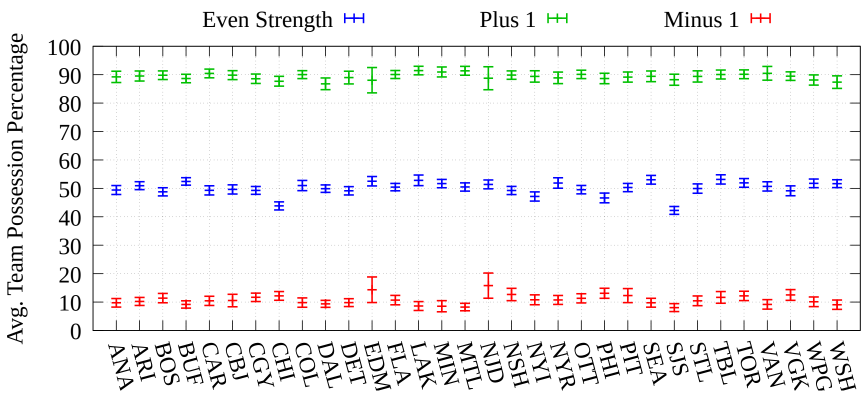

Fig. 4. Average team possession percentage: even strength, +1 and -1 (95% confidence intervals)

value of using the metrics in predictions), discrimination measures its ability to distinguish between players or teams, and independence assesses whether it provides unique insights when compared with existing metrics.

6.1 Stability

To assess the stability of Avg. OZPTD and determine its potential for predictive use, we calculate Avg. OZPTD separately for the first and second halves of the dataset. The observed strong correlation (r = 0.84) between Avg. OZPTD in the two halves, depicted in Figure 5, validates the metric's consistency. To further our understanding of the metric's stability, we conduct a rolling correlation analysis where the Avg. OZPTD is calculated for each team across incremental segments of the dataset, ranging from 5% to 50% and then these values are compared with Avg. OZPTD for the remaining games. The correlation starts at 0.68 when using the first 5% of the games to predict the Avg. OZPTD of the remaining 95% of the games and stabilizes above 0.80 when using the first 20% of the games to predict the remaining 80% of the games.

Predictive Power: To evaluate the predictive accuracy of Avg. OZPTD, we divided our dataset into two halves. Using data from the first half of our dataset, we built a linear regression model to establish the relationship between Avg. OZPTD and Avg. GoalDiff. We then tested this model with data from the second half of our dataset, using measured Avg. OZPTD to predict Avg. GoalDiff for each team. Our predictions were compared to the actual outcomes, resulting in an R^2 value of 0.49, and a correlation coefficient of 0.73. This correlation indicates a relatively strong correlation between the predicted and actual values.

To compare results obtained when using other metrics for predicting team success, we find that the 2012 study by Macdonald yield a correlation between actual and predicted goals of 0.69 using his ridge regression model [18]. Next, we found that a 2022 study, described on the Hockey-Statistics website [25], that reports that using their xG model and the xG model from Evolving-Hockey [1] to predict the expected goals for

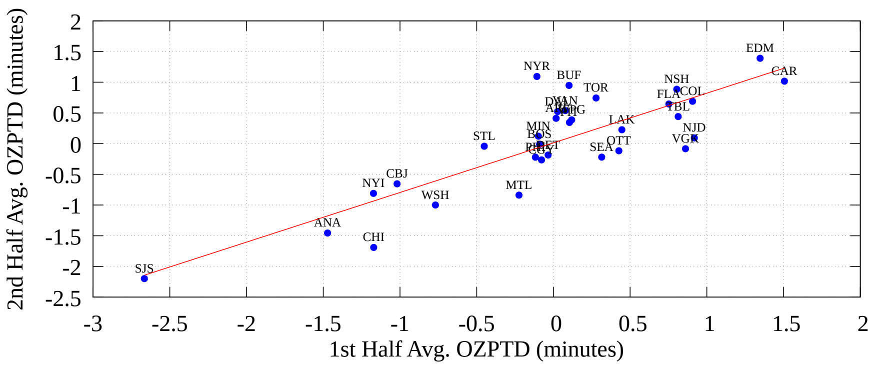

Fig. 5. Average OZPTD across dataset halves (r = 0.84)

percentage (xGF%) yielded an R^2 value of 0.49 in both cases. This prediction was based on the xGF% from the first 41 games of a season for each team to forecast the xGF% for the last 41 games. Note that xGF% is the ratio of a team's expected goals for compared to their opposition. Another study from 2015 considers a different expected goals model, and found that when using their model built using the first 40 games to predict GF for each team at the end of the season, they obtained an R^2 value of 0.51 [8].

While a more in-depth evaluation needs to be done using larger sample sizes with a direct comparison between metrics, this preliminary investigation indicates that our fairly simple Avg. OZPTD metric performs on par with existing, relatively complex models (because they typically use a large number of parameters that appear to require tuning) for predicting team success.

6.2 Discrimination

Our evaluation of Avg. OZPTD's discriminatory power, depicted in Figure 6, shows the Avg. OZPTD for each team, including 95% confidence intervals. There are statistically significant differences between some teams, however the overlap in confidence intervals for many teams indicates that the metric might have moderate discriminatory power.

6.3 Independence

In assessing the independence of Avg. OZPTD, we revisit SAT% (Corsi) and expected goals (xG). SAT% (Corsi) has traditionally been used to approximate possession by measuring the ratio of a team's shot attempts (goals, shots on net, shots that miss the net, and blocked shots) to the total shot attempts in the game. xG models attempt to improve on the predictive power of SAT% (Corsi) by including several variables related to the shot to better describe the context around the shot. To analyze the independence of Avg. OZPTD from these two metrics, we show the correlation between them, as well as each metric's correlation with team success (Avg. GoalDiff) as shown in Table 3. Note that the data used for the xGF% model is from Natural Stat Trick [2].

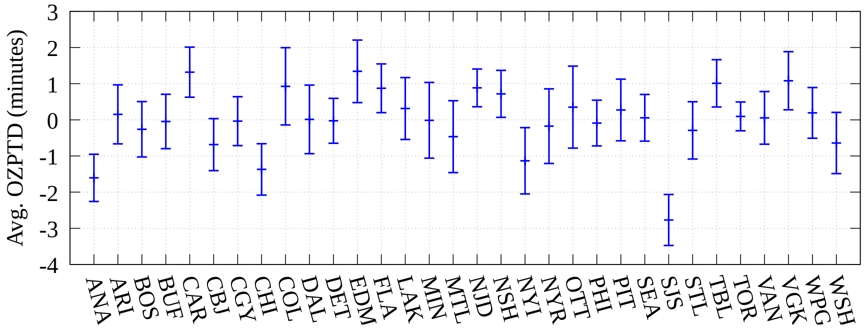

Fig. 6. Average team OZPTD, with 95% confidence intervals

The results indicate that Avg. OZPTD is strongly correlated to SAT% (Corsi) but shows a stronger correlation to Avg. GoalDiff compared to the correlation between SAT% (Corsi) and Avg. GoalDiff. This stronger correlation for Avg. OZPTD implies it provides additional insights beyond SAT% (Corsi), especially in relation to game outcomes. The results also indicate that Avg. OZPTD is strongly correlated to xGF%, with both metrics having the same correlation to Avg. GoalDiff. However, as mentioned previously, there are potential drawbacks to xG models, such as possible inconsistencies in parameters across different models and the complexity of determining specific actions to improve xG.

Metric	Correlation with Avg. OZPTD	Correlation with Avg. GoalDiff
Avg. OZPTD	1.00	0.77
SAT% (Corsi)	0.83	0.62
xGF%	0.88	0.77

Table 3. Correlation of Metrics with Avg. OZPTD and Avg. GoalDiff

In terms of evaluating established metrics, the work by Franks et al. [11] does evaluate some NHL metrics for individual players but does not include team metrics. As described in Section 6.1, some previous studies have examined the predictive power of various expected goal (xG) models. However, there is a lack of work in evaluating those metrics in terms of stability, discrimination and independence. In the future, we hope to evaluate established team performance metrics alongside our metrics.

7 Conclusions

In this paper we examine team possession metrics and whether they correlate with team success. Interestingly, we find that average team possession percentages are only weakly correlated with team success metrics like, average goals for ($r = 0.56$) and average goal differential (also $r = 0.56$). We introduce a new metric called the average offensive zone possession time differential (Avg. OZPTD) which measures the difference between the time that team A has possession of the puck while in their offensive zone and the time that the opposing team has possession of the puck while in their offensive zone (i.e., team A's defensive zone). We find that there is a strong correlation between Avg. OZPTD and Avg. GoalDiff (r = 0.77). Furthermore, we show Avg. OZPTD to be stable, capable of discriminating between teams, and providing new information over other metrics like SAT% (Corsi). The strong correlation and these attributes underscore its potential to provide deeper insights into team success.

The existence of the NHL's possession data paves the way for more detailed and exciting analysis. With our methodology for preparing, cleaning, and filtering possession data, we are poised to further investigate possessions in future work. On the team-level, it would be interesting to determine if time spent in the offensive zone correlates with team success or if puck possession is a key component. We would also like to examine chains (or sequences) of individual possessions. Metrics of interest would be the length of the chain and the number of different players in the chain. We would also like to study individual player possessions and correlations with player and team success.

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