In-field assessment of athletic performance and fatigue onset detection during ice skating using wearable sensors

by

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Abstract

Ice skating requires high aerobic and anaerobic fitness levels, well-coordinated body motion, and efficient neuromuscular systems functioning, requiring continuous performance assessment. Inertial measurement units (IMUs), widely used in tracking human motion for medical diagnostics and clinical evaluations, offer significant potential for enhancing athletic performance. Therefore, we developed and validated a wearable IMU technology for on-ice performance assessment, enabling us to assess skating biomechanics across various ice skating modalities in real-world settings.

First, we validated the novel algorithms to estimate skating temporal and spatial parameters by proposing an optimized configuration of wearable IMUs. Ten participants were recruited to skate on a 14-m synthetic ice surface built in a motion-capture lab. Stride time, contact time, stride length, and stride velocity were obtained with a 2-6% relative error compared to the in-lab motion capture reference system. We demonstrated that our wearable IMU technology on skates and pelvis could accurately and precisely estimate skating temporal and spatial parameters with similar relative errors compared to those obtained in IMU-based gait analysis.

Second, we explored the effectiveness of the on-ice distinctive features measured using these wearable sensors in differentiating low- and high-calibre skaters. Six high-calibre and six low-calibre skaters were recruited to skate forward on a synthetic ice surface. Five IMUs were placed on their dominant leg and pelvis. The 3D lower-limb joint angles obtained by IMUs showed a maximum root mean square error of 5 degrees against those obtained by a motion capture system. Our findings indicated that synthetic ice experiments impact skating 3D joint angles, blurring the differences between low- and high-calibre skaters typically seen in on-ice skating.

Third, we showed the potential of our wearable technology to track skaters' performance, predict perceived fatigue, and detect the onset of severe fatigue. In multistage aerobic experiments, nineteen high- and low-calibre skaters clustered by our proposed algorithm skated at a self-selected speed around an ice rink. Our developed algorithms measured 22 kinematic metrics using IMUs mounted on the dominant lower limb. The variations of inter-segment angle correlation, joint angle fluctuations, and trunk angle with perceived fatigue during aerobic ice skating were considerable. Finally, using the proposed kinematic metrics, we employed a gradient-boosting machine learning model to predict severe fatigue onset with high performance.

Fourth, we assessed skating performance using an expanded range of performance metrics obtained from our wearable technology in forward ice sprint tests. Nineteen ice skaters were recruited to sprint on ice with maximal speed while six IMUs recorded their movements. We found that stride velocity and stride length differed between low- and high-calibre skaters, and stride velocity differed between figure and hockey skaters. Also, figure skaters skated less complex and more coordinated than hockey players during the tests. Finally, we showed that the metrics we introduced can guide further research on exploring additional suitable off-ice tests, enabling the prediction of on-ice performance through off-ice measurements.

The outcome of this thesis research is a user-friendly wearable sensor system to provide an accurate outlook for ice skating coaches to improve their tutoring methods and youth/adult athletes' learning outcomes. This wearable technology demonstrated a significant potential to deepen our understanding of skating biomechanics and offer valuable insights for enhancing skating performance in multistage aerobic and sprint tests. Future studies could broaden the scope of this technology to include different skating styles and specific applications in hockey matches. Furthermore, IMU-based evaluations have indicated a potential for early detection of fatigue, aiming to reduce fatigue-induced injury risks in skaters of different calibres.

Preface

This thesis is an original work by Aminreza Khandan. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board under the project names: 'Biomechanical Analysis of Ice Hockey Using Wearable Technologies,' No. Pro00092821, approved on 25 September 2019, and 'On-Ice Hockey Player Performance Assessment Using Wearable Technologies,' No. Pro00114126, approved on 26 November 2021.

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*To my **family**,*

For their unwavering support and sacrifices

*To my beloved **Aghajan**,*
who taught me how to live with dignity

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who instilled in me the resilience to withstand adversity

*To my cherished **Khale**,*
who instilled in me a love for books

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Additionally, I would like to acknowledge that the University of Alberta resides on Treaty 6 territory, the traditional and ancestral territory of the Cree, Dene, Blackfoot, Saulteaux, and Nakota Sioux. I recognize that this territory is home to the Métis Settlements and the Métis Nation of Alberta, Regions 2, 3, and 4 within the historical Northwest Métis Homeland.

Finally, I wholeheartedly thank my family for their care, encouragement, and patience. Their sacrifices and support have been indispensable to this journey.

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Abbreviations

AD ankle dorsiflexion.

AP anterior-posterior direction.

CRP continuous relative phase.

HA hip adduction.

HF hip flexion.

IMU inertial measurement unit.

IQR interquartile range.

KF knee flexion.

ML mediolateral direction.

MSE multiscale entropy.

PSI postural stability index.

SI superior-inferior direction.

SSI step stability index.

TFI trunk forward inclination.

Chapter 1

Introduction

Ice hockey and figure skating are dynamic sports that require high-velocity movements on ice, necessitating skaters to develop and maintain significant power, speed, and agility during their skating [1–3]. Consequently, ice skaters are required to master highly coordinated body movements and ensure the optimal functioning of their neuromuscular and cardiovascular systems—essential for achieving high performance. Additionally, skating skills are upon which other skills like acceleration, stick handling, shooting, and agility are built [4, 5]. Therefore, reliable skating performance assessment tools provide essential information about skaters' overall performance by investigating skating biomechanics. Ice skating biomechanics has been studied using various optical and image-based methods [5–8]. However, the incorporation of wearable inertial measurement unit (IMU) technology in sports science recently heralds a new era for detailed and objective athletic performance analysis [9–11]. This thesis research aims to present an innovative effort in this direction, focusing specifically on skating performance assessment using IMU technology.

IMU technology has been widely implemented to measure human motion for medical purposes and clinical outcome evaluation [12–15]. However, the application of IMU technology for ice skating biomechanics assessment has been limited until now. Skaters' recorded kinematics and skating performance obtained from this wearable technology also enable the detection of player performance drops and have the potential to be a powerful tool to improve player efficiency and prevent fatigue-related injuries [16–18]. Therefore, by studying different skating modalities using IMU technology, we aimed to gain a holistic understanding of the skaters' performance and performance fatigue in ice skating.

We hypothesize that wearable IMUs can significantly enhance our understanding and analysis of ice skating by providing a comprehensive assessment framework in different on-ice skating modalities:

a. By estimating temporal and spatial parameters and three-dimensional (3D) joint angles of the lower limb, ice skating performance can be comprehensively assessed in natural settings. This foundational analysis sets the stage for deeper insights into skating dynamics in different skating modalities.

b. Then, using the data captured in (a), novel kinematic metrics can be proposed to quantify skating performance more effectively. These metrics will offer a detailed understanding of skating biomechanics and propose a new standard for assessing skaters' performance.

c. Using the kinematic metrics established in (b), the onset of performance fatigue can be detected during intermittent ice skating experiments, which is crucial for understanding how performance decays over time.

d. Finally, by employing new performance metrics in sprint tests, the impact of factors such as skill level and skating techniques in on-ice skating biomechanics can be studied. This step will demonstrate the proposed metrics' practical applicability and highlight the relationship between technique, calibre, off-ice measurements, and overall on-ice skating performance.

Together, this thesis research aims to form a comprehensive framework for assessing ice skating performance in the field, offering insights that are critical for both skating coaches and ice skaters.

1.1 Thesis objectives

This thesis research aimed to develop wearable sensor technology for the comprehensive on-ice assessment of skating performance. The targeted research outcome was a validated technology to: 1. Help coaches monitor and characterize ice skating performance quantitatively; 2. Determine the skating techniques of skaters of different calibre; and 3. Acquire a comprehensive understanding of performance fatigue and its relationship with perceived fatigue during different skating modalities. To this end, the specific phases, integrated in Figure 1.1, of this research project are as follows:

Phase I Determine temporal and spatial parameters of ice skaters by proposing an optimized configuration of IMUs and validating the technology's accuracy compared to in-lab systems,

Phase II Determine the technology's accuracy in obtaining the skater's 3D joint angles compared to those obtained by in-lab reference systems,

Phase III Propose performance metrics using the validated measurements of the proposed wearable technology (the output of Phases I and II) to characterize ice skating performance, track skaters' performance, and thus study performance fatigue in on-ice intermittent skating experiments,

Phase IV Conduct ice sprint tests on ice to assess the effectiveness of wearable sensor technology in comprehensively assessing hockey and figure skating biomechanics during on-ice sprint tests,

1.2 Thesis significance

Objective biomechanical assessment of athletes' motion has the potential to work toward improving skating performance and early detection of fatigue onset, thereby

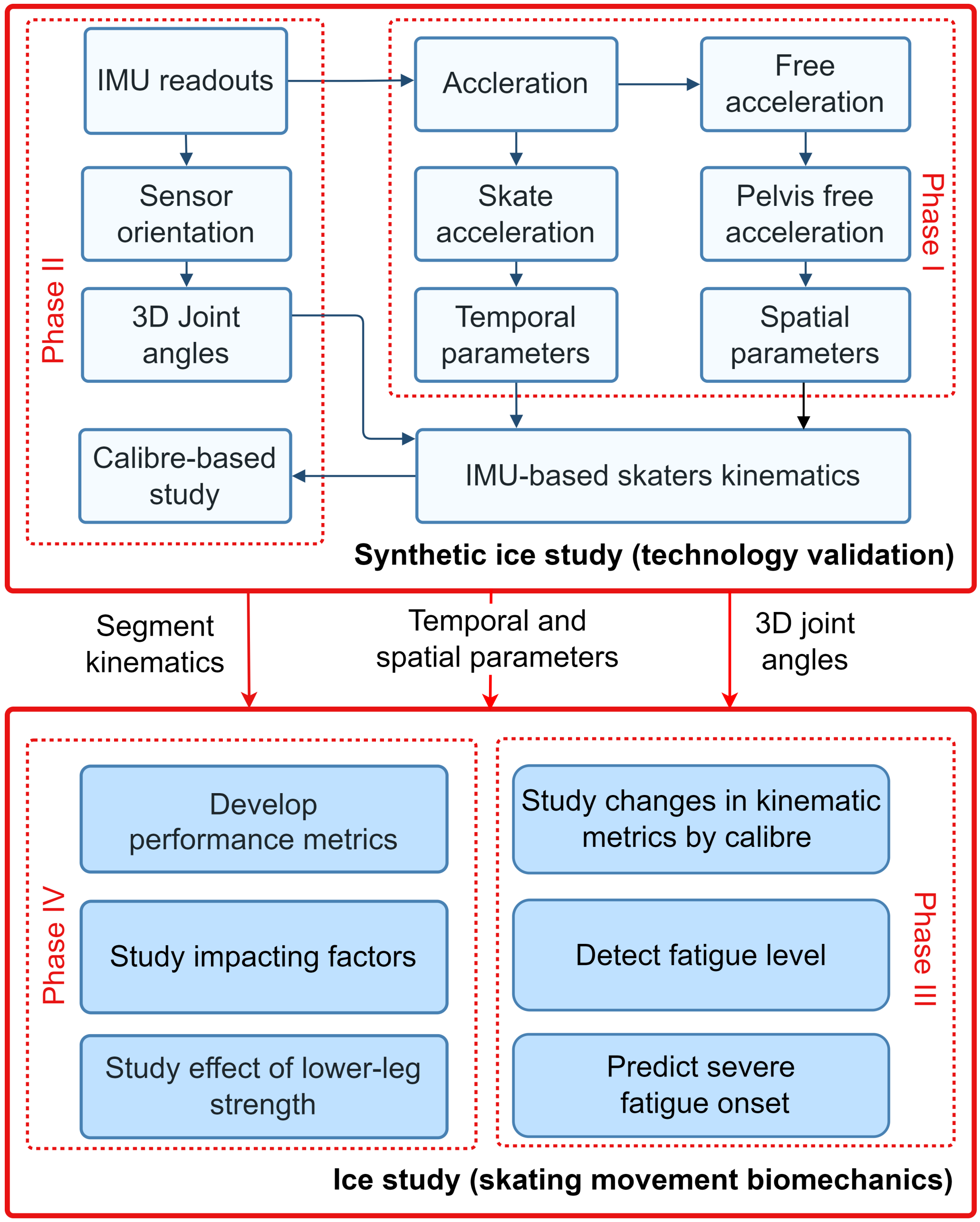

Figure 1.1: This flowchart illustrates the various phases involved in the study.

decreasing the subsequent fatigue-induced injuries. Our study has the potential significance in the following aspects:

1. Skating coaches and trainers can keep track of skaters' progress and improve their efficiency by assessing skating performance during training sessions and matches, even remotely,

2. Automatic onset detection of players' fatigue and on-time substitution with fresh players avoids consequent injury of players with chronic sequelae,

3. Equipping coaches with unique performance metrics offers in-depth insight into skating and the underlying inter-segment relationship during the skating,

4. Customizing training strategies aiming not only to boost the performance of novice players but also to reduce their injury rate in the long run.

5. Our findings will not only benefit athletes and coaches but also have broader implications for the design of training programs and the development of skating equipment for skaters of different calibres.

1.3 Thesis outline

The remainder of this thesis is organized as follows:

- Chapter 2 presents a comprehensive background on the current athletic performance assessment and fatigue onset detection in ice skating, particularly focusing on the application of IMU wearable technology. This chapter establishes an essential understanding of the innovative methodologies and studies forming the basis for the following chapters of this thesis.
- In Chapter 3, the temporal and spatial parameters of skating are estimated by proposing an optimized configuration of wearable IMUs and validating the system on synthetic ice compared to in-lab reference systems. This chapter is partially based on publication [19].
- In Chapter 4, the 3D angles of the lower limb joints of hockey skaters are obtained and experimentally validated by IMUs on synthetic ice. Also, the effectiveness of kinematic features obtained by IMUs in differentiating low- and high-calibre hockey skaters on synthetic ice is explored in this chapter. This chapter is partially based on publication [20].

- In Chapter 5, the potential of our proposed wearable technology to track skaters' on-ice performance is studied to predict perceived fatigue and detect severe fatigue onset. This chapter is partially based on a submitted manuscript.
- In Chapter 6, the effectiveness of our proposed wearable technology is assessed by comprehensively evaluating hockey and figure skating biomechanics during an ice sprint test. This chapter also studies the relationship of countermovement jump as an off-ice measure with a range of performance metrics, enabling a thorough assessment of skaters' overall performance. This chapter is partially based on a submitted manuscript.
- In Chapter 7, we provide the conclusions and future directions.

Chapter 2

Background and related work

This chapter presents an overview of the biomechanical studies of ice skating, employing a spectrum of analytical, statistical, and technical tools and methods and highlighting research opportunities in this area.

2.1 Introduction

Understanding human movement biomechanics plays a key role in enhancing sports performance and injury prevention by providing insights into the optimal techniques for athletes [21–23]. Additionally, it is instrumental in the design of equipment, assistive devices, training programs, and rehabilitation strategies to reduce injuries and improve players' quality of life and overall outcomes of the sports team [1, 24]. By employing techniques such as model-based estimation of muscle forces [25], sports biomechanics analysis using wearable sensors [10], and video-based biomechanics tools for injury assessment in sports [26], researchers and coaches can delve into the intricate details of human movement biomechanics in various sports. Therefore, the application of biomechanical principles in coaching has been proposed as a means to improve the understanding of player performance in sports. As a highly technical and dynamic sport, ice skating benefits significantly from understanding skating biomechanics to enhance athletic performance and reduce injury risks. Biomechanical assessments in ice hockey and ice skating can lead to targeted training interventions and equipment optimizations by analyzing the mechanics of skating movements. This approach supports skaters in achieving more precise, efficient, and powerful movement patterns, ultimately contributing to their competitive success and longevity in the sport [18, 27, 28].

2.2 Skating assessment tools

Ice skating originated with a unique twist in a classic origin story, involving the use of animal bones as skates in the frosty regions of the North [29], and now, ice hockey is a fast-moving game with millions of followers around the world. With the increasing popularity and market size, improvements in training and coaching strategies [30], using advanced technology for objective performance assessment is indispensable. Skating, among the required skills in hockey, is the skill upon which other skills like acceleration, stick handling, shooting, and agility are built [4, 5]. In figure skating, skating is the fundamental element that blends technical skill and artistic expression, allowing skaters to perform intricate maneuvers and choreography on ice with grace and precision [3]. Reliable assessment of ice skating during training sessions and matches helps coaches continuously monitor the players and the team and assist them in enhancing the team's overall performance. This performance assessment is crucial for identifying player strengths and weaknesses [31], enhancing training effectiveness [9, 32], and preventing fatigue-induced injuries by recognizing signs of performance drop [9]. It is typically conducted using biomechanical analysis with stationary, conventional motion capture systems or wearable sensors to measure and analyze skaters' temporal and spatial parameters and skating kinematics during training sessions and matches.

2.2.1 Conventional assessment systems

Traditionally, video cameras have been used to obtain ice skating performance. Using these cameras, the researchers studied two-dimensional (2D) or three-dimensional

(3D) kinematics of the lower-limb joints of individuals skating on ice in different phases and speeds [7, 33]. A motion capture video-based system was also used to assess the body kinematics of hockey players on the ice in several studies. In 1997, Marino used a Locam 16 mm camera to obtain and compare stride velocity, single support time, double support time, and stride length of ice skating at three different speeds [34]. They found out that single support time and double support time decreased significantly as skating speed increased. In 1999, Drouin used two video cameras to study the effects of fatigue on the mechanics of power skating and observed several alterations in the skating mechanics with fatigue [35]. Additionally, Upjohn et al. used a setup of digital video cameras to obtain 2D or 3D joint angles on a skating treadmill to contrast skating techniques between low- and high-calibre hockey skaters [7]. These studies were limited due to the static nature of camera angles, which often failed to capture the full range of motion and intricate details of the skaters' movements during skating. Additionally, the manual analysis of video footage has been time-consuming and subject to human error [36], limiting the depth and accuracy of performance assessments. These video camera-based methods also struggled with capturing multiple skaters simultaneously, particularly during complex routines where skaters rapidly change positions and orientations, hindering a comprehensive and accurate performance analysis using only video cameras.

Ice skating biomechanical research has been mainly focused on obtaining joint angles using motion capture systems in different environments. The kinematic and kinetic parameters of ice skating on a treadmill were studied using a set of motion capture cameras [8, 37, 38]. On the other hand, in 2010, Stidwill et al. used these cameras to study the overall movement patterns exhibited by skaters on synthetic ice and natural ice [39]. These researchers also used motion capture systems to compare hockey kinematics between high- and low-calibre and between male and female elite hockey players [4, 40]. Although these stationary motion systems are precise, their application is also limited in on-ice measurements due to their limited availability and capturing volume. Instead, employing wearable technology for performance assessment is a trended and acclaimed alternative [10, 36, 41].

2.2.2 Wearable technology

Wearable technology has been demonstrated to measure essential parameters in sports activity [10]. Wearable technology has enabled real-time monitoring of biomechanical parameters in athletes [10, 42, 43], providing valuable insights for optimizing workload and reducing fatigue-induced injury burden. The application of preventive biomechanics measures can significantly impact athlete health by reducing injury incidence [21]. Therefore, the integration of biomechanics in sports has paved the way for a deeper understanding of human movements, leading to advancements in performance optimization, injury prevention, and overall athlete health and well-being [44]. By leveraging innovative technologies such as wearable technology, sports biomechanics continues to evolve, offering valuable insights for athletes, coaches, and researchers.

A handful of studies on the application of wearable technologies in sports are related to the GPS and were carried out in open-field sports, where GPS works precisely [45, 46]. In a typical indoor ice hockey arena, smaller than a football, rugby, or soccer field, GPS signal may be more affected by errors than other outdoor areas. Besides, GPS does not provide physiologically relevant information, such as the players' phase of play or joint angle pattern. Therefore, despite the wealth of GPS measurements, they might not be efficient enough for regular on-ice assessments. Using a 3D accelerometer is another method to detect temporal events of ice skating on ice. Stetter et al. developed an innovative approach to determine strides, ice contact, and swing phases during ice hockey skating using a single accelerometer fixed to a hockey skate [6]. Additionally, this team showed the feasibility of using wearable accelerometers to identify the parameters to differentiate players of different skill levels [9]. Although these studies investigated spatial parameters of skating by 3D accelerometers, none measured joint angles using IMU sensors composed of a 3D accelerometer, a 3D gyroscope, and sometimes a 3D magnetometer.

Utilizing IMUs has revolutionized the detection of temporal events and the analysis of 3D joint angles in sports studies, enabling researchers to obtain 3D kinematics with high precision [10, 36, 44]. IMU technology has been widely accepted to measure human motion for clinical outcome evaluations [47–51] and performance monitoring [2, 52]. IMUs can be attached directly to the athlete and provide real-time data on movement patterns by measuring acceleration, angular velocity, and sometimes magnetic field. This technology allows for detailed and accurate assessment of the skater's motions, postures, and biomechanics, offering insights that were previously unattainable with traditional video analysis methods. The use of IMUs in ice skating research not only enhances the understanding of the sport's dynamics but also aids in developing targeted training and injury prevention strategies. However, the application of IMU technology for assessing ice skating biomechanics has been limited, hindering comprehensive performance assessments of on-ice skating to date.

Therefore, IMU technology has the potential to enhance our ability to analyze and understand the complex locomotor demands of various sports and our understanding of sport-specific physical demands [2, 10]. These devices are embedded within wearable units, allowing for the precise capture of athletes' movement patterns in real time. This capability marks a substantial leap forward from traditional system and analysis methods, enabling a more detailed and accurate assessment of athletic performance and the physical demands of sports in the field. IMUs have been extensively utilized across a broad spectrum of sports, including individual and team sports, water sports, and snow sports, to detect and quantify movements intrinsic to each sport [53–59]. These sensors thus can provide detailed insights into movement patterns, frequencies, and the forces exerted during athletic activities underscores their potential to revolutionize training methodologies, performance analysis, and injury prevention strategies.

Despite the promising applications of IMUs in capturing the nuances of sport-specific movements, Chamber et al. underscored the mixed evidence regarding the capability of IMUs to measure some movements precisely [53]. This gap in technology highlights the need for further research to refine the accuracy and applicability of IMU sensors in sports science. The call for additional validation studies emphasizes the ongoing quest to fully harness the capabilities of wearable IMU technology to understand the complexities of ice skating. In 2022, Evans discussed the integration of wearable technology in ice hockey, focusing on their application for performance analysis and injury prevention [2]. They highlighted how IMU technologies can capture detailed kinematic and kinetic data, offering insights into player movements, the impact of hits, and overall performance metrics. Evans et al. also emphasized the potential of IMU wearable technology to enhance understanding of the biomechanics involved in ice hockey, aiding in developing targeted training and rehabilitation programs to improve player safety and performance.

2.3 Skating performance assessment

Developing solid skating techniques is essential for hockey players as it enhances their performance across all facets of the game, ultimately leading to improved effectiveness and competitiveness on the ice [1]. In 2013, Pearsall et al. emphasized the importance of mastering powerful and efficient skating techniques, as players must cover significant distances quickly and with agility during a hockey game [31]. They discussed how the biomechanical principles underlying skating movements differ from those of walking and running, necessitating unique muscle activation and joint mechanics adaptations in skating. These adaptations enable athletes to execute the high-speed, complex maneuvers characteristic of competitive ice hockey. Furthermore, the study highlighted the significance of understanding these biomechanical factors for enhancing athletic training, injury prevention, and equipment design. By examining the specific demands placed on hockey players, this research offers insights into how targeted training and technological advancements can improve performance and safety.

Finally, this study underscored the potential for biomechanical research to inform practice and innovation in ice hockey, contributing to the ongoing development of the sport. In 2019, Stetter et al. suggested that body-worn accelerometers are applicable for obtaining skating performance data [9]. The study highlighted the potential for wearable performance sensors to benefit player development and training. The findings suggest that further research on monitoring biomechanical performance variables, such as stride propulsion, and the automated detection of such is informative. While most ice skating studies predominantly concentrated on varsity-level to professional hockey players, the biomechanical assessment of figure skaters has usually been overlooked. The differences in biomechanics between hockey and figure skating stem from distinct skate designs and the specialized training each discipline requires [21, 60]. Despite these differences, hockey coaching often integrates figure skating techniques to enhance agility and footwork. This integration necessitates a deep understanding by hockey coaches of the biomechanical nuances distinguishing the two sports, ensuring the effective adaptation of figure skating skills to improve hockey performance.

In figure skating, skating skills are also fundamental, serving as the bedrock for performance. In 2022, Ionesco et al. highlighted that the most significant skill in figure skating is skating effectively, as acknowledged by professionals in the field [60]. This study provided insights into the game-performance skating characteristics of figure skaters, stressing the relation between the performance of female figure skaters in agility and balance tests and their competition scores. They suggested that a comprehensive understanding of skating biomechanics is crucial for developing training programs to enhance figure skaters' performance [60]. The ability to execute various movements with precision and grace, from simple glides to complex jumps and spins, is directly influenced by a skater's proficiency in skating techniques. Speed, an essential component, not only enhances the aesthetic appeal of performance but also contributes to the technical execution of elements, allowing skaters to generate the necessary momentum for jumps and maintain control during spins. The mixture of advanced skating skills and speed underpins the artistic and technical excellence in figure skating, distinguishing elite skaters.

2.4 Skating environments

The skating environment, crucial to performance and training, varies widely, encompassing real ice, synthetic surfaces, and skating treadmills. Each environment presents unique benefits and challenges, influencing training outcomes and skater adaptation. Real ice offers authentic conditions but can be subject to weather and quality variability. Also, access to ice skating rinks can be seasonal and further restricted by the limited availability of open time slots, making consistent training and recreational skating challenging to schedule. Skating treadmill, on the other hand, is an alternative for focused training, allowing skaters to practice technique and endurance under controlled conditions. Finally, synthetic ice provides a year-round option with lower maintenance, and the skater's experience is similar to real ice. However, these two alternatives may not replicate the exact resistance and glide of real ice [37, 39, 61].

Skating on a treadmill has become a popular training environment for ice skaters, offering a controlled, non-reflective environment for focused skill development and conditioning. This environment allows for continuous skating without needing large ice surfaces, enabling detailed analysis and feedback on technique [37, 61]. However, the kinematic and kinetic parameters of ice skating on a treadmill were found different from those of skating on ice using a set of motion capture cameras [8, 37, 38]. These differences highlight the importance of understanding how treadmill skating may affect training outcomes and technique adjustments. Alternatively, synthetic ice can replicate the overall experience of ice skating effectively.

During the COVID-19 pandemic, with most public ice rinks closed, synthetic ice emerged as a viable alternative for skaters to maintain their training regime and for coaches to monitor athletes remotely. In 2010, Stidwill et al. demonstrated that the overall movement patterns exhibited by skaters on synthetic ice were closely similar to those on ice [39]. While gross movement patterns on synthetic ice closely mimic those on natural ice, notable differences in kinematics and posture were reported. These differences suggest that while synthetic ice can effectively mimic the general ice skating experience, there are distinct biomechanical aspects that differ between ice skating and skating on synthetic ice, including excessive knee extension on synthetic ice [39]. Therefore, an in-depth study is required to understand the impact of synthetic ice skating on the performance of skaters.

2.5 Skating modalities

Ice skaters are expected to demonstrate well-coordinated body motion and efficient functioning of neuromuscular and cardiovascular systems across various skating modalities. Researchers have studied the kinematics of skating, analyzing how skaters maneuver across various modalities on the ice, both in ice hockey and figure skating [3, 5, 60, 62, 63]. The use of on-ice aerobic testing, such as the 30-15 intermittent ice test, helps in assessing the maximal oxygen uptake and neuromuscular fatigue mechanism in professional hockey players [62, 63]. Furthermore, the skating ability of ice hockey players studied in repeated shuttle sprint tests on ice is essential for evaluating an ice hockey player's capacity for repeated high-intensity efforts [64, 65]. Together, studying skating kinematics in diverse skating modalities is essential in assessing skating quality and proficiency comprehensively.

2.5.1 Intermittent tests and fatigue

Aerobic experiments in ice skating are crucial for assessing athletes' endurance, capacity to maintain performance levels over time, and recovery rates. These tests, often conducted on ice to simulate real-world conditions, help identify the aerobic and anaerobic ability of ice skaters, guiding training programs toward improving cardiovascular fitness and optimizing on-ice performance [23, 63, 66]. Given the importance of aerobic capacity in prolonged activities and high-intensity intervals common in figure skating and ice hockey, such testing is instrumental. It informs coaches and athletes about the effectiveness of training regimens, potential areas for improvement, and strategies for enhancing overall athletic endurance [63]. These insights are valuable for tailoring conditioning programs that meet the unique demands of ice skating disciplines, ultimately contributing to improved competitive performance and reduced injury risk.

In aerobic on-ice experiments, the skating multistage aerobic test (SMAT) has been designed to measure the aerobic capacity of ice hockey players, closely replicating the actual playing conditions [63]. Participants skate forward back and forth over a 45-meter distance at a constant speed of 3.5 m/s, guided by audible signals. The test ends when a participant can no longer maintain the same pace. This setup effectively replicates hockey's specific ice skating patterns and intermittent nature, offering a precise metric of an athlete's aerobic capabilities. The skating multistage aerobic test's ability to simulate real conditions makes it an invaluable tool for assessing aerobic capacity, providing insights into fatigue's effect on performance and injury risk.

Fatigue leads to weariness, diminished alertness, and decreased concentration and affects muscle activity and lower limb kinematics during the activities. Thus, in-game fatigue can impact the player's injury risk [16, 18, 67] in hockey and ice skating, which involves a high risk of injury. Fatigue affects muscle activity, altering the efficiency and sustainability of performance and kinematics in athletes and impacting muscle coordination and force generation, which are critical in high-stamina sports like ice skating [16, 67–69]. Therefore, an objective performance study during ice skating must be integrated into the current subjective and instrumental fatigue measurement tools based on skaters' muscle activity during different skating modalities. Furthermore, despite some biomechanical studies examining fatigue mechanisms in skating [16, 67, 69], a comprehensive investigation into how fatigue impacts the kinematics of skaters has yet to be conducted. For instance, joint angle variability and inter-segment coordination were observed to indicate fatigue level [70, 71] and countermovement jump [72]. Fatigue can affect any skater's biomechanics, regardless of their skill level or experience [68]; however, its effect on the skaters' performance can differ between skaters of different calibre [18, 68], necessitating further investigation. Therefore, objective assessment of hockey players' movements on ice can help researchers monitor player performance to improve their efficiency and enable coaches to track player movement coordination and its contribution to the onset of fatigue and thus prevent fatigue-related injuries. Finally, this assessment facilitates the design and optimization of skating equipment tailored to skaters' biomechanics [30], enhancing performance by ensuring that the gears meet the diverse needs of a broader spectrum of ice skaters. Ice skating's dynamic demands precise coordination and a balance between aerobic and anaerobic capacity, enabling athletes to execute swift yet intricate movements.

2.5.2 Ice skating sprint

Ice skaters must master various skating modalities, including the ability to perform effectively in ice sprint tests. Stationary motion capture systems enable precise measurements of the skater's kinematics on a small part of the ice during these tests. In 2017, Shell et al. conducted a kinematic analysis of skating start propulsion in elite male and female ice hockey players using a stationary motion capture system. The study aimed to determine the impacts of sex on the kinematics of the hip and knee during the skating start and to identify the key performance indicators of skating start propulsion. Data were collected from 18 participants, and kinematic measurements were obtained using custom MATLAB scripts. In 2020, Budarick et al. focused on the biomechanics of high-calibre male and female ice hockey skaters during on-ice sprints [40]. The study analyzed the characteristics of the skater's body centre of mass (CoM) during the start and maximal speed phases and identified differences between male and female athletes. Finally, Robbins et al. studied the differences in skating stride between high- and low-calibre ice hockey players using these stationary systems [73]. While motion capture systems offer high precision, their use is limited in on-ice measurements, constrained by their limited accessibility and capture volume. Therefore, wearable technology has also been used to measure ice skating kinematics during ice sprint tests.

In 2015, Buckeridge et al. studied hockey skating biomechanics across acceleration and steady-skating phases of an ice sprint test using a variety of wearable technology, including 3D accelerometers [5]. The study included nine varsity-level players and nine recreational hockey players where they carried out a 30 m maximum effort forward skating drill, and their muscle activity and 3D acceleration were measured using various sensors. They found that varsity-level players showed significant differences from recreational hockey players in terms of several measured factors, including increased push-time, stride length, and muscle activity during push-off. They found that skating performance differed not only based on whether a player was on a varsity or recreational level but also on individual skating styles. In 2016, Stetter et al. introduced an innovative technique for the automated detection of ice hockey skating strides, employing 3D acceleration data to identify the blade-ice contact and swing phases of strides during a 30-m forward sprint [6]. With a 3D accelerometer attached to a skate and synchronized plantar pressure as a reference, the method's accuracy for various stride patterns was confirmed, showing minimal differences compared to motion capture data. Although these studies investigated temporal parameters of ice skating by 3D accelerometers, none measured 3D joint angles during ice sprint test. Therefore, IMU, introduced earlier, is a requirement that enables us to capture skating 3D kinematics and thus to develop skating kinematic metrics during ice sprint tests.

2.6 Skating kinematic metrics

Skating kinematic metrics have been shown to highlight the performance variations between male and female ice skaters. Researchers used video cameras to study 2D or 3D kinematics of the lower-limb joints of individuals skating on ice in different phases and speeds [34, 74, 75]. They found significant repeatability among participants of the same sex and proficiency level and notable differences among participants across different sexes and proficiency levels. In 2017, Shell et al. demonstrated that male hockey skaters achieved a higher maximum skating speed compared to females during skating start propulsion in ice sprint tests [76]. They observed notable differences in skating technique between the sexes: females displayed approximately 10 degrees less hip abduction during the skating stance and about 10 degrees more knee extension during the initial ice contact. This was notably accompanied by a short cessation in knee extension in female skaters at the moment of ice contact, a feature not present in male skaters. Also, in 2017, Budarick et al. found that males produced more forward acceleration during initial accelerative steps [4], but beyond this phase, stride-by-stride accelerations were similar between males and females up to maximal speed. Males exhibited increased hip abduction and knee flexion from ice contact to push-off in all trials. Researchers also found noticeable differences between the kinematics of skaters of different calibres.

Biomechanical differences between high- and low-calibre players' skating have been a focal point for understanding the link between skating biomechanics and performance. Hockey skating literature has consistently shown significant disparities in lower limb joint 3D angles and CoM movements across skill levels in ice experiments [5, 73, 77, 78]. They have identified significant differences in parameters like ankle plantar flexion, knee extension at push-off, and hip flexion, marking high-calibre hockey skating as distinct from lower-calibre skating. Buckeridge et al. used a portable system including accelerometers to assess on-ice hockey players' performance and found differences in the hip adduction of hockey players of different calibres [5]. They found that greater plantar-flexor muscle activity and hip extension were evident during acceleration strides, while steady-state strides exhibited greater knee extensor activity and hip abduction range of motion. Finally, Robbins et al. [73] employed principal component analysis in on-ice experiments to discern critical features differentiating the 3D joint angles of high and low-calibre hockey players. Nevertheless, replicating these studies and inter-study comparisons is challenging due to the subjective and not statistically-supported definition of skill level in the literature.

Current skill-based clustering approaches for skaters have frequently been imprecise. Being a part of a university team or having specific years of skating experience or skating speed has been the most common criterion for being considered as a high-calibre player [5, 73, 78]. However, interpretation of the results and inter-study comparisons are challenging due to three factors: 1) Being on a university team or having long-time experience or faster skating on ice does not necessarily mean performing well in all the skating aspects in the data acquisition time, 2) There is no statistical evidence to support the claim that skaters should be classified into only two or three distinct groups, and 3) It has not been investigated whether there is a significant difference in the skills of the participants in these groups. Therefore, addressing these challenges in clustering skaters is needed to investigate how the skaters' performance differs among skaters of different calibre.

Ice skating performance is influenced by myriad factors, including athletes' skill level, sex, and age, alongside the specific type of skating— figure skating or hockey. Studies have shown that these elements significantly impact the biomechanics of skating, such as 3D joint kinematics, affecting how skaters execute sprints and maneuvers on ice. While factors like calibre, sex, and age significantly influence skating performance, the type of skating—whether figure or hockey—also plays a crucial role in forward skating during ice sprint tests. While existing performance metrics offer some insights into skater proficiency, developing and applying novel metrics could enhance the understanding of diverse aspects of skating performance. These performance metrics on ice could have been predicted through off-ice tests, saving considerable labour and time. This approach suggests that assessing athletes' physical capabilities off the ice can offer valuable insights into their on-ice performance.

2.7 On- vs off-ice performance

Off-ice measurements have been shown to predict various on-ice parameters, offering strategic benefits in training and performance analysis. Bracko's series of studies investigated speed dynamics in ice hockey [21, 79, 80]. Collectively, these papers offered a unique perspective on how agility and quick directional changes impact performance in a team sport setting. In 2004, they focused on predicting the performance of female figure skaters using off-ice and on-ice variables. The study measured the participants' skinfold, height, and body mass. Then, various exercises such as push-ups, sit-ups, sit-and-reach vertical jumps and 40-yard dashes were conducted by each participant. In addition, the participants' predicted fat percentage was determined based on the skinfold measurements. On-ice variables such as acceleration, speed, agility, and anaerobic power and capacity were also measured for each participant. Results showed that off-ice variables such as vertical jump, 40-yard dash, and sit-ups were highly correlated with on-ice measures such as acceleration, speed, and anaerobic power.

In another study, Krause et al. examined the relationship between off-ice physical activity and on-ice performance among ice hockey players [81]. They asked 21 male participants to perform various off-ice tests, including five hops, three vertical jumps, eight dynamic balance tests, and a 40-yard sprint. The tests measuring on-ice performance used a crossover turn and the right and left short radii speed tests, among others. The hierarchical multiple regression was then used to interpret the predictive relationship of the off-ice performance variables to on-ice performance metrics. The results showed that forward skate time, right crossover time, left crossover time, right short radius time, and left short radius time significantly correlated with off-ice performance measures, indicating the predictive ability of off-ice performance. In 2009, Meylan et al. studied the impact of strength and conditioning programs on skating performance [82]. They assessed the horizontal and lateral jump abilities, as well as 10-m sprint times and change of direction (CoD) performance, of 80 men and women using contact mat and timing light technology. They particularly highlighted the role of lower body strength and power in improving propulsion and speed on the ice.

In 2015, the studies by Haukali et al. [83] and Janot et al. [84] explored the relationships between off-ice physical activities and on-ice performance in ice hockey players. They have also revealed key insights into how specific off-ice tests correlate with on-ice speed and agility. Haukali et al. found significant correlations between off-ice tests, such as sprints and jumps, and on-ice performance among young male players. Janot et al. further identified lower-body power and off-ice agility as crucial predictors of on-ice performance, emphasizing the importance of targeted physical training in enhancing ice hockey skills. Finally, Daehlin et al. explored the correlation between conditioning exercises and on-ice performance [85]. Their study emphasized the importance of sport-specific training, demonstrating how targeted conditioning exercises can lead to significant improvements in skating efficiency and endurance.

Looking forward, there is a need for continuous research in this area, particularly in the context of evolving training methodologies and technological advancements. More importantly, the relationships between off-ice measurements, such as the CMJ, and a wide range of on-ice performance metrics for figure and recreational hockey skaters of different ages remained unexplored. Therefore, future studies must aim to integrate innovative methodologies and techniques, further enhancing our understanding of this relationship.

2.8 Toward a comprehensive performance assessment in ice skating

A comprehensive performance assessment of ice skating necessitates the measurement of joint forces and moments to gain essential insights into player mechanics and effectiveness. Buckeridge et al. used muscle activation sensors (EMG) and force sensors to assess on-ice hockey players' performance during their forward skating technique [5]. In 2019, Nassen et al. measured skate-ground interaction forces to investigate the kinetic parameters of hockey, i.e., work, energy, and angular momentum [86]. They explored a modified skating stride featuring an extended gliding phase in a circular arc. Their suggested technique conserves angular momentum and increases speed when the skater's body CoM moves closer to the arc's centre [86]. Later, Pearsal and his team conducted a series of experiments to assess forces and pressures in different ice skating environments and recruited different skaters with different skates. First, they proposed a portable force measurement system for ice hockey skating, allowing for natural, unrestricted movement and yielding clear, distinct signal responses [87]. They also identified kinematic variations among ice hockey players using different skates and underscored the importance of a familiarization process for skaters to fully adapt to and gain the advantages of newly designed skates [88]. In another study [39], they studied skating in different environments, exploring the similarities and differences between synthetic and real-ice skating. A comprehensive performance assessment of ice skating necessitates analyzing muscle activity, joint forces, and moments to understand ice skating biomechanics thoroughly.

Understanding muscle activation and synergies is also crucial for effectively analyzing and enhancing on-ice performances [2, 89]. Also, it aids in identifying stress points and improper techniques, thus guiding training and equipment design to prevent muscle injuries [1, 30, 90]. Notably, hip adductor strains account for approximately 10% of all injuries sustained in ice hockey. Skating type (i.e., figure, hockey, or speed skating), skate design, and skating modalities require varied muscle activity and synergies. Understanding these variations is essential for tailoring training and rehabilitation programs that address the specific needs of the skaters, ensuring that muscle development and activation are aligned with the specific demands of their skating activities. Muscle activation and synergies in ice skating can also be influenced by skating speed. In 2018, Kim et al. [91] revealed that while higher skating speeds were associated with increased muscle activation, the muscle synergies remain consistent regardless of speed. By analyzing the muscle activity of ice skaters, it is also feasible to identify potential sources of injury, such as overuse, poor technique, or muscular imbalances [68]. Detecting the onset of fatigue is also vital to comprehensive performance assessments. Therefore, incorporating the study of performance fatigue and its effects on muscle activity and lower limb kinematics into research is essential for identifying and avoiding fatigue-induced injuries early on.

2.9 Conclusion

The historical journey from primitive bone skates to the high-paced world of modern ice hockey and figure skating highlights the evolution and significance of skating. Our discussion in this chapter has highlighted the critical need for advanced technologies to objectively assess skating performance—a skill foundational to the success and artistry of on-ice skating. We discovered that studying the biomechanics of human movement is integral not only for athlete development and performance enhancement but also has the potential for injury prevention, including ACL injury, concussion, and injuries related to loss of concentration. Therefore, ice skating, as the core skill in hockey and a critical part of figure skating, requires thorough and multifaceted assessment approaches to capture its complicated dynamics across different skating modalities.

Building upon these insights and directly addressing the gaps identified in this chapter, we are required to develop wearable sensor technology for a comprehensive on-ice assessment of skating performance. Drawing from the insights gained, our research objectives were outlined to include: 1) Obtaining temporal and spatial parameters and 3D joint angles of the lower limb during skating in different skating environments, 2) Extending the scope of performance metrics to monitor skating performance in different skating modalities, thereby enhancing our understanding of the correlation between off- and on-ice measurements; and 3) Investigating performance fatigue and how these performance metrics decay over time using IMU wearable technology. Measuring temporal and spatial parameters using the proposed IMU technology is the first and foremost step toward this comprehensive skating assessment.

Chapter 3

Measurement of temporal and spatial parameters using wearable sensors

This chapter proposed novel methods for estimating the temporal and spatial parameters of ice skating using wearable IMUs and experimentally validated against the in-lab reference systems. Portions of this chapter have been adopted and/or edited from:

A. Khandan, R. Fathian, J. P. Carey, and H. Rouhani, "Measurement of temporal and spatial parameters of ice hockey skating using a wearable system," Scientific Reports, vol. 12, no. 1, pp. 22280, Dec. 2022.

3.1 Introduction

Ice hockey requires high levels of aerobic and anaerobic fitness, well-coordinated body motion, and efficient functioning of the neuromuscular and cardiovascular systems [1, 33, 92]. Players with higher neuromuscular and cardiovascular abilities, capable of starting quickly and skating at higher speeds, are more likely to possess the puck and win face-to-face competitions in matches [9]. Accurate assessment of hockey players' skating movements during training sessions can help coaches continuously monitor players' performance with the aim of improving it during training. Spatial (e.g.(stride length (SL) and velocity (SV)) and temporal (e.g., stride time (ST) and ice contact time (CT)) parameters of skating serve as mobility biomarkers [93, 94] and are recognized as significant metrics to characterize any repetitive activity like forward ice striding. These parameters, traditionally, were obtained in human motion laboratories using stationary motion-capture (MoCap) systems. However, the application of these instruments is limited since they are not available in every ice rink, and their captured volume is confined to a small part of the rink, which can disrupt the natural skating patterns of ice skaters [40, 95, 96]. Thus, wearable and garment-embedded technologies are preferable for on-ice skating performance assessments [10, 97, 98].

Buckeridge et al. used a portable system composed of accelerometers, EMG modules, and force sensors to assess on-ice hockey player performance [5]. Also, Stetter et al. studied the feasibility of using wearable accelerometers to identify skating parameters such as ST and CT to differentiate players in terms of their skill level [6, 9]. However, these studies investigated the skating parameters using 3D accelerometers rather than inertial measurement units (IMU). IMU has been applied to measure human motion for clinical outcome evaluation [49, 99, 100], sports biomechanics evaluations [41, 43, 56, 101–104], and movement modalities detection [12, 48, 96]. They have the potential to obtain temporal and spatial parameters during hockey skating.

The computation of the temporal and spatial parameters, in the first step, requires the detection of skating temporal events. The accuracy of event detection using IMUs can vary significantly depending on the extraction method used [105, 106]. The second step is to estimate the participant's trajectory in each stride necessary to calculate the spatial parameters [107]. Finally, temporal and spatial parameters can be calculated by the detected temporal events and the participants' trajectories. Participants' trajectories can be calculated using double-time integration of the participant's acceleration in a global reference frame. However, due to the cumulative error in the numerical integration of IMU readouts, the obtained trajectory can be drifted and erroneous [108]. There are two types of error in calculating the stride length: the noise on the acceleration time series and the drift in the sensor orientation (used for double-integration of acceleration to estimate trajectory) obtained by the gyroscope readouts. In the gait analysis application, it has been suggested to correct foot velocity and, subsequently, foot trajectory time series by assuming zero velocity and minimum foot height during foot-flat periods [93]. However, a similar period to the foot-flat with zero velocity in all directions is absent in ice hockey skating strides, making foot velocity and trajectory estimation more challenging in hockey skating than on-land gait. This study addresses these challenges toward improving the accuracy of on-ice measurement of spatial and temporal parameters of ice skating using a set of IMUs fixed on the participant's skates, shanks, and pelvis on a synthetic ice surface. Synthetic ice surface, as an alternative to real ice with comparable forward skating mechanism [39], has the potential to be used in in-lab testing and training, particularly where ice access is limited.

The objective of this study was to: (1) detect temporal events of skating using skate-mounted IMUs, (2) estimate the skate trajectory using IMUs, (3) calculate the temporal and spatial parameters of skating using the obtained temporal events and corrected skate trajectory, and (4) experimentally validate the obtained results against those measured by in-lab motion-capture systems on a synthetic ice surface.

3.2 Methods and procedure

3.2.1 Participants

Ten able-bodied individuals (age 25 ± 8 years, height 179 ± 9 cm, body mass 78 ± 11 kg; mean ± standard deviation (SD) among participants, six male and four female) were recruited to participate in this study. All participants were free from injury and capable of skating comfortably. The study was approved by the research ethics board of the authors' current institution (Pro00092821), and all methods were performed in accordance with the relevant guidelines and regulations. All participants were informed of the experimental procedures and gave informed written consent before the test.

3.2.2 Experiments

Tests were carried out at an indoor synthetic ice rink ($14 \times 2\,\mathrm{m}^2$). Five IMUs (Xsens Technologies [109], The Netherlands, full-scale ranges are: acceleration: ±160 m/s^2, angular velocity: ±2000 deg/sec, and magnetic field: ±1.9 Gauss) were placed on the pelvis, shanks, and two skates of the participants. No sensor-to-segment calibration was used, and sensors' readouts were directly used to extract the temporal events. They were asked to wear tight-fitting pants or shorts, and the sensors were placed on the skates and skin of the participants or on the fitted pants to minimize the garment-to-skin motion artifact. Two reflective markers were placed on the two posterior superior iliac spines (PSIS) of the body, as demonstrated in Figure 3.1. As a reference system for temporal event detection, plantar pressure insoles (Pedar-X [110], Novel, DE) were placed in the skates (Figure 3.1) to measure the ground reaction force magnitudes and thus detect the instances of skate contacts on the ice. The pressure insoles were calibrated at the beginning of each session as a standard practice instructed by the manufacturer to remove the offset error. As the reference system for spatial parameters, 12 motion-capture cameras (eight Vero and four Bonita, Vicon, UK) were used to track the trajectory of retro-reflective markers. After 10 seconds of standing still, the participants skated forward alongside the synthetic ice rink for 14 meters. At the end of the forward skating trial, they also stood for 10 seconds quietly. During each trial, the IMUs, motion-capture cameras, and pressure insoles recorded their motions and ground reaction forces simultaneously. All the systems' sampling frequencies were 100 Hz, and each skating trial was repeated five times.

3.2.3 Temporal event detection

First, the IMU readouts measurements were filtered using a low pass 4th order Butterworth filter using 15 Hz. We developed eight original methods to detect skate strikes

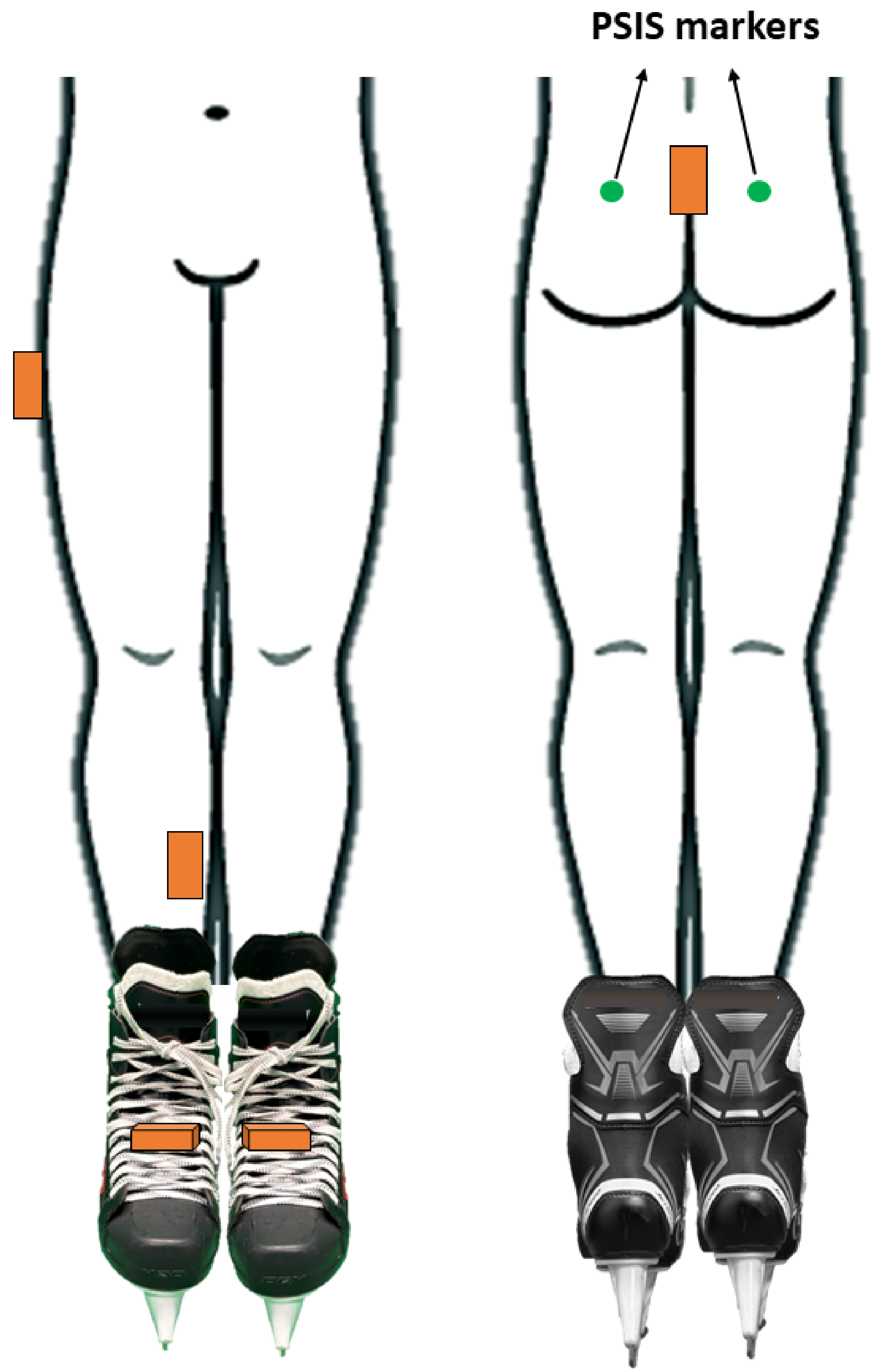

Figure 3.1: Five IMUs (orange boxes) were placed on the participants' pelvis, shanks and skates. Also, two pressure insoles placed in the skates and two retro-reflective markers on the PSISs (green circles) were used as a reference system for temporal event detection and stride length estimation, respectively.

(SS) and blades-offs (BO) instants using the IMUs' readouts. In addition to the originally proposed methods of temporal event detection, described in Table 1, three highly-cited gait event detection methods in literature [51, 107, 111] were adopted and implemented to detect the temporal events in skating. These 11 methods were implemented in MATLAB (Mathworks, USA) and obtained the events during five trials of each participant. These detected SS and BO were validated against those detected using the pressure insoles, with a 5 N threshold (Figure 3.2).

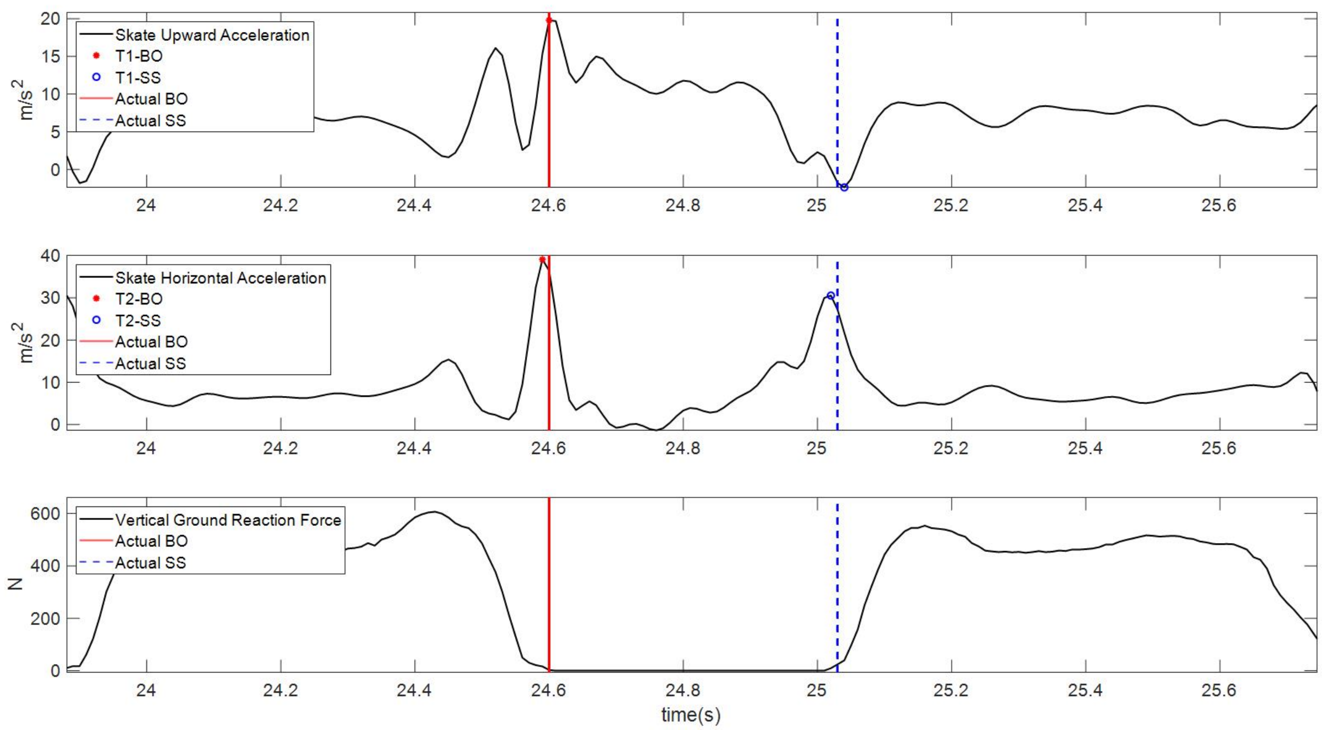

Figure 3.2: Exemplar recorded time series of skate upward and horizontal acceleration measured by the skate-mounted IMU in a skating trial. The figure also shows the temporal events (SS: skate strike and BO: blade off) detected by algorithms T1 and T2 and the actual events detected using the pressure insoles (gold-standard), based on a 5-N threshold on the vertical ground reaction force. Actual SS and BO were obtained from the first data points after the vertical ground reaction force passed the 5-N thresholds.

Table 3.1: Description of the methods originally proposed (T1 to T8) and adopted from the literature and modified (T9 to T11) for detection of Skate Strike (SS) and Blade off (BO) instants during forward skating using the readouts of IMUs placed on the shanks or skates. Similar to the original gait analysis studies (T9-T11), it was assumed that the participant starts skating from a stationary position and, thus, starts by a BO (toe-off in original studies). Therefore, the odd negative peaks indicate BO (toe-offs in original studies), and the even peaks indicate SS (heel-strike in original studies).

Methods	Time series used	Event	Features used in time series
T1	Upward acceleration of skate	BO	Positive peaks of the time series
		SS	The minimum of the time series occurred between two consecutive BOs
T2	Horizontal acceleration of skate	BO	The minimum of the time series occurred before the positive peaks
		SS	The maximum of the time series occurred between two consecutive BOs
T3	Upward velocity of skate	BO	Negative peaks of the time series
		SS	Positive peaks of the time series
T4	Norm of skate acceleration	BO	The last minimum of the time series occurred before the dominant positive peaks
		SS	The maximum of the time series occurred between two consecutive Bos
T5	Shank angular velocity	BO	Negative peaks in the sagittal plane angular velocity
		SS	Positive peaks in the frontal plane angular velocity
T6	Norm of shank angular velocity	BO	The minimum of the time series occurred before the dominant peak
		SS	The minimum of the time series occurred between two consecutive Bos
T7	Norm of skate acceleration	BO	Odd numbered positive peaks in wavelet coefficients in the highest energy concentration frequency obtained by a CWT (continuous wavelet transform) utilizing Coiflet wave shape

		SS	Even numbered positive peaks in wavelet coefficients in the highest energy concentration frequency obtained by a CWT utilizing Coiflet wave shape
T8	Norm of skate acceleration	BO	Positive peaks in the 3rd approximation of the time series in a DWT (discrete wavelet transform) using Coiflet wave shape
		SS	The minimum of the time series occurred between two consecutive Bos
T9	Shank angular velocity	BO	Odd-numbered negative peaks of the time series
		SS	Even-numbered negative peaks of the time series
T10	Norm of skate acceleration	BO	Odd-numbered negative peaks of the time series
		SS	Even-numbered negative peaks of the time series
T11	Norm of skate acceleration	BO	Local positive peaks of the time series
		SS	Local negative peaks of the time series

3.2.4 Skater's stride length estimation

The spatial parameters were calculated using the IMUs placed on the skates, shanks and pelvis. Any inherent signal bias in the sensor readouts is prone to accumulate in the integration process and corrupt the obtained velocity and trajectory of the skater. In the gait analysis application, the zero-velocity update (ZUPT) technique has been used to force the foot velocity to be zero during the stationary foot-flat period in each stride [93]. However, during contact time in ice skating, the skate keeps sliding on ice, making the ZUPT algorithm impractical in this application. In this study, four novel methods were proposed to eliminate the accumulating errors in the calculated velocity and trajectory of skaters:

- The accelerometer readout was transferred into the north-east-up (NEU) reference frame using the IMU orientation obtained by the Xsens software package.
- The gravitational acceleration was subtracted from the transformed acceleration to obtain the free acceleration of the sensor in the NEU frame.
- The skater's velocity was obtained using time integration of the free acceleration. The obtained velocity, however, was not zero in the resting periods due to the accumulated error of the IMU readouts,
- The accumulated error was removed, and the obtained velocity and acceleration time series were corrected using the assumption of zero velocity and acceleration in the resting periods. To this end, four original methods were developed and implemented. These methods removed sensors' acceleration biases (S1), acceleration bias and estimated noise profile (S2 and S3), and estimated velocity error time series (S4) using the assumption of zero acceleration and velocity in the resting periods (Table 2).
- The corrected velocity was used to obtain the skater position trajectory used to obtain the SL for each stride (see section 3.2.5 below).

All these four algorithms (S1–S4) used IMU readouts during the resting period. The effect of resting period duration was investigated on the stride length estimation error to recommend a minimum resting period duration. To this end, IMU readouts collected during time windows from 0.1 to 10 secs, by the increment size of 0.1 secs, out of the two 10-sec resting periods originally considered for data collection before and after the motion, were used in S1 to S4. Then, the shortest resting period duration that would not significantly affect the stride length estimation error compared to longer resting periods was explored. Temporal and spatial parameters estimation ST was computed from one SS to the subsequent SS of the same skate, and CT, the time when the skate is in contact with the ice, was calculated from one SS to its subsequent BO. Also, the SL in each stride was calculated using the estimated sensor trajectory. The SL, then, was defined as the two norms of a 2D vector containing the travel distance in the mediolateral (P_{ML}) and anteroposterior (P_{AP}) directions in each stride (Equation 3.1).

$$SL = \sqrt{P_{ML}^2 + P_{AP}^2} \tag{3.1}$$

SL was calculated using each of the four proposed velocity and acceleration correction methods. Finally, SV is calculated based on the corrected velocity time series obtained by the stride length estimation methods.

3.2.5 Data analysis

To compare the ability of the proposed methods against pressure insole in detecting the temporal events, the accuracy (mean) and precision (SD) of the errors were computed. To compare the SL estimated by the methods described in section 3.2.4, the mean and SD of the relative error, in addition to the error against the camera recording, were calculated. There was no significant difference between the stride length obtained based on the markers on the pelvis and that obtained based on markers on the skate (rank-sum test (r = 0.98) indicated a failure to reject the null hypothesis at the 5% significance level). Additionally, unlike the markers on skates, markers on the pelvis have smoother motion and would be a reliable reference for stride length measurement during each stride. Therefore, the reference SL is taken as the average travel distances of the PSIS markers in a stride. Finally, the set of best temporal event detection and SL estimation methods were selected to estimate the temporal and spatial parameters using IMU readout. These parameters were cross-validated against those calculated by in-lab reference systems recordings presented as the mean and SD of the relative error. Furthermore, a Bland-Altman plot modified for repeated measures [112, 113] has been provided to explore the agreement between the temporal and spatial parameters obtained by IMUs and those obtained by the reference parameters using Stata Statistical Software: Release 1741. Figure 3.3 shows the flowchart to calculate the temporal and spatial parameters using IMU readouts and validate the obtained parameters against the ones obtained by pressure insole data and camera recordings.

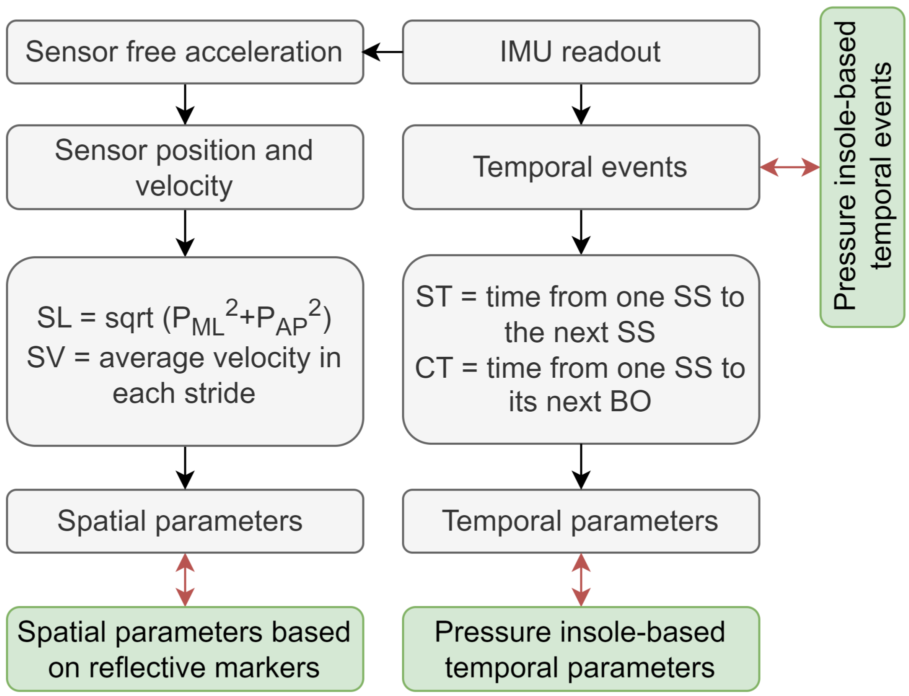

Figure 3.3: Flowchart of the measurement of temporal and spatial parameters of ice skating using IMU readouts and comparing it with the ones obtained by stationary in-lab reference systems. Here, sqrt stands for square root, P_{ML} and P_{AP}, respectively, are the travel distance in the mediolateral and anteroposterior directions in each stride.

3.3 Results

3.3.1 Temporal event detection

In total, 184 SS and 186 BO were identified and then compared with those obtained by the pressure insole. The finding from method T4 revealed that temporal event detection with an average 0.01-sec error using IMU readouts is achievable, equivalent to one sampling period (Table 3). Also, T9, adopted from gait analysis studies, obtained comparably 'accurate' results in skating event detection applications, i.e., an average error of 0.04 sec and 0.05 sec for detecting SS and BO, respectively. Yet, other event detection methods adopted from gait analysis studies (T1 to T8, T10, T11) could not detect temporal events, particularly SS, with high 'precision,' as indicated by the relatively high SD of the obtained errors. The mean ± standard deviation (SD) of the errors among study participants, reported in Table 3, suggest that the most effective methods in finding SS events were T1 (0.00 ± 0.03 sec), T2 (-0.01 ± 0.03 sec), and T4 (-0.01 ± 0.04 sec). Also, T3 (-0.00 ± 0.05 sec), T2 (-0.05 ± 0.04 sec), and T1 (-0.03 ±0.08 sec) were more effective in detecting BO events in skating (Table 3). The negative errors indicate the SS or BO were detected before the actual event, as identified by the reference system (i.e., pressure insoles).

Table 3.3: Accuracy and precision of the developed and adopted methods in detecting 184 Skate strikes (SS) and 185 Blades offs (BO). The results are expressed as mean and standard deviations (SD) of the errors (in second, across participants) obtained by all methods described in Table 1 for detected temporal events using IMUs against those obtained using pressure insoles.

Methods	SS (sec)	BO (sec)
T1	0.00 ± 0.03	-0.03 ± 0.08
T2	-0.01 ± 0.03	-0.05 ± 0.04
T3	-0.17 ± 0.09	0.00 ± 0.05
T4	-0.01 ± 0.04	-0.10 ± 0.04
T5	0.03 ± 0.20	0.09 ± 0.03
T6	-0.12 ± 0.06	-0.05 ± 0.07
T7	-0.19 ± 0.11	-0.06 ± 0.05
T8	-0.03 ± 0.04	-0.08 ± 0.04
T9	0.04 ± 0.18	0.05 ± 0.22
T10	0.04 ± 0.29	$-0.09 + 0.13$
T11	-0.25 ± 0.23	-0.05 ± 0.04

3.3.2 Stride length estimation

The skaters' speed was 1.71 ± 0.61 m/s and ranged from 0.88 to 2.63 m/s among this study's participants. The relative errors of SL estimation using IMU readouts based on methods described in Table 2 compared to the ones obtained by motion-capture cameras were investigated. S1–S3 required only a 0.5-sec resting period right before the motion to correct the velocity, and longer resting periods did not enhance their performance (rank-sum test (r = 0.96)). They decreased the SD of the relative error to the range of 19% - 25% (compared to 47% when no correction method was implemented) when the free acceleration of pelvis-mounted IMU was used (Table 4). On the other hand, the velocity correction method (S4) required at least two 3-sec resting periods right before and after the motion to correct the velocity, and longer resting periods did not enhance its performance (rank-sum test (r = 0.99)). However, S4 was able to decrease the relative error from 7 ± 47%, obtained without any correction, to a range of 2 ± 6% based on pelvis IMU readout (Table 3.4). In this method, the velocity was corrected by making the velocity time series to be zero in the resting periods.

Table 3.4: The mean and standard deviation (mean ± SD) for errors and relative errors of the stride length (SL) obtained by IMUs' readout against the SL calculated based on markers trajectory captured by the motion-capture cameras. The errors were calculated with and without applying the velocity correction methods (S1–S4, described in Table 3.2) using IMUs placed on the participants' pelvis, shank, and skates.

	ERROR (cm)			RELATIVE ERROR (%)		
METHOD	Pelvis IMU	Shank IMU	Skate IMU	Pelvis IMU	Shank IMU	Skate IMU
NO CORRECTION	-39 ± 109	-6 ± 58	-1 ± 106	-7 ± 47	-4 ± 26	-2 ± 41
S1	14 ± 53	14 ± 51	23 ± 47	9 ± 19	6 ± 22	9 ± 17
S2	14 ± 53	12 ± 49	19 ± 42	6 ± 23	6 ± 21	8 ± 16
S3	14 ± 53	14 ± 52	24 ± 47	7 ± 25	6 ± 23	9 ± 17
S4	3 ± 14	15 ± 30	-12 ± 40	2 ± 6	7 ± 13	-6 ± 14

3.3.3 Temporal and Spatial parameters

ST and CT were calculated based on the temporal events identified by T1 and T3: the best methods in detecting SS and BO, respectively. Also, SL was calculated based on the trajectory estimated by the velocity correction method (method S4: the best method in SL estimation). Finally, SV was calculated as the average of the sensor velocity estimated by method S4. Using the IMU readout, ST, CT, SL, and SV were estimated with 3 ± 3%, 4 ± 3%, 2 ± 6%, and 2 ± 8% relative error, respectively, compared to those obtained from in-lab reference systems' recordings. Other than the bias errors mentioned above, the Bland-Altman plot (Figure 3.4) suggested no apparent relationship between the errors of the IMU-based developed methods and the magnitude of the temporal and spatial parameters.

3.4 Discussion

In this study, for the first time, the measurements of the wearable IMUs were used to obtain the temporal and spatial parameters of forward skating (ST, CT, SL, and SV) using various methods, and the results were validated against those obtained by the reference system, i.e., pressure insole and motion-capture cameras. 11 methods were implemented to obtain the temporal events with high accuracy and precision in forward striding in ice skating using wearable IMU readouts. Also, four methods were implemented to correct the stride length estimation using IMU readout. The accuracy of temporal and spatial parameters in skating (on average less than 4% of relative error) in this study was comparable with those reported in gait analysis (less than 2% relative error [13, 107]). Also, almost the same accuracy in calculating ST has been obtained compared to the other studies on long-track speed skating (3.6%) [97]. Finally, the accuracy of CT and ST obtained by IMU in this study was comparable with those reported in a previous study on ice skating [6], investigating the accuracy of CT and ST estimated on the real ice (on average, 1% and 2%, respectively). The

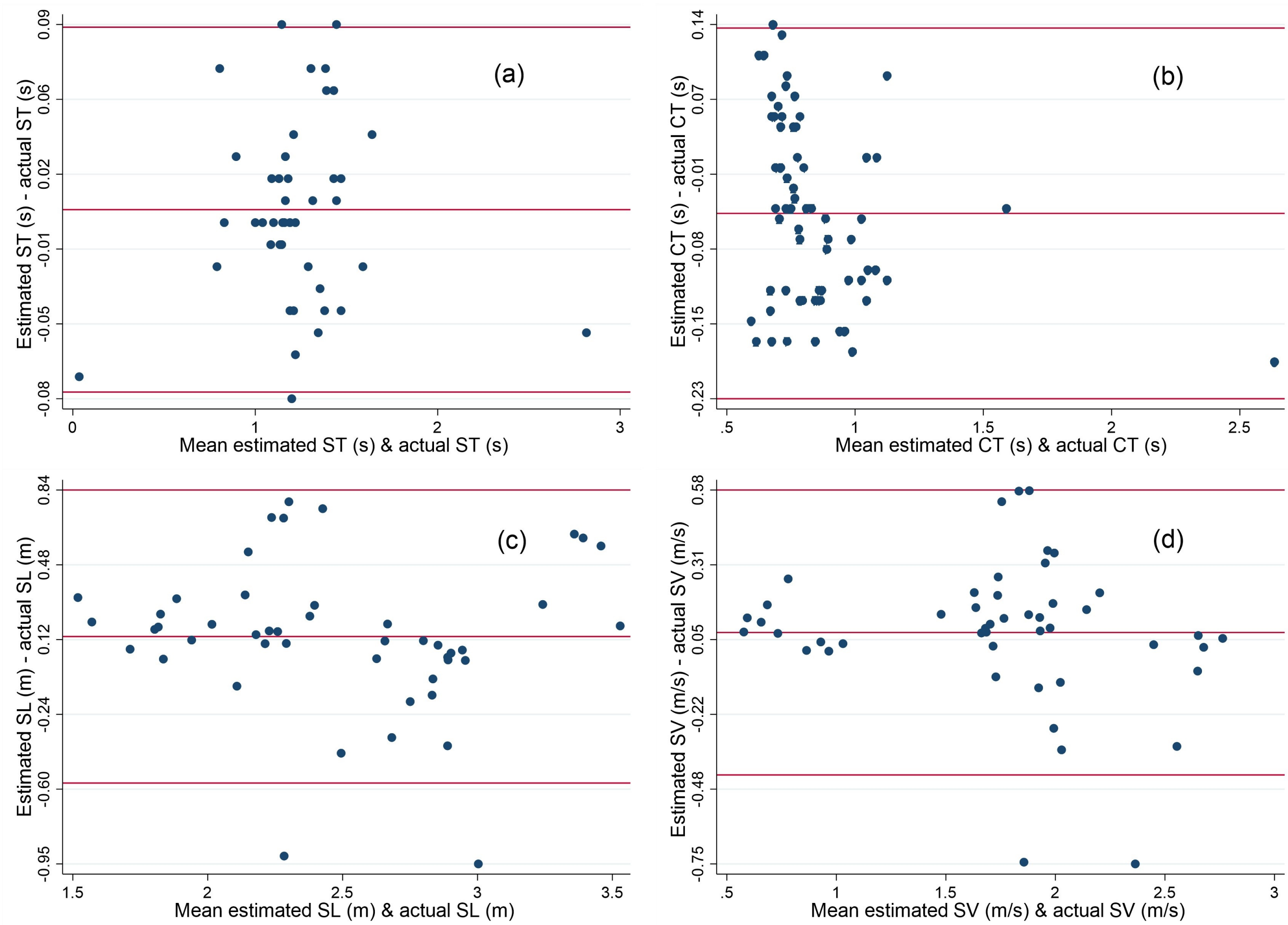

Figure 3.4: Bland–Altman plots modified for repeated measures, illustrating the agreement between the IMU-derived estimates (ST (a), CT (b), SL (c), SV (d)) and the actual values obtained from reference systems. Pressure insoles provided data for ST (interquartile range: [1.14 s, 1.40 s]) and CT (interquartile range: [0.72 s, 0.86 s]), while a motion capture system measured SL (interquartile range: [2.11 m, 2.86 m]) and SV (interquartile range: [1.55 m/s, 2.23 m/s]). The plots include lines of bias, upper and lower 95% limits of agreement (LOA), and the line of equality (zero error). These plots indicated no significant relationship between the measurement errors of the developed IMU-based methods and the magnitudes of the measured temporal and spatial parameters.

relatively higher errors in this study compared to the previously mentioned study were due to three factors:

1. Lack of a foot-flat period in ice skating: The proposed methods for skater posi-

tion estimation benefited from velocity correction only once at the end of each measurement trial, while the ZUPT technique in gait analysis can be implemented during the foot-flat period in each gait cycle [93].

2. Lack of familiarity with the synthetic ice: The skaters, even higher calibre skaters, may not have much experience with synthetic ice skating, and thus, they skated less consistently compared to real ice.

3. Skating in a shorter skating area requires faster acceleration and deceleration compared to skating on a standard ice rink [39], where the players tend to skate. Hence, skating on a 14m-length ice rink could result in more inconsistency in the participants' skating.

Due to the factors above, the performance of the proposed methods implemented for estimating the spatial and temporal parameters of ice skating was more inconsistent compared to gait or real ice skating. Thus, the standard deviation of obtained errors was larger than those previously reported for gait or real ice skating. Finally, similar to the findings in a gait analysis study [107], skate acceleration was the most effective time series for on-off ice event detection. Also, to estimate spatial parameters, the suggested methods work more precisely on the pelvis-mounted IMU readouts compared to the readouts from shank- and skate-mounted IMUs. Therefore, only the three IMUs mounted on the skates and pelvis are recommended for estimating the temporal and spatial parameters of ice skaters in forward striding.

3.4.1 Temporal parameters estimation using skate-mounted IMUs

IMU-based systems have been widely used for temporal event detection in gait analysis and have advantages over other devices such as pressure insoles [107]. The pressure insole has been validated for force measurement and temporal event detection during gait [110, 114], and in this study, we carefully placed them in skates and used them as a reference for short-term trials. Yet, the insoles might not be suitable for long-term skating trials due to: i) their slippage in the skates during long-term dynamic motions and ii) the inconvenience of carrying a data logger and batteries in a belt connected to the insoles via cables.

The temporal events (SS and BO) detected using IMU readouts showed high accuracy and precision (errors, on average, around one sampling period obtained by T1, T2, and T4 to detect SS and T3 in detecting BO). The methods (T1–T4) that used the upward and forward accelerations of the skate to detect SS and BO were more effective than those that used angular velocities to detect SS and BO (T5, T6, T9, and T10). Implemented methods from gait analysis (T9 and T10) strongly depend on the false positive or false negative detection and the chain of the events detected by these methods. Although these methods were comparably precise in skating event detection, false positive or false negative detection (T9 and T10) of one event influences the proceeding event detections. As a result, the effectiveness of these methods (T9 and T10) requires a repetitive skating pattern leading to repetitive time series all over the trial, which may not be easily achievable, particularly in lower calibre skaters. In summary, the most effective methods were T1, T2, and T4 in finding SS events and T3, T2, and T1 in detecting BO events in skating when skate-mounted IMUs' readouts were used. Also, the skate-mounted IMUs' readout outperformed the shank-mounted IMUs' readout in temporal events detection (i.e., T1-T4, T7, T8, and T10 compared to the others). As a result, only the two skate-mounted IMUs are recommended for detecting bilateral skating temporal events.

3.4.2 Spatial parameters estimation using a pelvis-mounted IMU versus skate-mounted IMUs

Four methods were proposed and implemented to remove drifts in the acceleration and velocity time series toward estimating the skater's trajectory using the IMUs recorded on the skater's body. Methods S1–S3 improved the precision of SL estimation by up to 60% compared to no correction scenario. Also, they required only a 0.5-sec resting period, making them implementable when there is only one short quiet standing before the motion. On the other hand, Method S4, which removed drifts and corrected the velocity of the pelvis-mounted IMU using the resting periods at the beginning and end of each trial, outperforms the other methods. The relative error obtained by S4 was comparable to those reported in the literature for gait analysis using the ZUPT algorithm [93, 107, 115].

Furthermore, removing the acceleration's DC offset (calculated at the beginning of the trial in S1) considerably reduced the SL estimation error, and none of the added noise estimation methods, i.e., white noise and discreet wavelet transform (DWT) details, in S2 and S3 further reduced the SL estimation errors. This was evident by the Pearson's correlation coefficient of 0.99 between SL obtained by S1 and SL obtained by S2 and S3. In summary, the acceleration obtained by the pelvis-mounted IMU corrected by S4, among the other IMUs and methods, obtained the most precise SL estimation. Also, according to the Bland-Altman plots (Figure 3.4), none of the observed estimation errors were a function of the magnitude of the temporal and spatial parameters. In summary, to estimate the temporal and spatial parameters in skating, two skate-mounted IMUs—for temporal event detection—and one pelvis-mounted IMU—for spatial parameter estimation—are recommended.

3.4.3 Limitations

Development and validation of the proposed methods to estimate the temporal and spatial parameters of ice skating have potential limitations. First, unlike event detection algorithms developed for gait analysis [107], the norm of acceleration and angular velocity measured by IMUs were less effective in detecting the temporal events of skating. Therefore, acceleration time series were used in the forward or upward directions for temporal event detection, and thus, the obtained accuracy and precision can be affected by the misalignment of the IMUs relative to the skate. Second, extrinsic factors such as temperature, which is different on ice compared to the lab's temperature, can influence the value of IMU readouts. However, they can hardly affect the negative and positive peaks of the IMU readouts [107] used in the developed event detection methods. Third, our proposed methods were validated only in 14-meter trials and forward skating slower than 2.63 m/s. Future studies are needed to investigate the validation of our proposed methods for the measurement of temporal and spatial parameters of ice skating in longer distances, faster skating, and other skating types such as turning. Yet, this study showed that methods S1–S3 by using only 0.5-sec resting periods could significantly enhance the stride length estimation precision, at least in short-term (i.e., 8 sec) forward striding experiments and the observed errors in estimating temporal and spatial parameters were independent of skating speed. Fourth, identification, modelling, and eliminating other sources of error during skating can promise better precision and accuracy in IMU position estimation in miscellaneous skating types in longer experiments. Finally, the effectiveness of IMU pelvis-based methods for temporal event detection can be further investigated in future studies.

3.5 Conclusions

For the first time, novel methods were proposed for estimating the temporal and spatial parameters of ice skating using wearable IMUs and their accuracy and precision were validated against the in-lab reference systems. Among different sensor configurations, the optimal set of IMUs for this purpose consists of two skate-mounted IMUs (for temporal parameters measurement) and one pelvis-mounted IMU (for spatial parameters measurement). The proposed methods estimated the ST, CT, SL, and SV of the ice skaters with relative errors close to those previously reported for gait analysis. The proposed methods detected SS and BO within 0.01-sec accuracy using a skate-mounted IMU readout. We improved the SL estimation precision between 53% and 88% using a pelvis-mounted IMU readout. The next step toward developing this wearable technology is to validate the 3D joint angles obtained by the IMUs.

Table 3.2: The skater's velocity and trajectory are obtained by time integration and double-integration of the free acceleration obtained by the pelvis-mounted IMU. Methods were originally proposed (S1 to S4) to remove the drift in these integration processes.

Method	Procedure
S1	i. Calculate the mean of free acceleration value in the 0.5-sec window resting period at the beginning of the trial right before the motion and subtract its representation in sensor frames from the raw acceleration time series and store it as corrected acceleration time series ii. Calculate the corrected free acceleration (during motion) using the corrected acceleration time series (output of S1.i) and the sensor orientation iii. Obtain trajectory using double-time integration of the corrected free acceleration
S2	i. Similar to S1.i ii. Generate white Gaussian noise using a MATLAB wgn function (input arguments: the signal-to-noise ratio: -15 decibels (dB), and its length equal to the sensor acceleration time series). Then, scale it to match the corrected sensor acceleration amplitude range in the selected resting period. Afterward, subtract the obtained output from the corrected sensor acceleration time series and store it as corrected acceleration time series iii. Calculate the corrected free acceleration (during motion) using the corrected acceleration time series (output of S2.ii) and the sensor orientation iv. Similar to S1.iii
S3	i. Similar to S1.i ii. Apply DWT to the corrected sensor acceleration (output of S3.i). Then, remove the first three DWT's (discrete wavelet transform) details coefficients utilizing the Coiflet wavelet basis function from the whole time series and store it as corrected acceleration time series iii. Calculate the corrected free acceleration (during motion) using the corrected acceleration time series (output of S3.ii) and the sensor orientation iv. Similar to S1.iii
S4	i. Calculate velocity using time integration of free acceleration ii. Estimate the noise profile using two resting periods at the beginning and end of each trial (right before and after the motion and with a length of at least 3 secs), using piecewise cubic Hermite interpolating polynomial curve fitting and subtracting it from the output of S4.i and store it as corrected velocity iii. Obtain trajectory using time integration of corrected velocity (output of S4.ii)

Chapter 4

Assessment of three-dimensional kinematics of high- and low-calibre hockey skaters on synthetic ice using wearable sensors

In this chapter, we calculate and experimentally validate the 3D angles of lower limb joints of hockey skaters obtained by inertial measurement units and explore the effectiveness of the on-ice distinctive features measured using these wearable sensors in differentiating low- and high-calibre skaters.

A. Khandan, R. Fathian, J. Carey, and H. Rouhani, "Assessment of Three-Dimensional Kinematics of High- and Low-Calibre Hockey Skaters on Synthetic Ice Using Wearable Sensors," Sensors, vol. 23, no. 1, pp. 334, Dec. 2022.

4.1 Introduction

One of the key components of ice hockey players' skills is skating [1, 116]. Similar to other sports activities, skating has traditionally been assessed by video and motion capture cameras [7, 78, 117]. These cameras have been used to study two-dimensional (2D) or three-dimensional (3D) kinematics of the lower-limb joints of individuals skating. A setup of digital video cameras was used to obtain 2D or 3D joint angles on ice [4, 75, 78] or on a skating treadmill [8, 37]. Also, in [4, 75, 76, 78], motion capture systems were used to obtain the kinematics of high- and low-calibre or male and female high-calibre hockey players. Although these motion capture systems are precise and taken as a reference system, their application is bound to in-lab measurements due to their limited availability and capturing volume. Instead, wearable technology is a trended and acclaimed alternative for performance assessment and can be used in in-field measurements [53].

Wearable technologies like GPS and accelerometers measure essential kinematics in team sports [6, 9, 46, 102, 118–120]. A 3D accelerometer enables researchers to determine temporal events during ice hockey skating and also differentiate players in terms of their skill levels [5, 6, 9]. However, neither 3D accelerometers alone nor GPS can measure 3D joint angles. GPS works precisely in open-field sports; however, the signals of GPS may be considerably affected by errors in indoor areas. Also, GPS does not provide physiologically relevant information, such as the players' phase of play during ice hockey. Therefore, despite the wealth of accelerometers and GPS measurements, they cannot provide inclusive biomechanical information for comprehensive on-ice assessments. Instead, inertial measurement unit (IMU) technology can be used for on-ice athletics performance assessment, similar to their established acceptance in clinical outcome evaluations [49, 99, 107]. Moreover, IMUs' readout can precisely calculate the joint angles and temporal and spatial parameters of athletic activities [13, 107] and potentially differentiate players according to their skill levels.

Biomechanical variances between high- and low-calibre players skating have been emphasized to understand the relationship between skating biomechanics and players' performance. Previous research has highlighted substantial differences between groups of players with different skill levels in ice experiments [5, 76–78]. They have found significant differences between 3D angles of lower limb joints and body center of mass (CoM) movements between low- and high-calibre players. In another study, Robbins et al. [73] used principal component analysis (PCA) to extract the most significant features to differentiate high- and low-calibre players' 3D joint angles in on-ice experiments. In these studies, parameters such as higher ankle plantar flexion, knee extension at push-off, and higher hip flexion were found to be different in high-calibre players' skating compared to low-calibre players' skating. These on-ice calibre-based distinctive kinematic features (or simply distinctive features), however, may not be distinctive on synthetic ice.

While most public ice rinks were closed due to COVID-19, synthetic ice showed to be an alternative for skaters to exercise and be prepared for competitions and assists coaches in monitoring their players remotely. Stidwill et al. [39] showed that the gross movement patterns of skating on synthetic ice surfaces were similar to skating on ice. However, they reported differences in the kinematics and postures of the participants skating on synthetic ice compared to ice. Therefore, skating on synthetic ice can also affect the distinctiveness of the on-ice distinctive features between high- and low-calibre hockey skaters (or simply skaters) on synthetic ice. The objectives of this study are to: 1) calculate the 3D angles of lower limb joints of participants skating using IMUs, 2) experimentally validate the accuracy of the obtained angles against those measured by a motion capture system, and 3) experimentally investigate if the kinematic features of lower limb joints during skating on synthetic ice measured by this wearable system can differentiate low- and high-calibre skaters. The outcome of this technology will be an optimal set of wearable IMU sensors ready to be used in on-ice and on-synthetic-ice experiments to measure the 3D kinematics of the skaters.

4.2 Methods

4.2.1 Participants

Twelve able-bodied individuals were recruited to participate in this study. By a K-means clustering algorithm based on the participant's years of ice skating experience, they are clustered into two groups of six high-calibre skaters (age 24 ± 4 years, height 164 ± 3 cm, body mass 66 ± 7 kg, ice skating experience 18 ± 4 years, four female and two male) and six low-calibre skaters (age 24 ± 4 years, height 174 ± 8 cm, body mass 72 ± 11 kg, ice skating experience 6 ± 6 years, two female and four male). All participants were healthy individuals and could skate on synthetic ice without trouble. They were informed of the experimental procedures and gave informed written consent before the test. This study was approved by the University of Alberta's research ethics board (Pro00092821).

4.2.2 Experimental procedure

The tests were performed on a motion capture lab walkway covered with $14 \times 2\,\mathrm{m}^2$ synthetic ice panels. Five IMUs composed of accelerometers, gyroscopes, and magnetometers (Xsens Technologies, NL, full-scale ranges: acceleration: $\pm 160\,\mathrm{m/s}^2$, angular velocity: $83 \pm 2000\,\mathrm{deg/s}$, and magnetic field: $\pm 1.9\,\mathrm{Gauss}$, plate size: $10 \times 7\,\mathrm{cm}$) were placed on the pelvis, thighs, shanks, and hockey skates on the dominant legs of the participants without constraining their movements (Figure 4.1). As the gold standard for 3D joint angles, a motion capture system with 12 infrared cameras (eight Vero and four Bonita, Vicon, UK) was used to obtain the 3D marker trajectories. These markers were placed on the participant's body's anatomical landmarks following an experimental protocol suggested by Cappozzo et al. ([121], Figure 4.2). The participants were asked to skate until they confirmed that they were comfortable skating on synthetic ice. Then, from a stationary position on one side of the synthetic ice surface, they skated forward and stopped at the other end of the surface. This skating trial was repeated five times, and marker trajectories and IMU readout were captured simultaneously at a sampling frequency of 100 Hz.

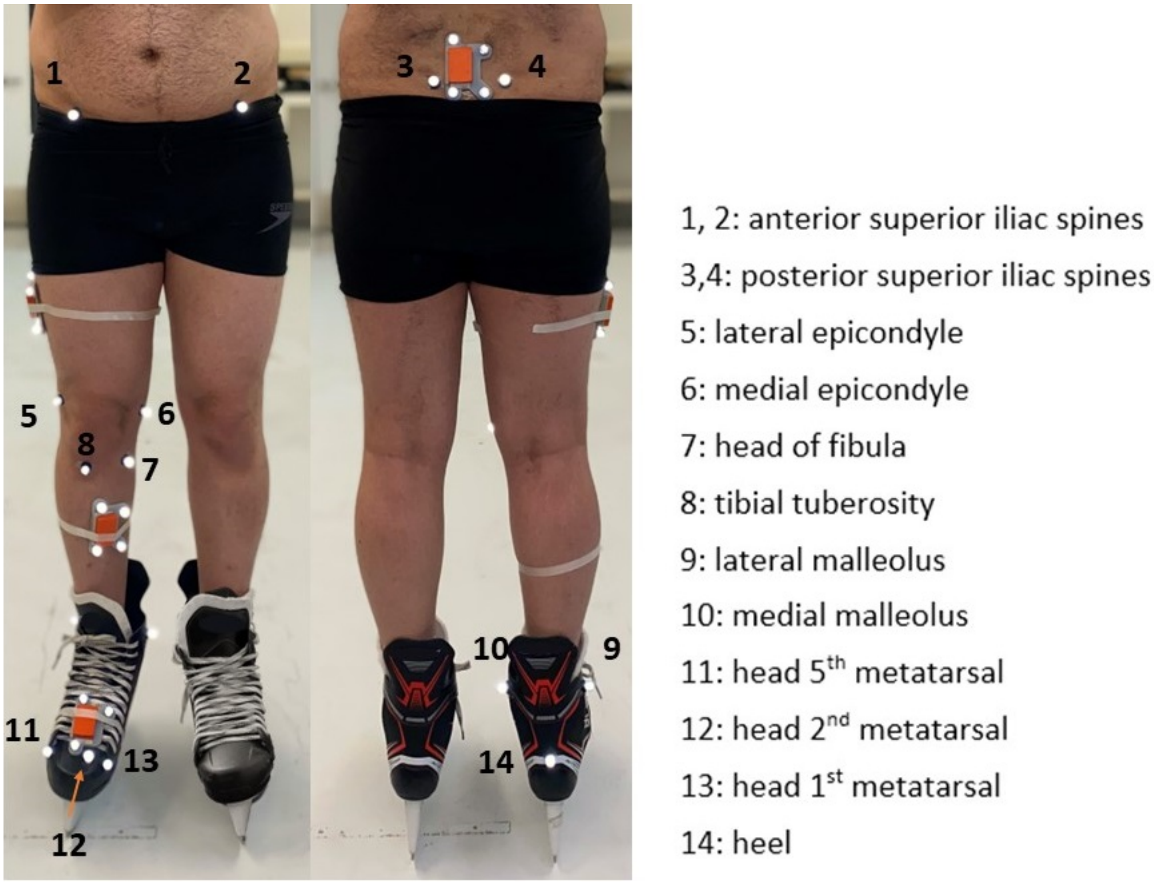

Figure 4.1: Four IMUs (orange boxes) were placed on the participants' pelvis, shanks and skate. Also, 14 retro-reflective markers were used for 3D joint angle estimation using a motion capture system.

4.2.3 3D joint angles validation

IMU readouts, including the tri-axial gyroscope, accelerometer, and magnetometer measurements, are used to obtain the sensor orientations using sensor fusion algorithms [108, 122, 123]. These orientations are usually subject to uncertainties and errors due to sensors' biases and noises [108]. The sensor fusion algorithms address these uncertainties and help obtain a more accurate sensor orientation used for 3D joint angle estimation [123]. The 3D joint angles obtained in this study were estimated using the sensor fusion algorithm developed and presented in the Xsens software package (MT manager [109]). In this study, the IMU readouts were first filtered using a 4th-order low-pass Butterworth filter with a cut-off frequency of 15Hz. Then, the sensor orientations (also known as IMU frames) were obtained in lab global reference frames using the retro-reflective markers fixed on the plates (plate orientations) and sensor-to-plate orientations obtained following the procedure suggested in [50, 123, 124] (Figure 4.2). Next, the segment orientations were calculated using the corrected sensor orientations of IMUs and sensor-to-body orientation obtained by sensor and segment frames obtained from the plate and anatomical markers [121], respectively, at the beginning of the capturing session [50, 123]. Finally, using the obtained segment orientation, ankle, knee, and hip joint angles in the captured trials were calculated and expressed by the joint coordinate system (JCS) [92]. At the same time, the 3D joint angles were obtained using the markers placed on anatomical landmarks. The flowchart of the 3D joint angles calculation using IMU readouts and validation of the angles against those obtained by camera recordings as the reference system is shown in Figure 4.2.

Finally, the Root mean square (RMS) between the 3D joint angles calculated from the IMUs' readout and the angles calculated from the reference system were obtained:

1. The RMS errors between IMU-based and camera recordings-based angles for each trial of all participants were calculated,

2. The average of the RMS error was calculated over all trials of each participant, and

3. The computed average value for each participant is presented as boxplots for each 3D joint angle.

In the next step, using these validated angles and the on-ice distinctive parameters, a supervised classification analysis was developed to differentiate low- and high-calibre skaters' profiles using the on-ice distinctive features.

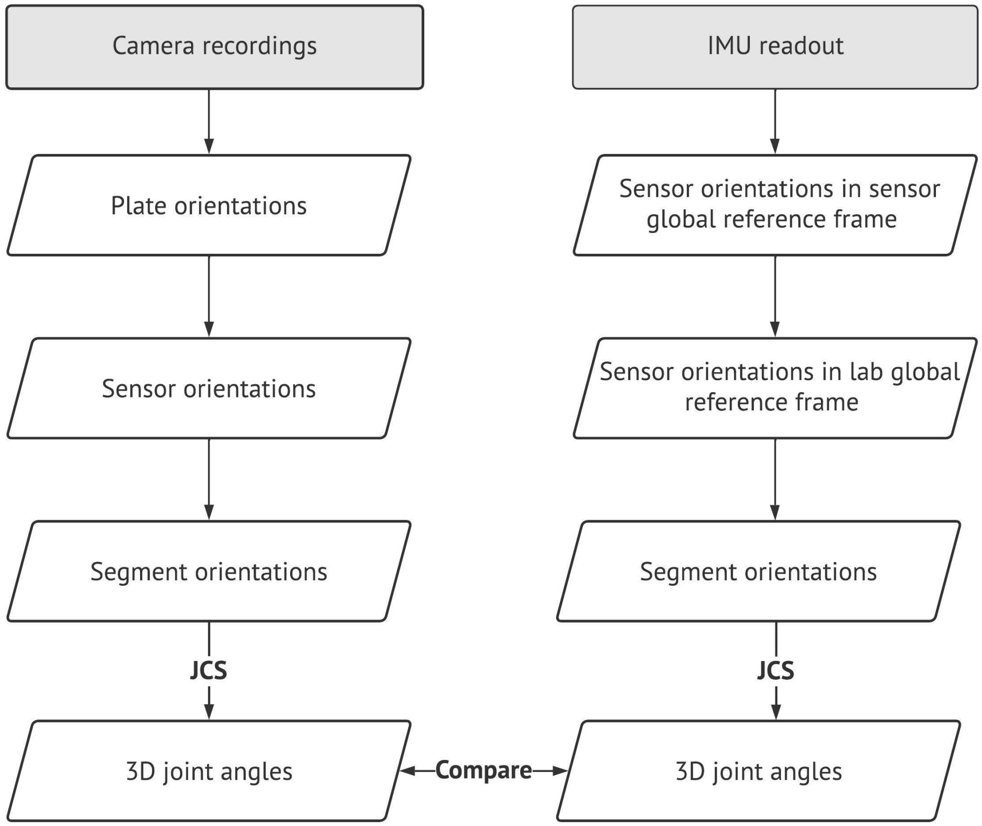

Figure 4.2: Flowchart of obtaining 3D joint angles of ice skating using IMU readouts and comparing them with the ones obtained by a stationary motion capture system.

4.2.4 Calibre-based classification analysis

First, we experimentally investigated if the distinctive features measured by this wearable IMU system would be different between low- and high-calibre skaters on synthetic ice. All the temporal events of skating were obtained based on the camera recordings as the reference system in order to avoid mixing errors due to sensor orientation estimation and temporal event detection. Then, a Friedman's test was used to verify whether the distinctive features obtained from the literature studies (listed in Table 4.1) significantly differed between high- and low-calibre skaters skating in this experiment. When a p-value was lower than or equal to 0.05, the feature was chosen to classify high- and low-calibre skaters in this study. Then, the k-nearest neighbour (KNN) model was used to classify high- and low-calibre skaters (Figure 4.3). This supervised classifier was selected because of its reliability, simplicity, and small sample size in this study. The KNN was implemented for k=1 to k=15 to classify high- and low-calibre skaters using a cross-validation analysis using the following steps:

1. Each of the five trials of the participant was labelled according to the participant's calibre,

2. Three participants' data (25% of the data) were randomly selected and added to the testing set, and the other participants' data (75% of the data) were added to the training set,

3. A KNN classification was trained for k = 1 to k = 15, and the sensitivity, specificity, precision, and accuracy of these classifiers were calculated for the testing sets,

4. Steps (1-3) were repeated 12 times so that each participant was added to the testing set three times; and,

5. The average of all obtained sensitivity, specificity, precision, and accuracy for these repeated measures was calculated for each k.

Alternatively, while preserving the essential information, a principal components analysis (PCA) was used to optimize the feature space dimensions used in the cross-validation analysis. The best three components obtained from the PCA on on-ice distinctive features were selected as the new feature space of the KNN classification, and steps (1-5) were repeated (Figure 4.3).

Table 4.1: On-ice distinctive features that differentiate high- and low-calibre hockey players on ice are listed here. The Friedman test was used to investigate whether they significantly differ in high- and low-calibre skating on synthetic ice experiments. The features with a p-value lower than or equal to 0.05 was labelled by an asterisk (*) and were used to classify high- and low-calibre skaters using KNN (Table 4.1).

Features	Friedman test (p-value)
Dorsiflexion range*	0.03
Ankle adduction at the end of push-off instant	0.80
Hip flexion in initial contact instant	0.67
Hip adduction in push-off instant*	0.03
Hip adduction at initial contact instant	0.15
Dorsiflexion in push-off instant	0.39
Knee flexion in push-off instant*	0.03
Hip flexion average	0.73
The interquartile range of CoM1 motion2 in the body mediolateral plane	0.23
Range of CoM motion in the body's mediolateral plane	0.67
The interquartile range of CoM1 motion2 in the body sagittal plane	0.73
Range of CoM motion in the body sagittal plane	0.67

4.3 Results

4.3.1 3D joint angles validation

Sixty measurement trials from the twelve participants, five trials for each, were obtained (Figure 4.4); one complete skate stride of the dominant leg of the participants is available in each trial. According to Figure 4.5, the maximum average RMS errors of the lower limb 3D joint angles during skating obtained by IMUs readout against those obtained by camera recordings across different joints was 5 deg (knee adduction).

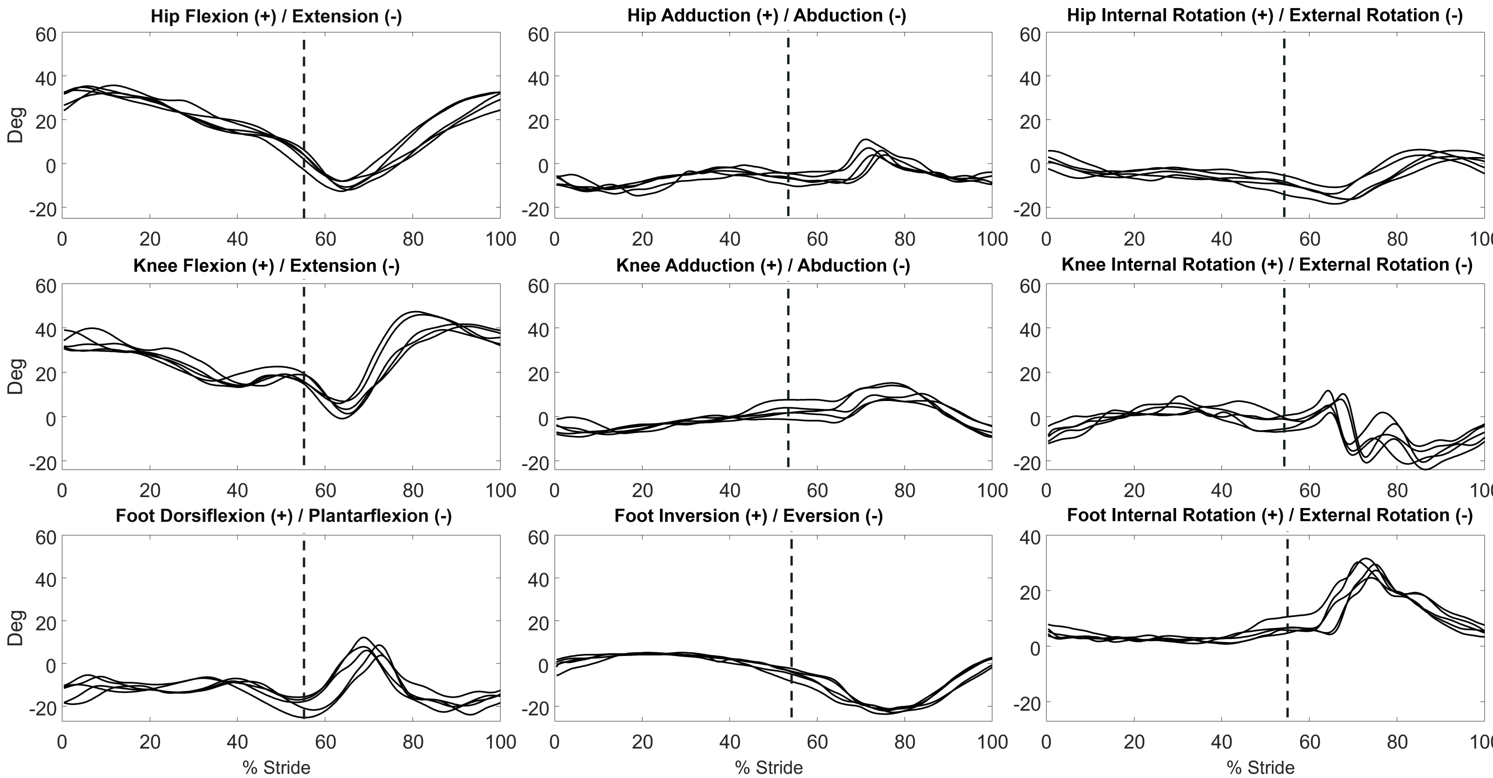

Figure 4.4: Exemplar 3D lower limb joint angles during five skating trials of a participant obtained from IMU readouts. Skate strikes were indicated at 0% and 100% in the graph, and the vertical dashed line represents the blades-off instant.

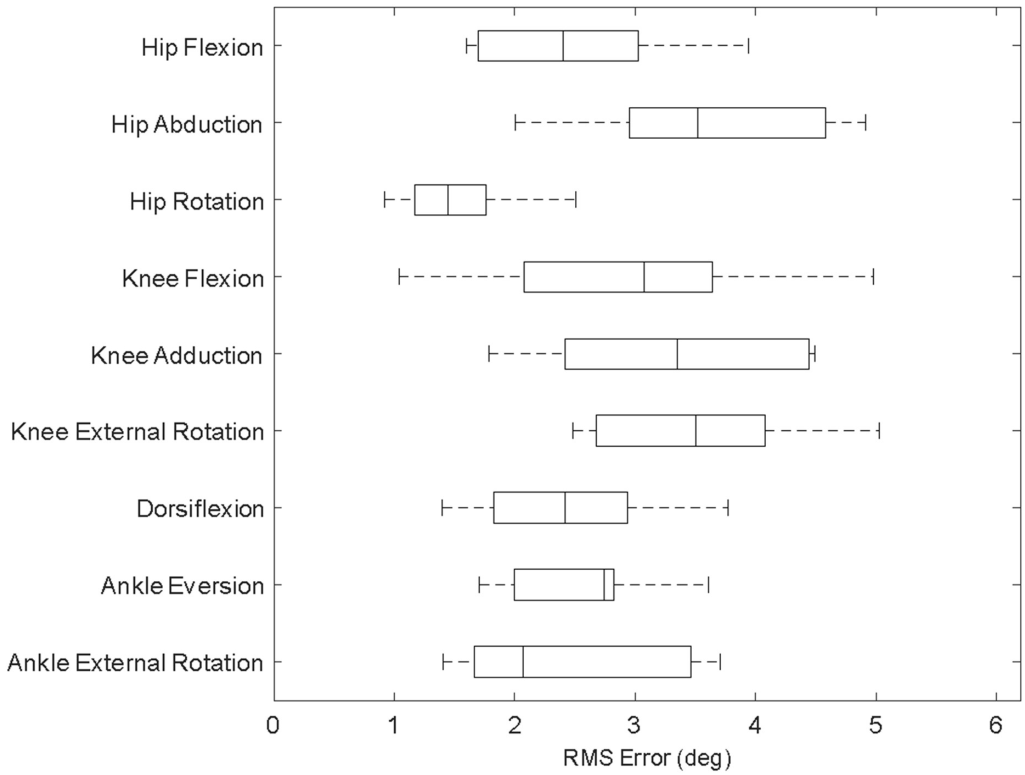

Figure 4.5: Root mean square (RMS) errors between the 3D angles obtained by IMUs readout and those obtained using camera recordings (as the reference system). First, the RMS error was attained between IMU-based and motion capture-based angles for each trial. Then, these values were averaged over all trials of each participant. Then, the RMS of all the participants' obtained average values is presented as boxplots.

4.3.2 Calibre-based classification analysis

Based on a Friedman's test, only three out of 12 on-ice distinctive features were different between low- and high-calibre skaters skating, based on 3D lower limb joint angles during skating on synthetic ice (Table 4.1, p-value < 0.05): (i) ankle dorsiflexion range, (ii) hip adduction angle in push-off instant, and (iii) knee flexion angle in a push-off instant, referred to hereafter as selected features. When the KNN classification with k varying from 1 to 15 was used based on these three selected features to differentiate high-calibre skaters from low-calibre skaters, the classifiers' sensitivity, specificity, precision, and accuracy ranged from 46% to 67%, 61% to 86%, 47% to 67%, and 59% to 75%, respectively (Table 2). Additionally, using PCA's first three principal components implemented on these three selected features, the classifiers' sensitivity, specificity, precision, and accuracy ranged from 46% to 71%, 58% to 78%, 53% to 58%, and 68% to 74%, respectively (Table 4.2).

Table 4.2: The sensitivity, specificity, accuracy, and precision from a cross-validation analysis using the KNN models with k=1 to k=15 in classifying high- and low-calibre skaters. The feature spaces of the KNN models are either selected kinematic features of lower limb joint motions, obtained from Table 1, or the best three components obtained from the PCA on on-ice distinctive features.

	K	Sensitivity (%)	Specificity (%)	Accuracy (%)	Precision (%)
Using the selected features	1	59	86	64	75
	3	67	82	67	71
	5	60	72	58	69
	7	50	72	54	70
	9	46	70	51	70
	11	52	61	50	63
	13	50	61	47	59
	15	50	61	47	68
The three best features obtained from PCA	1	59	86	64	75
	3	61	60	55	68
	5	61	66	57	70
	7	54	68	54	69
	9	53	75	57	74
	11	48	73	53	69
	13	48	72	53	70
	15	46	78	55	74

4.4 Discussion

The 3D joint angles of ice skating were obtained by wearable IMUs and cross-validated against the angles obtained by a motion capture system. The accuracy of the 3D joint angles in synthetic ice skating (less than 5 deg of error) was comparable with those reported in gait analysis as a well-studied application of IMUs (1 to 4 deg [13, 125]). The slightly higher errors compared to gait analysis can be due to the higher range of motions of lower limb joints in ice skating. The 3D joint angles of the lower limbs of low- and high-calibre skater groups showed significant differences in several distinctive features (listed in Table 4.1). Nevertheless, in our experiments on synthetic ice, only one-fourth of these on-ice distinctive features showed a significant difference between lower limb joint angles of high- and low-calibre skaters. For instance, hip adduction at initial contact – known to be effective in most on-ice studies [5, 73, 77], was not significantly different between high- and low-calibre skaters in this study. We concluded that skating on synthetic ice altered the kinematics of the participants' lower limbs compared to ice such that most of the on-ice distinctive features were no longer different between low- and high-calibre skaters on synthetic ice. Concurrently, it was shown that skating on synthetic ice changes the skaters' kinematics and temporal and spatial parameters compared to on-ice skating [126] and lack of familiarity, shorter skating distance, and different surface friction coefficients were introduced as the possible factors:

1. Lack of familiarity with skating on synthetic ice may have affected the skating patterns of the participants since most of the study's participants, even high-calibre ones, had not had much experience with synthetic ice skating prior to the skating sessions,

2. Skating on a shorter distance – here, a 14m-distance – requires faster acceleration and deceleration than real ice skating [39], which could affect the skating patterns of the participants on the synthetic surfaces.

3. The reported surface-skates blades friction coefficient of the synthetic surfaces (0.27-0.37) is higher than the reported ice skating surfaces (0.002 to 0.007) [39, 127–129].

Furthermore, even the three best distinctive features could not increase the accuracy and sensitivity of the KNN models by more than 64% and 53%, respectively. Even the first three principal components obtained from the feature space could not increase the accuracy and sensitivity by more than 65% and 53%, respectively, which are almost the same as the previously selected feature space. Therefore, a newly updated feature space extracted from a larger synthetic ice skating sample—from both male and female ice skaters—is required in future studies to achieve improved KNN performance on these synthetic surfaces.

One of the limitations of this study was the small sample size. However, the study's sample size was sufficient for the objective of this study and to observe significant differences between the two groups (power = 0.88 using effect size F = 0.4, calculated by G*Power 3 [130]). Second, the participants were asked not to hold hockey sticks during their skating because of the lab's safety issues. Not holding hockey sticks can make a difference in the skaters' skating patterns, which must be further investigated. Third, comparing the kinematics of low- and high-calibre skaters on ice can support the findings of this study and must be taken as a potential future direction. Fourth, to validate the kinematics measured by the IMUs against the optical motion capture system, we had to use the sensor-to-body frame alignment based on markers. Because we had to present the measurements of both systems in the same frame and isolate only the IMUs' orientation estimation error compared to the optical motion capture system. In the field, however, one can use a functional calibration algorithm (similar to our previous works [49] and [123]) that does not need recordings of an optical motion capture system. Similarly, an algorithm to detect temporal events of skating using IMUs should be used for in-field recordings. We recently proposed such algorithms in [19]. Fifth, the inconsistencies in the definition of low- and high-calibre skaters can add more complexity to inter-study comparisons. Alternatively, observational indices using the camera recordings of participants' skating or performance questionnaires developed for on-ice skating analysis can make these comparisons more consistent.

4.5 Conclusions

The first step toward improving hockey players' efficiency in ice hockey matches and training is accurate performance assessments, and wearable technology helps hockey coaches do this assessment in a less intrusive way. In this study, 3D joint angles of ice hockey skaters were obtained using an IMU-based wearable technology and experimentally validated their accuracy against a camera-based motion capture system. Further, a supervised learning algorithm was developed to classify low- and high-calibre skaters' kinematics using on-ice calibre-based distinctive features. We discovered that skating on synthetic ice alters the skaters' skating patterns such that the on-ice distinctive features could not differentiate low- and high-calibre skaters on synthetic ice with high accuracy and sensitivity. Characterizing the biomechanics of skating on synthetic ice and comparing it with on-ice skating biomechanics is important since it is an alternative to on-ice skating. The next step of this technology development would be using it on ice to analyze the player performance on ice experiments. Using the output of this technology, skating coaches and trainers can keep track of the skaters' progress and improve their efficiency by assessing their skating performance during training sessions and matches, even remotely. This wearable technology has the potential to assist hockey coaches in monitoring their players, detecting their performance drop early, and predicting their perceived fatigue level.

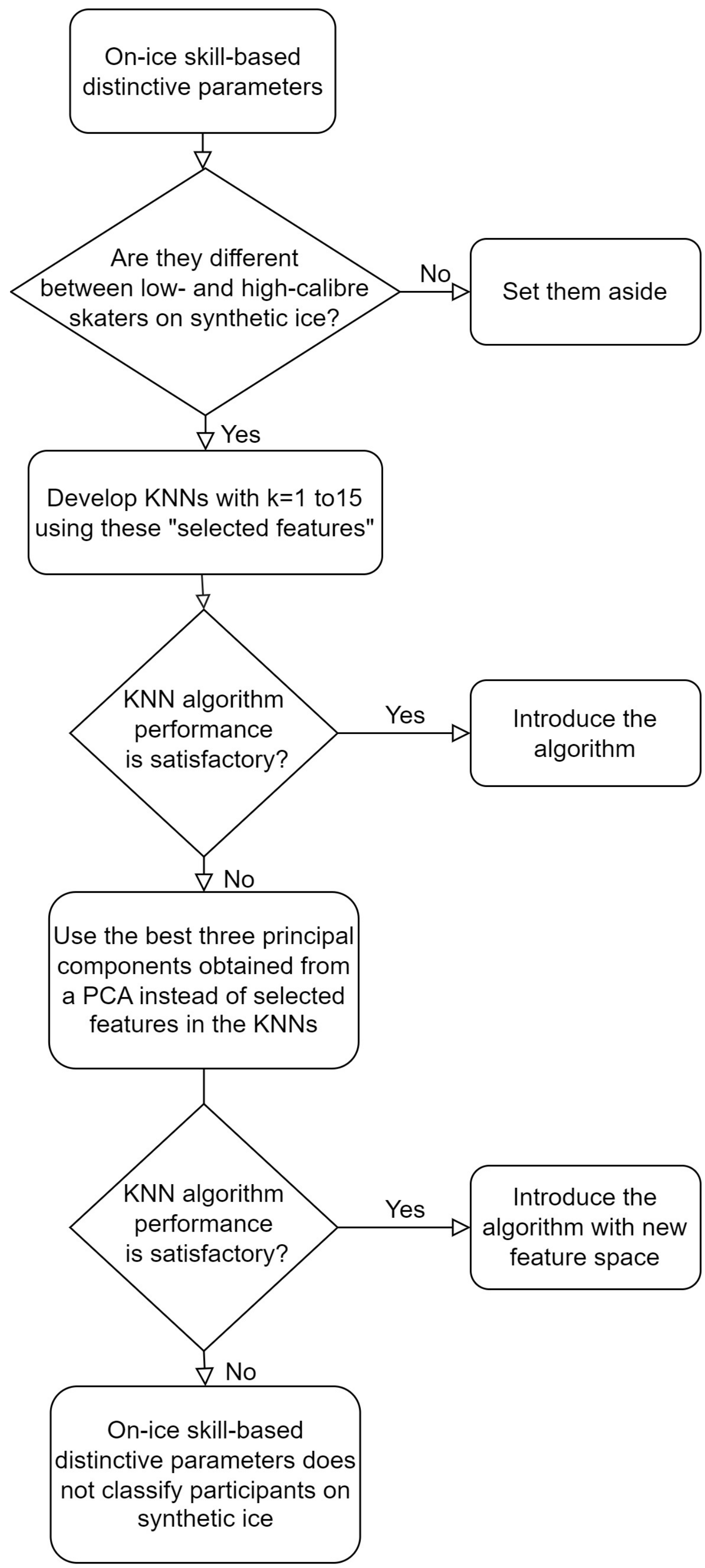

Figure 4.3: Flowchart of feature selection for KNN algorithms, checking the performance of the algorithms utilizing the selected features or principal components obtained by a PCA.

Chapter 5

Variation of kinematic metrics with perceived fatigue in ice skating measured using wearable sensors

In this chapter, twenty-two kinematic metrics were developed based on wearable sensors' measurements, and their variation with perceived fatigue and skater calibre was investigated during an intermittent skating experiment. This study also proposed a novel approach to classify ice skaters based on recorded skating videos and implementing optimal clustering algorithms, which has the potential to be implemented in sports biomechanics research.

5.1 Introduction

Skating is the core skill upon which other hockey skills, including acceleration, stick handling, shooting, and agility, are built [1]. Therefore, skating biomechanics assessment can provide essential information about player performance in hockey. Hockey and ice skating biomechanics have been studied using various tools, such as optical motion capture systems, electromagnetic sensors, and wearable inertial measurement units (IMU) [2, 19, 20, 30, 131].

Wearable IMUs, in particular, can be used to measure the skater's Kinematics, detect physical activity, and characterize players' performance in large ice rinks and thus have the potential to be widely used in fields [5, 6, 9, 19, 20]. Buckeridge et al. used a portable system composed of accelerometers, muscle activation sensors, and force sensors to assess on-ice hockey players' performance [5]. Also, Stetter et al. developed an innovative approach to determine strides, ice contact, and swing phases during ice hockey skating using a single accelerometer fixed to skates [6, 9]. Finally, Khandan et al. obtained skaters' temporal and spatial parameters and 3D joint angles with high accuracy and precision using wearable IMUs [19, 20]. These recorded kinematic parameters obtained from wearable sensors can be used to detect player performance drop or fatigue onset [52, 78].

Fatigue causes weariness, reduces alertness and concentration, and can increase the player's risk of injury, including ACL injury [18]. Hockey and ice skating are considered sports with a high risk of injury, and in-game fatigue is an important factor when considering injury [16]. However, few biomechanical studies have investigated performance fatigue mechanisms during skating [18, 67, 69], and none have comprehensively investigated the effect of fatigue on skaters' Kinematics. For instance, joint angle variability and inter-segment coordination were observed to indicate fatigue onset in ratcheting [40] and countermovement jump [102]. Fatigue can affect any skater's biomechanics, regardless of their skill level or experience [67]; however, its effect on the skaters' performance can be different between skaters of different calibre [68], necessitating further investigation. During forward skating, inter-segment coordination, joint angles, temporal and spatial parameters, and center of mass movements differed at some levels between high- and low-calibre players [5, 20, 73]. Nevertheless, replicating these studies, inter-study comparisons, and investigating the fatigue effect is challenging due to the subjective and not statistically supported definition of skill level in the literature.

Current skill-based clustering approaches for skaters are frequently imprecise. Being a part of a university team or having certain years of skating experience or skating speed has been the most common criterion for being considered a high-calibre player [5, 73, 78]. However, interpreting these results and comparing them across studies is challenging for several reasons: 1) Membership in a university team or having long-term experience or faster skating does not necessarily correlate with high performance in all aspects of skating at the time of data acquisition, 2) There is no statistical evidence to justify classifying skaters into only two or three distinct groups is the optimum number of clusters, and 3) The significant differences in skills among these groups have not been sufficiently studied. Thus, addressing these challenges in clustering skaters is crucial for understanding how fatigue affects skaters of different skill levels.

This study thus aimed to investigate how the body kinematics of skaters measured on ice using wearable IMUs changes with fatigue and skill level in an intermittent skating experiment and whether we can detect severe fatigue onset using body kinematics. For this purpose, we 1) developed a novel approach to classify ice skaters based on the recorded skating videos, 2) introduced kinematic metrics recorded using IMUs, and investigated their relationship with self-reported perceived fatigue during an aerobic test considering the effect of players' skill level, 3) investigated the kinematic metric's variations with perceived fatigue among skaters of different calibres, and 4) developed a machine learning method to detect the onset of severe fatigue by observing these kinematic metrics.

5.2 Methods

5.2.1 Experimental procedure

Six IMUs (Xsens Technologies, The Netherlands, full-scale ranges are: acceleration: ± 160 m/s^2, angular velocity: ± 2000 deg/s, and magnetic field: ± 1.9 Gauss) were placed on the trunk, pelvis, and skates of the participants and thigh and shank of their dominant leg (Figure 5.1)). To minimize garment-to-skin motion artifact, each participant was asked to wear tight-fitting pants or shorts, and the sensors were placed on the skates and on either their skin or fitted pants. Before each experiment, participants did ten successive hip flexions and extensions and ten successive squats, after five seconds of quiet standing, required by the protocol [132]. IMU readouts recorded during these motions were used to calculate a sensor-to-segment rotation matrix and find the body segments' anatomical frame [123, 124]. IMU readouts during the actual skating experiment were transformed into anatomical frames obtained via this functional calibration procedure. The entire experimental procedure was adopted from the multistage aerobic test (SMAT) [63] and modified due to the limitations of our experimental setting: 1. The experimental procedure included a series of up to 15 skating stages. Each skating stage was composed of 10 sec of quiet standing and then skating around the ice rink for one minute while the IMUs recorded the participants' body motion at a sampling frequency of 100 Hz. 2. At the end of each stage, the participants were asked to rate their perceived fatigue using a numeric fatigue rating scale [95] (hereafter called Fatigue Index: FI), ranging from 0 (alertness vigorous) to 10 (extremely fatigued). 3. After a 30-second rest, they repeated this skating stage around the ice rink at the same pace until they felt considerably fatigued (FI $>$ 6.5).

Figure 5.1: Six IMUs, coloured in orange, were placed on the participants' trunk, pelvis, skates, and thigh and shank of the dominant leg. Participants wore either hockey or figure skates.

5.2.2 Participants

Nineteen ice skaters (age 26 ± 7 years, height 170 ± 10 cm, body mass 71 ± 12 kg) participated in this study at our institution's ice rink. This study was approved by the research ethics board of the authors' current institution, and all methods were performed in accordance with the relevant guidelines and regulations. All participants were informed of the experimental procedures and gave informed written consent before the experiment.

5.2.3 Clustering analysis

In this study, two hockey experts (certified by Hockey Canada) were asked to rate the participant's balance in the change of direction, stability, and fitness level from 0 to 5 [133] with an increment of 0.5 using the recorded videos from the experiments. The experts rated participants' performance from 0.5 to 4.5; none were rated 0 or 5 out of 5 in any item. Subsequently, employing the experts' ratings, participants were clustered using a k-means algorithm, while the optimal number of clusters was determined through Silhouette analysis: A k-means algorithm with a varying k from 2 to 10 was used to cluster the participants into k groups. The Silhouette score, which measures how well each point fits into its assigned cluster [134], was calculated for each data point. The Silhouette score ranges from -1 to 1, with higher values indicating better cluster assignments [134]. Then, the average Silhouette score was calculated by averaging the Silhouette scores of all data points within that cluster configuration for each number of clusters (i.e., k). The number of clusters maximizing the average Silhouette score was obtained. Then, the final cluster assignment was obtained by the k-means algorithm with this optimal cluster number (i.e., k_o). This Silhouette analysis showed that the optimal number of clusters (k_o) for these participants was two, meaning the participants can be optimally clustered into two groups of 7 low-calibre (balance in the change of direction: 1.6 $\pm$ 0.9, stability: 1.5 $\pm$ 0.9, and fitness level: 2.2 $\pm$ 0.3) and 12 high-calibre skaters (balance in the change of direction: 3.2 $\pm$ 0.5, stability: 3.2 $\pm$ 0.4, and fitness level: 3.6 $\pm$ 0.3), employing the experts' rating. Figure 5.2) shows the Silhouette scores of the k-means clustering algorithms with k from 1 to 10.

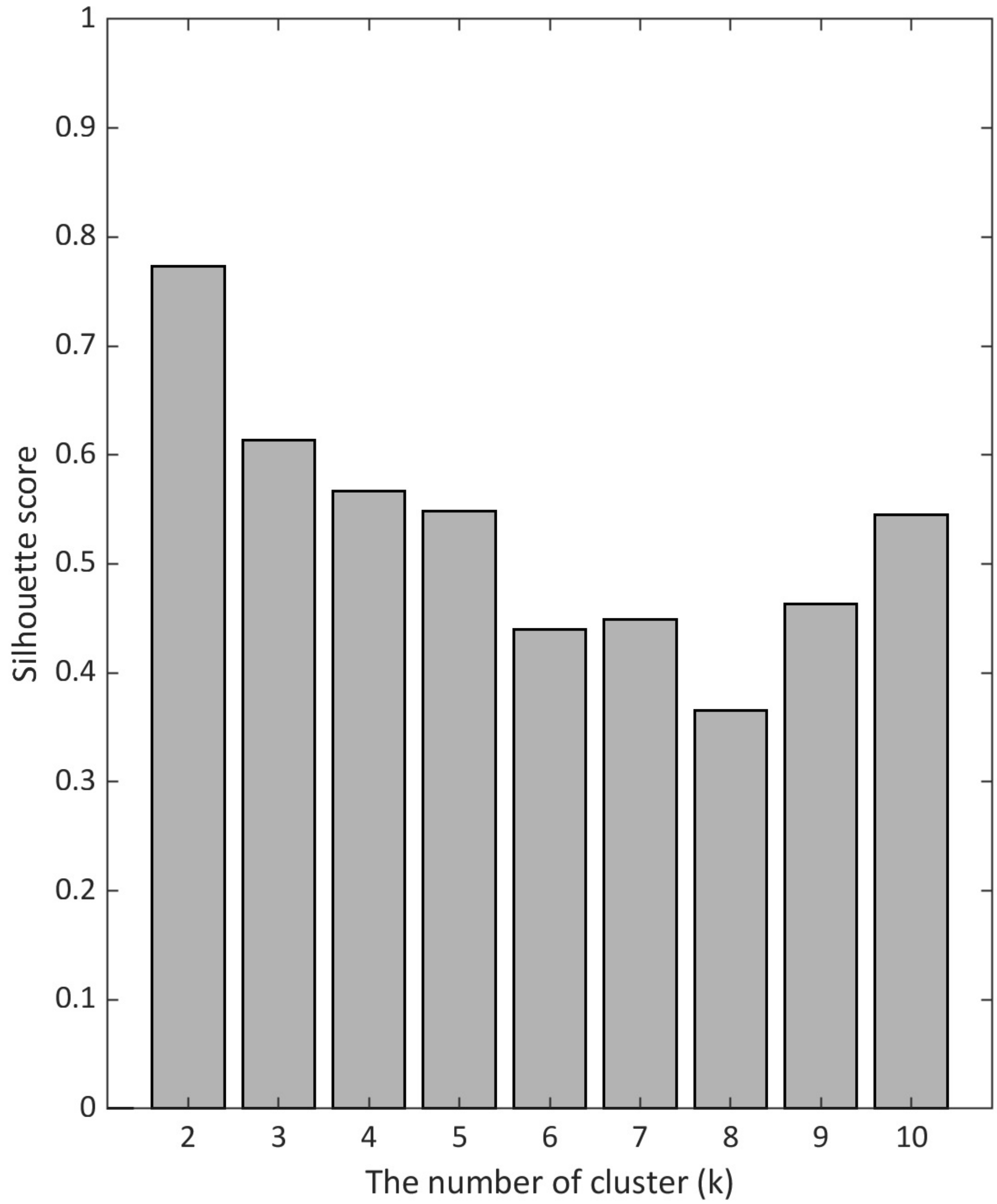

Figure 5.2: Optimizing the number of clusters based on skaters' calibre. Silhouette score measures how well each point fits into its assigned cluster and was used to obtain the optimum number of clusters (k).

5.2.4 Kinematic metrics

We calculated the kinematic metrics listed in the following using IMUs readouts based on lower limb kinematics for the first time on ice, according to our previous works

[19, 20]. We chose these kinematic metrics because they were mostly used in the literature to characterize running and walking stability [135], inter-joint coordination [131, 136], range of motion and acceleration [73, 78], motion jerkiness [73, 137], and signal fluctuation and complexity [138] during the experiments.

Postural and step stability index

Postural stability index (PSI) and step stability index (SSI) were previously defined based on the intrinsic mode functions (IMFs) using the obtained ensemble empirical mode decomposition (EEMD [135]) of acceleration time series for gait analysis and fall detection [135]. As the participant's movement patterns got less stable, these indices were expected to decrease. We slightly modified the original formulas [135] to be applicable to skating in this study (Equations eq. (5.1) and eq. (5.2)).

$$PSI = \frac{\text{CI of IMF}_3}{\text{CI of IMF}_1 + \text{CI of IMF}_2 + \ldots + \text{CI of IMF}_6} \tag{5.1}$$

$$SSI = \frac{\text{SD of IMF}_3}{\text{SD of IMF}_1 + \text{SD of IMF}_2 + \text{SD of IMF}_3} \tag{5.2}$$

Where CI and SD are, respectively, the complexity index and the standard deviation of each IMFs. IMF3 was selected as the dominant IMF because its frequency was closely related to the frequency of skating strides (which is 1.4-2.0 Hz [38]) for different skating speeds). PSI and SSI were calculated for pelvis acceleration time series in superior/inferior (SI), anterior/posterior (AP), and mediolateral (ML) directions.

Impact acceleration on upper body

The upper body's impact accelerations (or simply Impact) reflect the shock that the upper body experiences with each stride and were defined as the size of the acceleration peak generated by a skate strike, measured on the upper body [52]. Long runs were discovered to increase the Impact, which raised the risk of injury [52]. In the running, the body did not reduce the shock caused by the foot strike in the later stages, which was seen as the body's larger acceleration peaks [52]. Similarly, in ice skating, as time went by, we expected to observe larger impacts as skaters got fatigued.

Trunk forward inclination

Trunk forward inclination (TFI) was defined as the angle between the upper body of the skaters and the vertical line. In skating, the forward lean helps optimize weight distribution and allows for proper leg extension [18]. Contrary to running [52], in skating, we expected that as the participants felt fatigued, the skaters' upper bodies became more upright [18], possibly due to the decreased muscle control and loss of focus.

Multi-scale entropy

Multi-scale entropy (MSE) identifies the differences in fluctuations of a time series and extends sample entropy (SE) to multiple time scales or signal resolutions when the time scale of relevance is unidentified [138–140]. MSE's biomechanics application has mainly focused on detecting driving fatigue using electroencephalogram signals [141], and its application in human movement biomechanics has been limited. We expected the complexity of the 3D joint angles to increase as time went by during skating, and therefore, the higher value of MSE was anticipated at the later stages of the experiment.

Continuous relative phase

The following steps were implemented to calculate the continuous relative phase (CRP) between two segments angles suggested by [142]: 1) The amplitudes of the angles were centred around zero, 2) Using the Hilbert transform, the analytic signals were created for the two time series, 3) The phase angle was calculated based on the analytic signals, 4) The CRP was obtained by subtracting these phase angles, and 5) The root mean square of the obtained CRP was measured during each stage. This metric was obtained for 1) shank angle in the sagittal plane (shank-sagittal) vs. thigh angle in the sagittal plane (thigh-sagittal), 2) shank angle in the sagittal plane (shank-sagittal) vs. thigh angle in the frontal plane (thigh-frontal), and 3) foot angle in the sagittal plane (foot-sagittal) vs. shank angle in the sagittal plane (shank-sagittal). These are known to be the most significant segment angles used for the biomechanical characterization of ice skating [73]. A CRP analysis studies inter-segment coordination [142], and we expected the inter-segment coordination to decrease as participants got fatigued during the experiment, and therefore, a higher root mean square of CRP was anticipated at the later skating stages.

5.2.5 Statistical analysis

In the first step, the relationship between perceived fatigue and calibre on the introduced kinematic metrics was investigated by employing a linear mixed model. A linear mixed model analyzed data considering fixed and random effects and estimated the variance for each effect using R. In linear mixed models, fixed effects represent population parameters assumed to be present in each collected data point, and random effects are sample-dependent random variables. Then, a machine learning algorithm was employed to detect the onset of severe fatigue using the proposed kinematic metrics. These steps are described in the sections below and depicted as a flowchart in Figure 5.3.

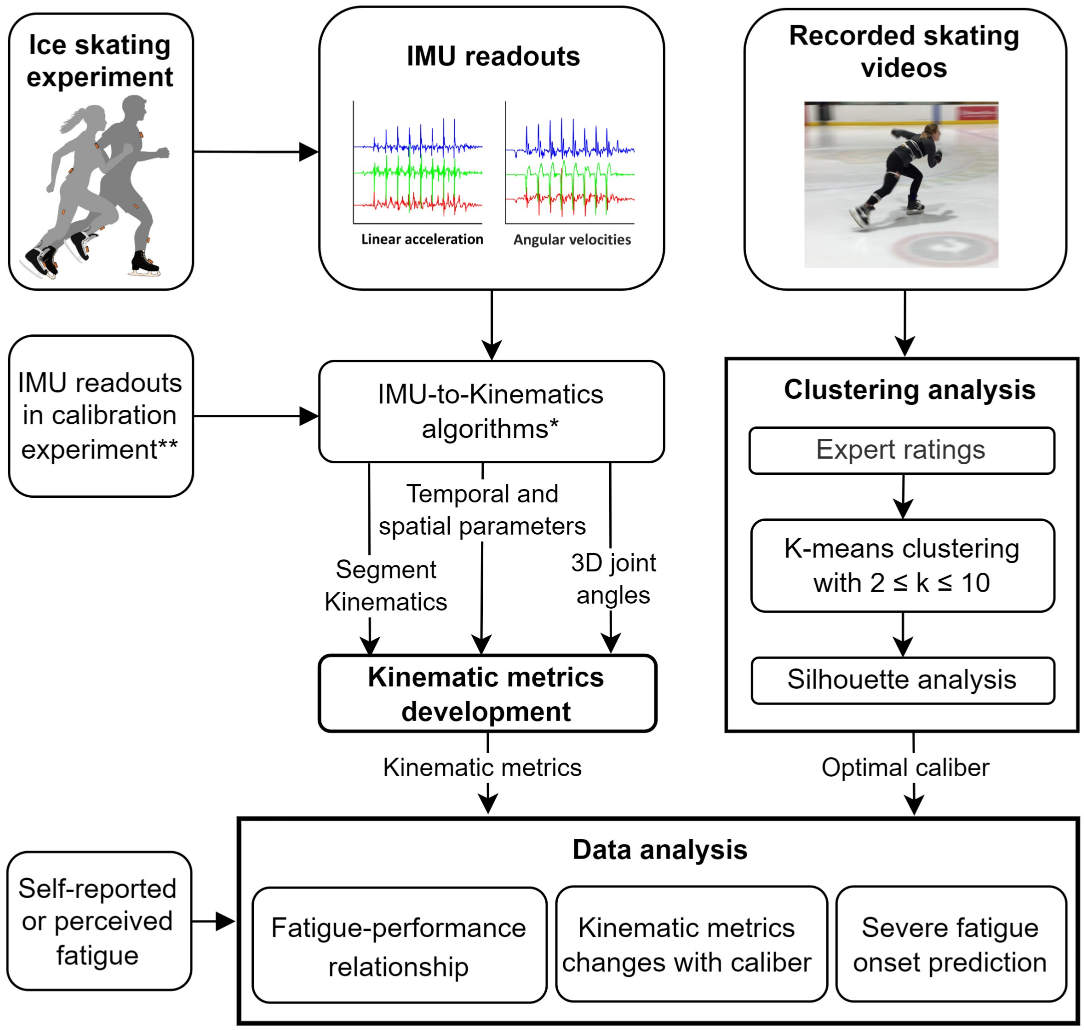

Figure 5.3: The flowchart of the data analysis steps of this study (see highlighted in **bold** in the flowchart). * The algorithms to obtain the temporal and spatial parameters, the segment Kinematics, and the 3D joint angles of skating based on the IMU readouts were previously described and validated [19, 20]. ** The calibration experiments consisted of ten successive hip flexions and extensions and ten successive squats after five seconds of quiet standing, which we asked the participants to perform prior to the skating experiments [124, 132].

5.2.6 Change of kinematic metrics with perceived fatigue (perceived fatigue-performance relationship)

In this part, fatigue index (or FI) and participants' calibre obtained by clustering algorithm were taken as the model's fixed and random effects, respectively. This study used the random-intercept/random-slopes approach to determine each group's regression lines. Then, the slope of these regression lines was 1) multiplied by the FI range, 2) normalized by each metric's range, and 3) reported in percentage as the metric's normalized change during the experiment.

5.2.7 Change of kinematic metrics with calibre (calibre effect)

Then, in the next step, the fatigue index (FI) was taken as the random effect, while the participants' calibre was the model's fixed effect. Similar to the previous step, this study used the random-intercept/random-slopes approach to determine the corrected regression line of the metrics versus calibre. The slope of these regression lines was 1) normalized by each metric's range and 2) reported in percentage as the metric's normalized inter-calibre change.

5.2.8 Severe fatigue onset prediction using a gradient-boosting method

Gradient boosting methods (GBMs) perform favourably for classifying tabular data due to their architecture for handling structured data with many features [143]. In this study, LightGBM [144] was fed with tabular data containing our calculated kinematic metrics and participants' calibre during each stage. The dataset was split into training and test sets using a four-fold leave-one-out cross-validation where each fold contained the data of four to six participants randomly grouped together. Finally, each data row was labelled as 1 (indicating severe fatigue, $FI > 6$) or 0.

5.3 Results

5.3.1 Perceived fatigue-performance relationship

A linear mixed model assessed the normalized changes of the kinematic metrics with perceived fatigue. As an exemplar figure, Figure 5.4 visualizes the data points and regression line for each group as well as the model's regression line for participants in all groups with the inter-calibre error around the regression line. Table 5.1 shows that TFI, Impact, MSE for hip adduction (HA) angle, MSE for hip flexion (HF) angle, CRP for shank-sagittal vs. thigh-sagittal, CRP for foot-sagittal vs. shank-sagittal, interquartile range (IQR) of pelvis acceleration and motion jerk in the superior-inferior (SI) direction, and PSI in the SI direction had an absolute normalized change of higher than 5% for over all participants (6 to 17% of absolute normalized changes). Impact and PSI did not show an absolute normalized change higher than 5% for low-calibre skaters among these metrics. On the other hand, MSE for ankle dorsiflexion (AD) showed an absolute normalized change of higher than 5% only for low-calibre skaters. Other metrics did not show consistent change with perceived fatigue.

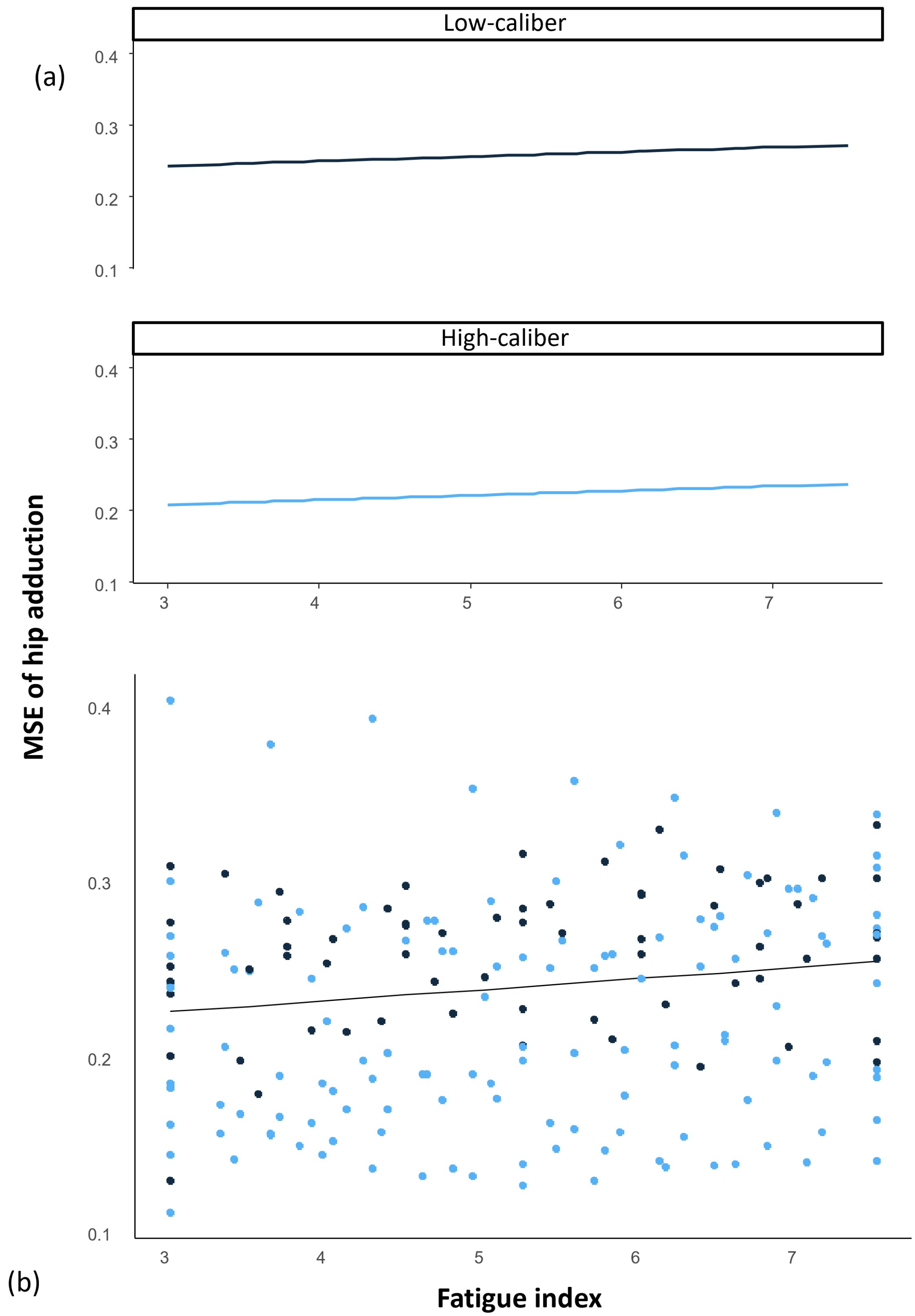

Figure 5.4: A representative presentation of a kinematic metric (MSE) against fatigue index (FI) grouped by the participants' calibre (a) and for all participants (b) considering the inter-group variations between skaters of different calibre.

Table 5.1: The percentage of increase in the kinematics metrics by fatigue index (FI) during the session (Fatigue effect) or being a high-calibre vs. low-calibre skater (Calibre effect), normalized with the metric range in all of the experiments, was obtained by the linear mixed model.

Kinematic metric	Component	Fatigue effect			calibre effect
		Low-calibre	High-calibre	All calibres	
PSI	AP	2%	4%	3%	8%
	ML	-2%	4%	2%	5%
	SI	-1%	-9%	-6%	-7%
SSI	AP	-2%	1%	0%	-6%
	ML	1%	0%	0%	-6%
	SI	2%	2%	2%	6%
IQR of pelvis acceleration	AP	4%	4%	4%	4%
	ML	1%	3%	2%	4%
	SI	9%	8%	8%	13%
	Norm	1%	1%	1%	8%
IQR of pelvis motion jerk	AP	3%	3%	3%	4%
	ML	2%	2%	2%	2%
	SI	2%	5%	4%	6%
TFI		17%	17%	17%	6%
Impact		3%	12%	9%	18%
MSE	HF	12%	6%	8%	-2%
	HA	9%	10%	10%	-13%
	KF	-6%	8%	3%	-5%
	AD	11%	-2%	2%	-19%
CRP	shank-sagittal vs. thigh-sagittal	6%	6%	6%	2%
	shank-sagittal vs. thigh-frontal	11%	7%	8%	2%
	foot-sagittal vs. shank-sagittal	-1%	-2%	-2%	-4%

5.3.2 Calibre effect

Intergroup variation analysis showed a significant difference (>5% variation) between high- and low-calibre skaters in the following kinematic metrics: IQR of pelvis acceleration and pelvis motion jerk in the SI direction, TFI, Impact, MSE, and PSI and SSI of high-calibre in all directions. PSI (SSI) was higher (lower) in high-calibre skaters in AP and ML directions in contrast to the SI direction, where low-calibre skaters had higher PSI (lower SSI). Again, only in the SI direction was the IQR of pelvis acceleration and pelvis motion jerk significantly higher in high-calibre skaters. Additionally, Impact and TFI were higher, and MSE was generally lower in high-calibre skaters.

5.3.3 Severe fatigue onset prediction

In a total of 196 stages captured from 19 participants, the average precision of 78%, the sensitivity of 81%, the accuracy of 74%, and the F1 score of 78% were obtained by LightGBM in detecting severe fatigue during skating. Figure 5.5 shows the contribution of each kinematic metric as a feature input for LightGBM. Also, it was observed that the distribution of feature importance represented was consistent among features and had higher variation represented by its relatively high standard deviation. The kinematic metrics that contributed the most to detecting severe fatigue onset (see Figure 5.5) were not necessarily the same ones that showed change with fatigue based on the linear mixed model (see Table 5.1). Only TFI, MSE for hip flexion and hip adduction, and IQR of pelvis acceleration in the SI direction both showed change with fatigue in an aerobic skating test and contributed much to detecting severe fatigue onset.

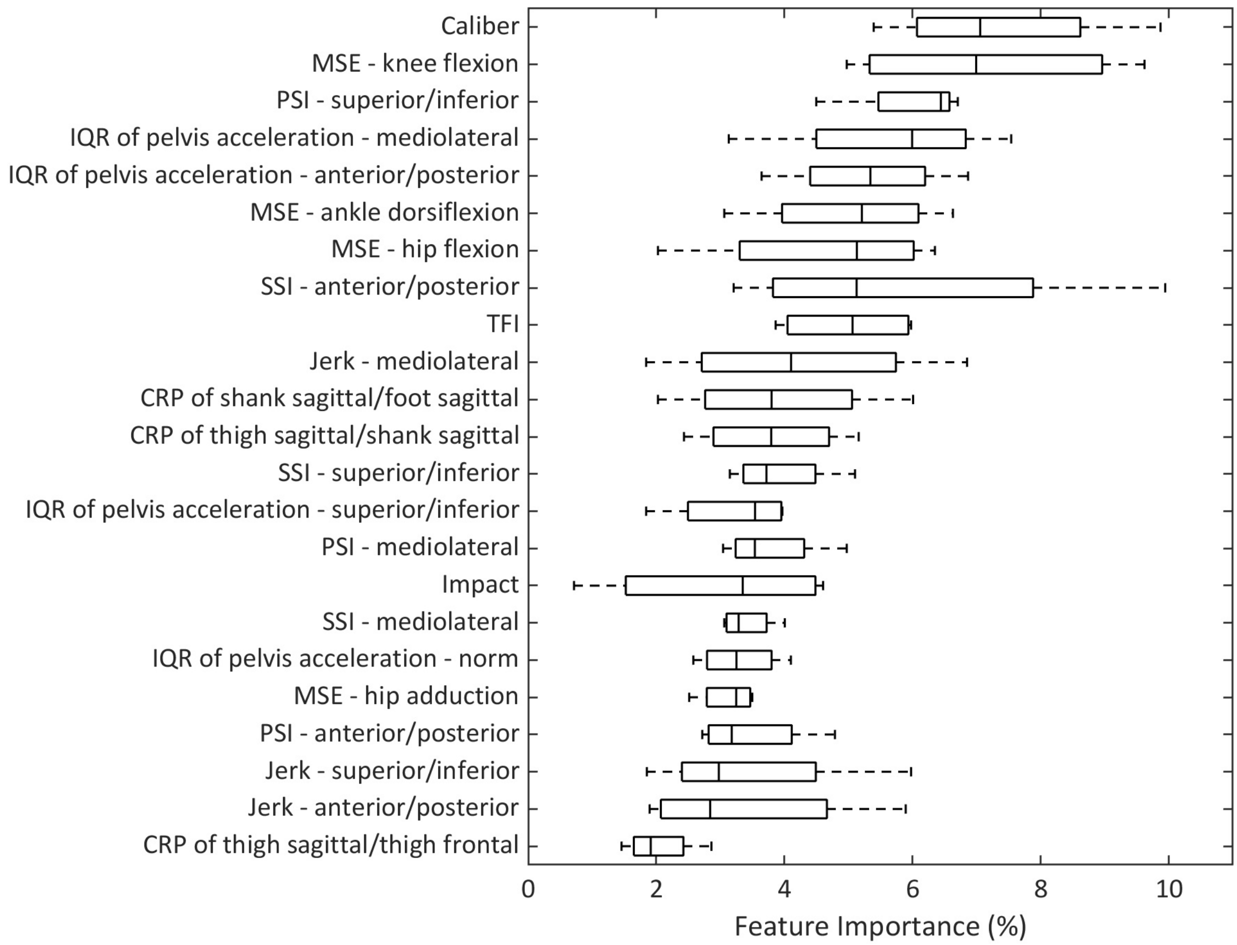

Figure 5.5: Feature importance in the LightGBM model to predict severe fatigue onset (FI > 6) expressed as percentage using the kinematic metric as the model's features. Mean and standard deviation are shown as horizontal bar plots. Calibre and MSE for knee flexion, hip adduction, hip flexion, PSI in the SI direction, SSI in the AP direction, IQR of pelvis acceleration in the AP and ML directions, and TFI altogether presented more than 50% of feature importance.

5.4 Discussion

In this study, ice skaters' performance quantified by kinematic metrics obtained from the output of wearable IMUs was investigated over a fatiguing aerobic test. Below, we discuss the original contributions and main findings of this study.

5.4.1 Clustering analysis

Reliable clustering of the skaters into groups based on their calibre is a prerequisite to investigating any association between skating kinematics and skaters' skills in the experiments. We proposed a novel approach to cluster the study's participants into two groups based on their skills and performance in their experiments using the recorded skating videos rated by two hockey experts. Instead of the less precise and subjective approach of clustering ice skaters into only two or three skill-based groups, our proposed clustering approach combined the stability, balance in the change of direction and fitness scores rated by experts and formed clusters to maximize the distinction between the groups determined by a k-means clustering algorithm. Thus, using the experts' ratings, the Silhouette score analysis discovered that the optimized number of clusters in the k-means algorithm was two, and the participants can be optimally clustered into two groups with distinct performance. The proposed algorithm also has the potential to be the new standard for clustering players not only in ice hockey and ice skating but in all sports applications.

5.4.2 Perceived fatigue-performance relationship

We used a linear mixed model to characterize the change of each kinematic metric as an indicator of performance with perceived fatigue. Performance and perceived fatigue are intertwined, driven by different factors, including intermittent tests, and influenced by various factors, including skill level [68]. The linear mixed model finds the relationship between variables while accounting for the variance introduced by other fixed and random effects. Using this model, kinematic metrics TFI, Impact, MSE for hip adduction (HA) angle, MSE for hip flexion (HF) angle, CRP for shank-sagittal vs. thigh-sagittal, and CRP for foot-sagittal vs. shank-sagittal displayed the largest relative changes with perceived fatigue, indicating that these metrics could serve as potential fatigue indicators during the ice skating aerobic experiments. Consistent with this finding, Coweley et al. discovered that the pattern of inter-joint coordination—measured by CRP—changed when participants felt fatigued during ratcheting [131]. In our study, TFI decreased during the experiment, consistent with the other observations of fatigued ice skaters and hockey [145]. The acceleration impact, in our study and similar to running [52], increased in high-calibre skaters as time passed, and the participant felt fatigued during the skating experiment. Finally, the increase in MSE in the 3D joint angles indicated higher complexity, fluctuations, and potentially irregularity and instability in the later skating stages of participants when they felt fatigued. MSE changing pattern, however, was not consistent among all joint angles and was different in knee flexions in low-calibre skaters. Flexing knees in ice skating helps them to maintain balance and exert more power during push-offs. Therefore, lower knee flexion fluctuation measured by MSE during the later stages can indicate the existence of a learning curve in the skating of low-calibre skaters as time passed.

Furthermore, PSI decrease in the SI direction showed that the participants' stability was compromised [135] in this direction as time went by in the skating experiments. Concurrently, an increase in the IQR of pelvis acceleration also suggests that stability was diminished in the SI direction as participants' fatigue set in. Additionally, PSI in the SI direction in the low-calibre skaters showed less variation with fatigue compared to the high-calibre skaters, probably due to the lower skating speed and differences in the dominant frequency during their skating, affecting this frequency-based metric. However, both PSI and IQR of pelvis acceleration in other directions did not exhibit significant changes, indicating lesser variation in stability in other directions. Comparably, the variations of SSI and IQR of the jerk measurement variations were small as the participants felt fatigued, meaning that they were not the best indicator of fatigue during skating.

5.4.3 Calibre effect

The linear mixed model not only analyzed the relationship of perceived fatigue with the kinematic metrics but also enabled the investigation of the participant's calibre effect on these metrics. We observed that TFI, PSI, and MSE could not only set apart fatigued from non-fatigued skaters but also differentiate high-calibre skaters from low-calibre ones. As expected, PSI in AP and ML directions correlated to higher movement stability in high-calibre players in those directions. However, PSI in the SI direction was lower in high-calibre players, which can be due to the spikes in the acceleration in the SI direction caused by skate-ice contacts. As shown by acceleration Impact, there was a significant normalized difference between high- and low-calibre skaters, with a higher increase in high-calibre skaters as they felt fatigued. Therefore, high-calibre skaters experienced higher acceleration impact and, therefore, higher forces on their joints and bones during skating, which can lead to increased risk of injury in the long run [52]. This higher acceleration impact was also observable in increased motion jerks in high-calibre skaters which must be further analyzed in the future and, if deemed necessary, incorporated into training strategies. Finally, contrary to this study, Robbins et al. observed different CRP patterns between low- and high-calibre hockey players in an ice sprint test [73], possibly due to the different definitions of calibre and different skating modalities, which highlights the importance of a consistent clustering approach suggested in this study. Although many of these kinematic metrics change with fatigue, these slow changes might not precisely detect the onset of severe fatigue. Therefore, a follow-up question would be whether a combination of these metrics can predict the onset of severe fatigue during a fatiguing aerobic test, which is discussed in the next section.

5.4.4 Severe fatigue onset prediction

We predicted the onset of severe fatigue using the kinematic metrics, as input features, by a machine learning approach (i.e., LightGBM). Using proposed kinematic metrics, this method effectively predicted severe fatigue onset during the aerobic ice skating test, with good (i.e., 70% or above) average accuracy, precision, and sensitivity. Among these kinematic metrics, calibre and MSE in knee flexion had the highest feature importance. In GBMs, feature importance is defined based on the contribution of each feature to the reduction in the cost function[143, 144], and it assesses how much each feature improves the model's performance and interprets the model. Therefore, contrary to the linear mixed model, the high importance of the calibre and MSE in severe fatigue detection using the LightGBM model does not mean a high correlation of these metrics with fatigue. For instance, while SSI in the AP direction is another significant contributor to our GBM, this metric did not show significant changes as time passed in the skating experiment.

Monitoring the body kinematics changes with perceived fatigue in ice skating using wearable IMU sensors has potential limitations. First, even though the GBMs were designed to perform well on small sample sizes, the model's performance can be further enhanced by increasing the size and diversity of the data. For instance, integrating professional skaters can broaden the study's output to a more diverse group of skaters. Second, the participants did not hold hockey sticks during their skating due to the experiment's ice rink limitations. Therefore, the results of this study must be treated with caution for hockey players holding hockey sticks during their skating trials. Third, this wearable technology's output has been validated for forward striding during a practice session. Thus, further investigation is required to determine the applicability of this technology in real hockey games, as many determining factors can affect the collected data, such as game intensity, higher impacts, time constraints, psychological factors, and variations in skating style. Fourth, the application of wearable IMUs can be further expanded if the obtained kinematics and temporal and spatial parameters of skating can be validated in various skating types in longer experiments. Finally, since fatigue is a multifactorial experience, a more comprehensive understanding of fatigue during ice skating can be gained by integrating these kinematic metrics with non-kinematic metrics such as EMG and heart rate and perceived fatigue ratings for future studies.

5.5 Conclusions

The concurrent study of perceived and performance fatigue will elucidate the intricate relationships among different fatigue dimensions and thus enhance our understanding of how these dimensions interact and are influenced by various modulating factors in ice skating. In an aerobic skating test, we showed the relationship between perceived and performance fatigue in skaters of different skill levels, where we showed how proposed kinematic metrics could also indicate perceived fatigue. We also showed how machine learning could detect the onset of severe fatigue using a combination of kinematic metrics and observed that these kinematic metrics could predict severe self-reported fatigue similarly across different skill levels. Objective biomechanical assessment of ice skating can thus be extended to use for early detection of severe fatigue onset, thereby decreasing the subsequent risk of fatigue-related injuries. Automatic onset detection of players' fatigue and on-time substitution with fresh players reduces the risk of injuries with chronic sequelae. Therefore, this wearable technology can highlight the limitations of existing training strategies and thus help diminish internal forces on joints and bones during skating. These applications of our proposed technology and measurement methodology must be further studied in the future.

Chapter 6

A novel approach to assessing ice skating sprint performance using wearable sensors

In this chapter, we proposed an extended range of performance metrics obtained from wearable sensors to assess skating performance in forward ice sprint tests. These metrics showed evidence of validity against traditional skating performance metrics in our experimental study. As such, they can enrich the assessments of ice skaters' performance and provide a deeper insight into the relationship between off- and on-ice skating parameters.

6.1 Introduction

The dynamic nature of ice skating requires well-coordinated body motion and necessitates high aerobic and anaerobic fitness to perform high-speed but delicate on-ice movements while balancing on a thin blade [1, 2, 40]. Faster sprints empower skaters to outmaneuver their opponents; for example, they enable hockey players to catch and cover effectively and gain an advantage in the race for the puck [40]. Faster sprints are also crucial in figure skating, enabling them to execute intricate maneuvers, achieve impressive jumps, and add dynamic elements to their performances [3, 60]. Skating performance assessments allow for a more detailed and comprehensive assessment of the skater's technical proficiency and physical conditioning [2, 31]. Therefore, ice skating sprint analysis allows us to comprehensively understand and characterize skating mechanisms by considering the factors affecting skater performance in hockey and figure skating.

Skating performance research has been performed to obtain two-dimensional (2D) or three-dimensional (3D) kinematics of the lower-limb joints of skaters using stationary video cameras and motion capture systems, force transducers, and wearable technology in different phases and speeds [6, 7]. For instance, Upjohn et al. and Hellyar et al. used digital video cameras on a skating treadmill to determine hockey players' lower limb kinematics during forward skating [7, 117]. In other studies, noticeable differences between the 3D joint kinematics of individuals of different sexes and calibres were discovered in different hockey skating modalities [5, 6, 20]. However, calibre, sex, and age are not the sole impacting factors on skaters' performance. Skating types (i.e., figure or hockey skating) can also impact ice skaters' performance in an ice sprint test and have not been fully studied. However, there has been no comprehensive research on the impact of different impacting factors on skating biomechanics in ice sprint tests.

While most ice skating studies predominantly concentrated on varsity-level to professional hockey players, biomechanical assessment of figure skaters and average and below-average recreational and younger skaters have usually been overlooked. In hockey, 7% to 30% of all winter sports injuries are related to collegiate/youth-level players [146, 147]. Understanding the biomechanics of recreational skaters can help identify potential risk factors for skating injuries and help develop guidelines and training programs to reduce injury risks [40, 146, 148]. Also, this understanding can guide the design and improvement of skating gears to better suit figure and recreational hockey skaters' needs [30].

On-ice training can be limited due to costs and ice time availability, and off-ice measurements such as countermovement jump (CMJ) have been a valuable tool to enhance our understanding of and predict skaters' on-ice performance before skating

[81]. Researchers have discovered that the 40-yard dash, vertical jump, and CMJ are key predictors of skating speed in different groups of hockey players, but with varying correlations based on age, sex, and skill level [21, 82, 84]. Yet, the relationship between off-ice measurements, such as the CMJ, and a wide range of on-ice performance metrics for figure and recreational hockey skaters remains unexplored. At the same time, wearable inertial measurement units (IMU) technology has demonstrated accurate measurements of the CMJ [102] and has been validated for capturing temporal and spatial parameters and sensor orientations and kinematics across different environments, including ice skating [19, 20, 44, 49, 108]. Therefore, IMU technology could be used to assess skaters' performance off and on ice comprehensively. By investigating whether on-ice performance metrics and off-ice measurements (such as CMJ), both measured by wearable IMUs, have significant relationships, we can characterize the effectiveness of off-ice measurements in accurately predicting on-ice performance. Additionally, this exploration will allow us to identify which specific on-ice performance metrics are associated with particular off-ice training activities.

This study aimed to assess the effectiveness of wearable IMUs in evaluating skating performance through on-ice measurement of a broad set of performance metrics during ice sprint tests. This study, therefore, used wearable IMUs during forward ice sprint tests to 1) calculate 3D joint angles and temporal and spatial parameters, 2) obtain an extended set of performance metrics based on the skater's kinematics, 3) assess the variation of these metrics concerning participants' calibre and skating types, and 4) determine the effectiveness of these IMU-measured metrics during an ice sprint test by evaluating their correlation with lower-body strength, assessed by CMJ height, as an off-ice measure.

6.2 Methods

6.2.1 Experimental procedure

Nineteen skaters of different calibre (Table 1) skated as fast as they could on an ice rink. Six IMUs (Xsens Technologies, The Netherlands) were attached to the trunk, pelvis, skates, and thigh and shank of the dominant leg of the participants. Prior to each experiment and before putting on their skates, all participants performed two CMJs off the ice. The jump height was determined using an IMU attached to their pelvis, employing a validated algorithm [102]. The highest jump out of the two attempts was recorded as the CMJ height. After a 5-minute warm-up period on the ice, participants were asked to skate forward as fast as possible (sprint) from one end of the testing area to the other without using a crossover start, taking up to two minutes of active rest between each trial, according to Figure 1. This reciprocal activity was repeated three times. Our previously validated algorithm [19] was used for the detection of 219 skating strides for 19 participants.

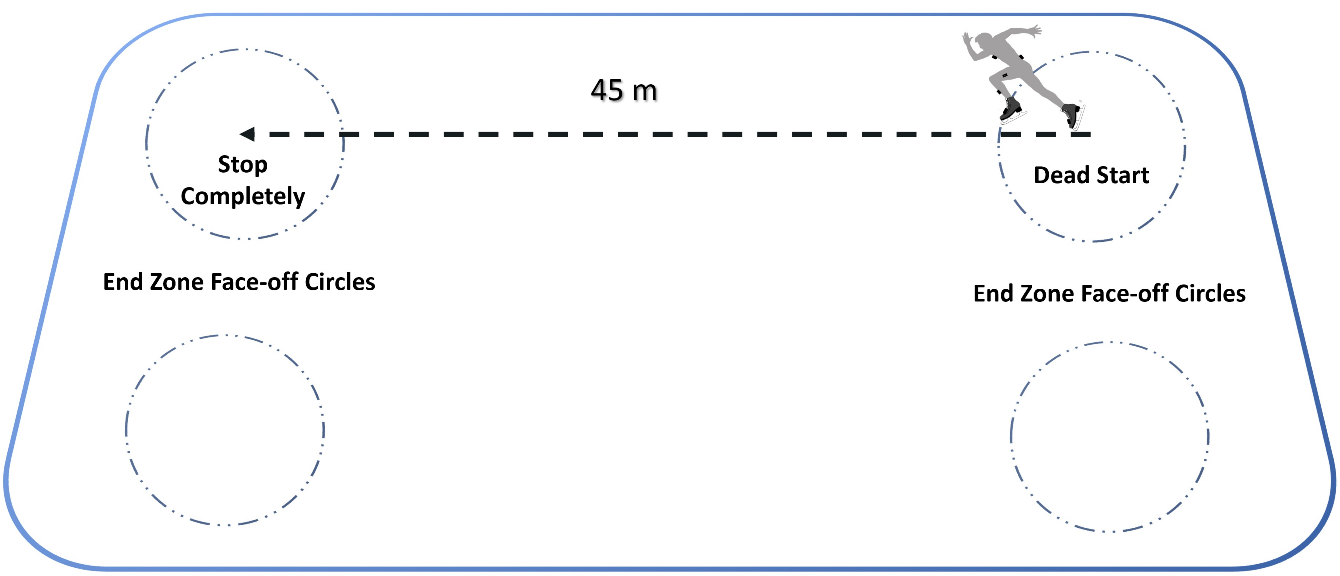

Figure 6.1: Testing area experiment schematic: Participants skated forward as fast as possible from one side to another without using a crossover start. Subsequently, they were allowed one to two minutes for an active break on ice, depending on their preference. After the break, this whole process was repeated twice.

Table 6.1: Participants' demographic information and expert rating.

Participant	Average expert rating			calibre	Sex	Height (cm)	Skating type
	Stability	Balance	Fitness				
1	1	1	2	LC	M	174	HS
2	0.5	0.5	2	LC	M	180	HS
3	4	4	4	HC	M	174	HS
4	3	3	3.5	HC	M	183	HS
5	4	4	4	HC	F	164	FS
6	3	3	3.5	HC	F	157	HS
7	3.5	3.5	3.5	HC	F	160	HS
8	1	1	2	LC	F	167	FS
9	2.5	2.5	2	LC	M	178	HS
10	3.5	3	3.5	HC	F	165	FS
11	3.5	3	3.5	HC	M	180	HS
12	3	2.5	3	HC	M	173	HS
13	1.5	1	2.5	LC	M	188	HS
14	3.5	3	4	HC	F	165	HS
15	2	1.5	2.5	LC	F	156	FS
16	3	3	2.5	LC	F	152	HS
17	3	3	3.5	HC	F	170	HS
18	2.5	3	3.5	HC	F	170	HS
19	2.5	3	3.5	HC	M	180	HS

6.2.2 Optimized k-means clustering

Clustering skaters based on team status or years of experience in ice skating can lead to imprecise and indistinct groupings. This imprecision complicates the interpretation of results and hinders consistent comparisons across different studies due to the variability in how skill groups are defined. In this study, two hockey coaches (certified by Hockey Canada) were asked to rate the participant's balance in the change of direction, stability, and fitness level from 0 to 5 using recorded videos from the intermittent skating experiments. Subsequently, employing the coaches' ratings, participants were clustered using a k-means algorithm into two groups of 7 low-calibre (height: 171 $\pm$ 13 cm, weight: 69 $\pm$ 10 kg, balance in the change of direction: 1.6 $\pm$ 0.9, stability: 1.5 $\pm$ 0.9, fitness level: 2.2 $\pm$ 0.3, three female, and four male) and 12 high-calibre skaters (height: 170 $\pm$ 8 cm, weight: 74 $\pm$ 16 kg, balance in the change of direction: 3.2 $\pm$ 0.5, stability: 3.2 $\pm$ 0.4, fitness level: 3.6 $\pm$ 0.3, six female, and six male), optimized by Silhouette analysis.

6.2.3 Primary performance metrics

Primary performance metrics were stride velocity, stride time, contact time, swing time, and stride length, traditionally used to evaluate the overall performance of ice skaters during sprint tests and can be utilized to rank the performance of different ice skaters. We calculated metrics in the steady-state phase [5, 19, 20] using our previously validated algorithms [19, 20].

6.2.4 Secondary performance metrics

Secondary performance metrics are not primarily used to assess the performance of ice skaters during an ice sprint test but can contribute to a broader understanding of sprint performance and can impact primary performance metrics. It has been discovered that inter-segment coordination, center of mass movements, and morphology of the 3D joint angles differed between varsity level and recreational hockey players [5, 40] during forward skating sprint tests and, thus, were also used to obtain secondary performance metrics. Also, hip flexion, hip adduction, and knee flexion— among the most significant angles for the biomechanical characterization of ice skating [73]—were the focus of this study. As a result, the following parameters based on these 3D joint angles were considered as the secondary performance metrics:

(a) Range of motion: Joint angles' range of motion can impact a runner's stride length, joint stability, and foot strike pattern [1, 73, 75].

(b) Stance peaks: Stance peaks refer to the extreme values of the most significant 3D joint angles in ice skating, centred around zero and occurring during the weight-bearing phase of the skating stride.

(c) 3D joint angles standard deviation: We first calculated the inter-stride standard deviation of the 3D joint angles for each participant in each trial. Then, the root mean square of these standard deviations was calculated for each trial. Finally, the average root mean square value was calculated for each participant.

(d) Multi-scale entropy: Multiscale entropy identifies the time series fluctuations, measures the amount of information each signal contains, and assesses the irregularity of significant 3D joint angles in this study [140, 149].

(e) Lower-body angular velocity: High angular velocity of the pelvis, thigh, shank, and foot segments determines the speed and efficiency of the runner's leg movements and can lead to a longer stride length and a faster running pace [1, 73, 75]. We calculated the root mean square of the angular velocity norm during each stride and averaged them in each trial. Finally, the average value for the lower-body segments was reported for each participant.

(f) Continuous relative phase: The continuous relative phase was calculated using the steps proposed and validated by Lamb et al. [142] for shank angle in the sagittal plane (shank-sagittal) vs. thigh angle in the sagittal plane (thigh-sagittal), shank angle in the sagittal plane (shank-sagittal) vs. thigh angle in the frontal plane (thigh-frontal), and foot angle in the sagittal plane (foot-sagittal) vs. shank angle in the sagittal plane (shank-sagittal) (see Figure (6.2)).

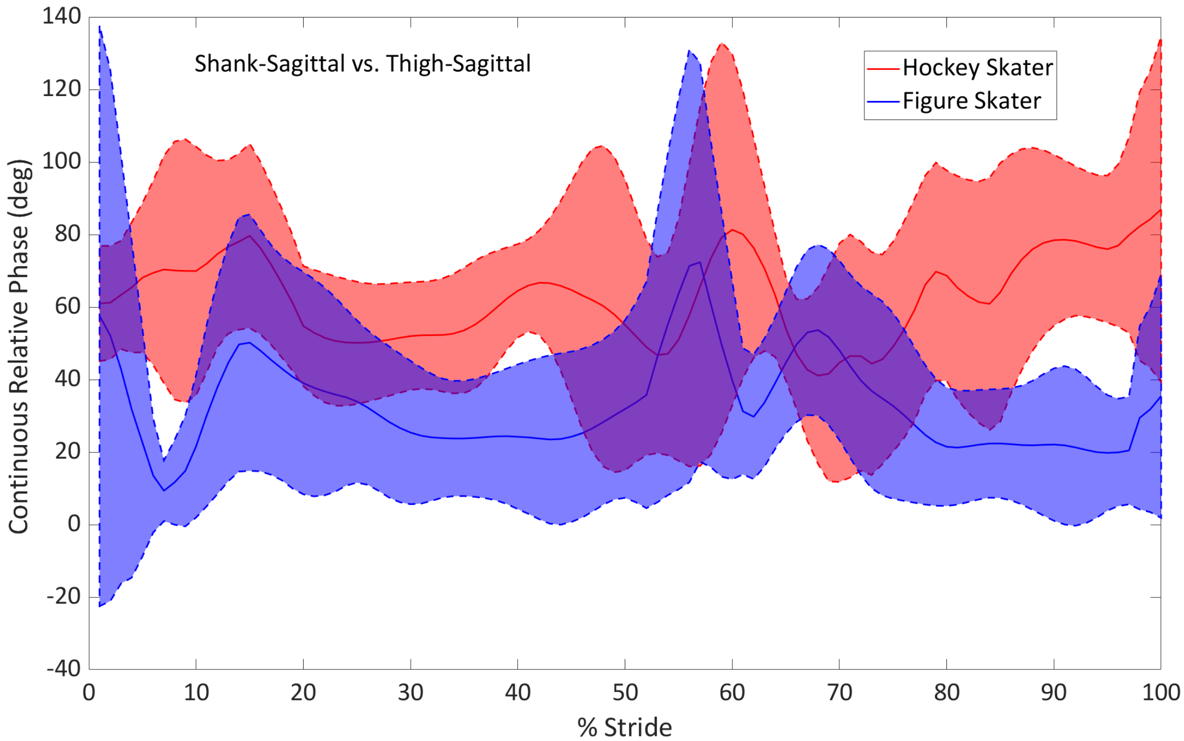

Figure 6.2: An exemplar figure showing continuous relative phase between shank- and thigh-sagittal for a hockey (red) and a figure skater (blue). Solid lines indicate the mean phase angles, and shaded areas represent the standard deviation across three trials for each skater. The study showed lower continuous relative phase angle (indicative of higher inter-segment coordination) in figure skaters compared to hockey skaters (see Table 6.3).

6.2.5 Impacting factors in ice skating

The trials were classified participants' calibre and skating type to evaluate the impact of these factors on the primary and secondary performance metrics.

a. Skater's calibre: High-level skaters have higher training and frequently demonstrate higher technical skills and accurate movements, resulting in a more optimized performance on the ice [5, 75]. On the other hand, low-calibre skaters were previously found to skate slower in sprint tests and used different joint angles compared to high-calibre skaters [5].

b. Skating type: Four out of 19 participants were figure skaters (two high- and two low-calibre skaters), and the others were hockey skaters. While figure skaters may incorporate sprinting into their training program, it is not typically a key training of their sport [3]. On the other hand, an ice hockey sprint is a typical training drill used at all levels of ice hockey, from youth leagues to professional teams [150]. As such, we expect this training to impact the sprint performance metrics differently in these two groups.

6.2.6 Lower body strength

Lower-body strength as an off-ice measurement could impact primary and secondary performance metrics. Consequently, our data analysis aimed to uncover the relationships between lower-body strength, quantified by the CMJ height, and the skater's performance, quantified by the performance metrics. Because CMJ height is a continuous variable rather than a binary variable similar to the two impacting factors above, so its corresponding data analysis approach differed. Therefore, first, acceleration and angular velocity signals were low-pass filtered using a recursive 6th-order Butterworth filter with a 40 Hz cut-off. Next, the pelvis orientation was determined from 3D acceleration during quiet standing, using this data to transform IMU readouts into the pelvis' anatomical frame, aligning the y-axis vertically. Then, the accelerometer data from a sacrum-mounted IMU was converted into a global frame, and gravitational acceleration was subtracted to obtain the sensor's free acceleration. Then, numerical double-integration of the CoM acceleration was conducted, applying zero velocity and zero vertical displacement corrections to minimize integration errors using piecewise cubic Hermite interpolating polynomial. The detailed procedure can be found here [102].

6.2.7 Data analysis

In this study, the mean values of the performance metrics in each trial were used for the statistical analysis. First, we assessed data sphericity, using Mauchly's test to measure the equality of variances among different participant trials. Then, a non-parametric Wilcoxon rank-sum test was used to examine the significance (p-value < 0.05) of variations between ice skating performance metrics grouped by different impacting factors. Then, a post-hoc analysis was performed to find the group with a higher median. Finally, Spearman's correlation coefficients were used to determine the strength of the monotonic relationship between CMJ height and the performance metrics (Figure 6.3). Also, the post-hoc power analysis was conducted using G*power [130] using a one-tailed bivariate normal model with $\alpha = 0.05$.

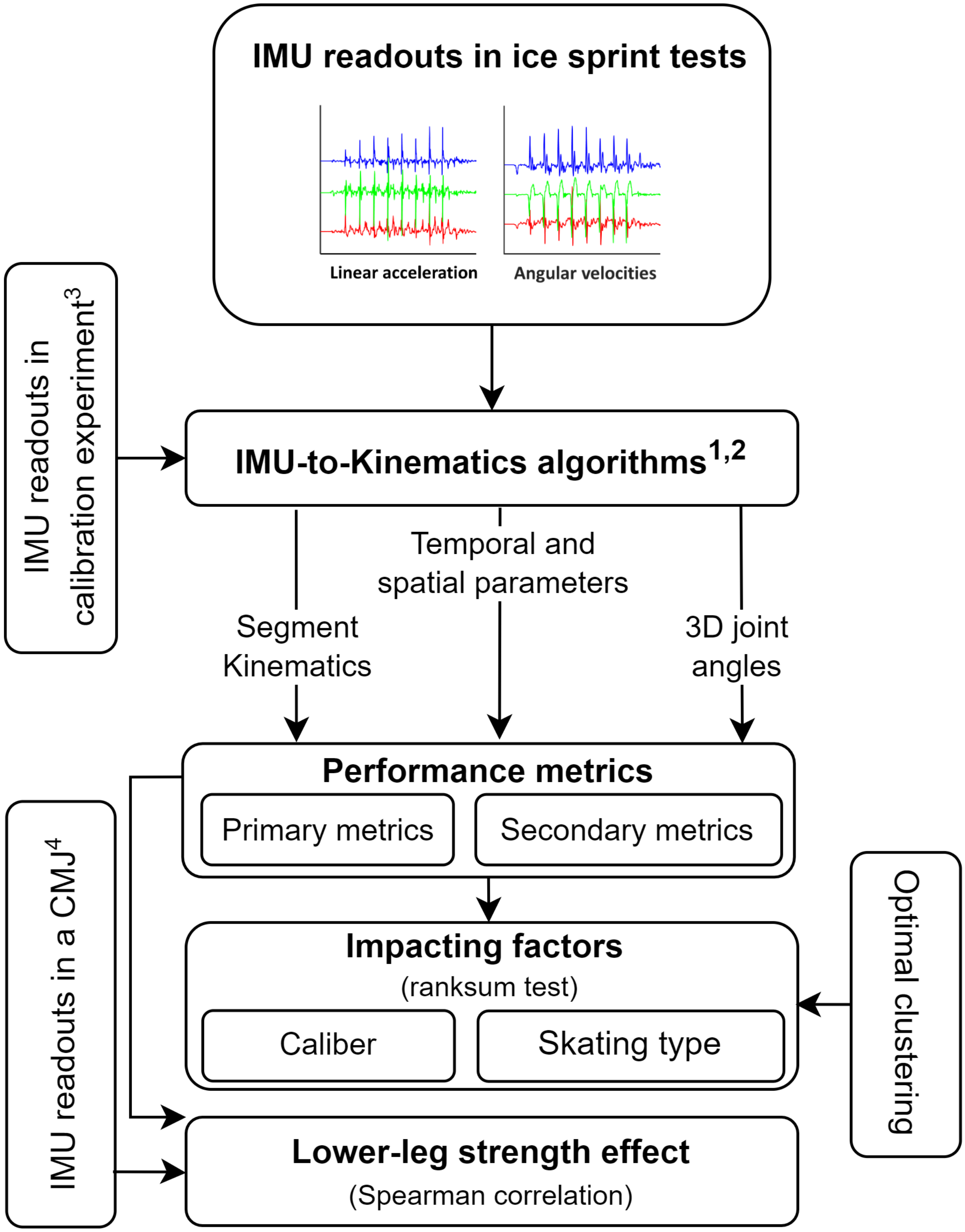

Figure 6.3: The flowchart of the data analysis steps of this study. 1,2,4. The algorithms to obtain the temporal and spatial parameters [19], the segment kinematics, and the 3D joint angles of skating [20], countermovement jump (CMJ) height [102] based on the IMU readouts were previously validated. 3. The calibration experiments consisted of ten successive hip flexions and extensions and ten successive squats after five seconds of quiet standing, which we asked the participants to perform prior to the skating experiments [124, 132].

6.3 Results

6.3.1 calibre and skating-type impact

Primary performance metrics: Skaters' stride and contact times were unaffected by any impacting factors (Table 6.2). However, stride velocity and swing time differed between low -and high-calibre skaters and the type of skating. Stride length was only significantly different between skaters of different calibres.

Table 6.2: The impact of the different impacting factors on the skater's primary performance metrics (using p-value) and the mean ± standard deviation in each group were presented.

Primary performance metrics	Calibre effect	LC	HC	Skating type	HS	FS
Stride time (s)	0.17	1.11 ± 0.10	1.13 ± 0.16	0.08	1.15 ± 0.14	1.04 ± 0.13
Contact time (s)	0.29	0.66 ± 0.11	0.61 ± 0.08	0.12	0.63 ± 0.07	0.63 ± 0.16
Swing time (s)	0.04	0.36 ± 0.19	0.52 ± 0.11	0.00	0.52 ± 0.1	0.41 ± 0.06
Stride length (m)	0.02	3.93 ± 2.34	6.74 ± 1.4	0.15	6.40 ± 2.1	4.29 ± 2.12
Stride velocity (m/s)	0.02	3.63 ± 1.55	6.11 ± 0.93	0.01	5.63 ± 1.31	2.40 ± 1.92

Secondary performance metrics: The metrics describing the 3D joint angles morphology, including stance peaks, joint angles standard deviation, range of motion, and the one directly related to the angles, i.e., lower-body angular velocities, significantly differed between skaters of different calibre (Table 6.3). However, no significant difference was discovered between multiscale entropy and continuous relative phase between high- and low-calibre skaters, except for those related to the frontal plane. Conversely, while continuous relative phase and multiscale entropy were higher in higher skaters, other secondary performance metrics were not significantly different between figure and hockey skaters.

Table 6.3: The impact of different impacting factors on the secondary metrics on the skater's performance (using p-value) and the mean ± standard deviation in each group were presented.

Secondary performance metrics		calibre effect	LC	HC	Skating type	HS	FS
Range of motion (deg)	HF	0.03	19 ± 3	41 ± 18	0.21	37 ± 19	15 ± 5
	HA	0.05	12± 2	23 ± 9	0.56	20 ± 10	23 ± 10
	KF	0.01	22 ± 10	40 ± 16	0.11	37 ± 17	20 ± 6
Lower-body angular velocity (deg/sec)	Pelvis	0.00	2 ± 1	6 ± 2	0.06	5± 2	3 ± 2
	Thigh	0.00	7 ± 4	19 ± 6	0.30	15 ± 8	7 ± 2
	Shank	0.01	14 ± 5	22 ± 9	0.25	21 ± 9	13 ± 5
	Foot	0.00	18 ± 7	32 ± 11	0.36	31 ± 10	15 ± 6
Stance peaks (deg)	HF	0.01	26 ± 11	47 ± 19	0.30	43 ± 19	27 ± 17
	HA	0.00	15 ± 3	32 ± 9	0.56	26 ± 10	31 ± 10
	KF	0.00	23 ± 5	52 ± 15	0.08	45 ± 18	36 ± 19
Joint angles standard deviation (deg)	HF	0.00	3 ± 1	5 ± 2	0.25	5 ± 2	5 ± 2
	HA	0.02	3 ± 1	4 ± 1	0.93	4 ± 1	4 ± 1
	KF	0.00	4 ± 1	5 ± 2	0.33	4 ± 1	5 ± 1
Continuous relative phase (deg)	shank-sagittal vs. thigh-sagittal	0.48	93 ± 21	109 ± 32	0.03	110 ± 27	75 ± 13
	shank-sagittal vs. thigh-frontal	0.02	105 ± 14	131 ± 25	0.05	126 ± 25	106 ± 20
	foot-sagittal vs. shank-sagittal	0.10	83 ± 21	110 ± 33	0.01	106 ± 29	80 ± 38
Multiscale entropy	HF	0.66	0.29 ± 0.06	0.28 ± 0.07	0.01	0.61 ± 0.13	0.52 ± 0.12
	HA	0.38	0.31 ± 0.11	0.38 ± 0.13	0.05	0.85 ± 0.29	0.54 ± 0.02
	KF	0.48	0.32 ± 0.08	0.33 ± 0.09	0.18	0.73 ± 0.25	0.54 ± 0.11

6.3.2 Effect of lower-body strength

High- and low-calibre skaters jumped 66 ± 18 cm and 53 ± 15 cm, respectively, off the ice, as estimated by a previously validated algorithm [102]. Also, shank-sagittal vs. thigh-frontal inter-limb coordination, stance peaks in hip adduction and knee flexion, and lower-body angular velocities and range of motion only in knee flexion had a medium correlation with CMJ height. Also, a medium correlation with higher power (power > 0.8) was observed between CMJ height range of motion and stance peaks in knee flexion. The results showed a weak or negligible correlation between CMJ height and all the other primary and secondary metrics (Table 6.4).

6.4 Discussion

We studied the 3D kinematics of figure and hockey skaters using wearable IMUs and assessed their performance during an ice skating sprint test. For the first time, the skater's performance was expressed into two groups of primary and secondary performance metrics, both measured using the wearable IMU, where primary metrics are traditionally regarded as the skater's overall performance. Secondary performance metrics, on the other hand, enrich the assessments of ice skaters' performance and enhance our understanding of the relationship between off-ice and on-ice skating parameters. First, we assessed the effects of different impacting factors, i.e., skater's calibre and skating type (figure or hockey skating) on the skaters' performance metrics. We showed how both primary and secondary performance metrics could highlight their impacts. We found that the rhythm of skating, indicated by stance time and contact time, was barely affected by any of the impacting factors, while the spatial parameters of skaters were impacted by skating type and skater's calibre. As such, we investigated how primary and secondary metrics, all measured on ice using wearable IMUs, may reveal different aspects of skaters' performance. Finally, we investigated how primary and secondary performance metrics correlated with the skaters' lower-

Table 6.4: The correlation between the primary and secondary performance metrics and the CMJ height. The post-hoc power analysis was conducted using a one-tailed bivariate normal model with = 0.05, shown in the bracket.

	Performance metrics		**Correlation coefficient (power)**
Primary performance metrics	Stride time		0.16 (0.16)
	Contact time		0.05 (0.07)
	Swing time		0.22 (0.23)
	Stride length		0.27 (0.30)
	Stride velocity		0.25 (0.27)
Secondary performance metrics	Range of motion	HF	-0.10 (0.10)
		HA	0.38 (0.5)
		KF	0.59 (0.88)
	Lower body angular velocity	Pelvis	0.32 (0.39)
		Thigh	0.39 (0.53)
		Shank	0.41 (0.56)
		Foot	0.32 (0.39)
	Stance peaks	HF	-0.20 (0.21)
		HA	0.42 (0.58)
		KF	0.61 (0.90)
	Joint angles standard deviation	HF	0.15 (0.15)
		HA	-0.04 (0.06)
		KF	0.19 (0.12)
	Continuous relative phase	shank-sagittal vs. thigh-sagittal	-0.04 (0.06)
		shank-sagittal vs. thigh-frontal	0.40 (0.54)
		foot-sagittal vs. shank-sagittal	-0.23 (0.25)
	Multiscale entropy	HF	0.27 (0.30)
		HA	0.08 (0.09)
		KF	-0.08 (0.09)

body strength characterized by CMJ height off the ice. Therefore, the introduced IMU-measured metrics not only broaden our understanding of on-ice skating but also can potentially identify relevant off-ice tests that can predict on-ice performance or vice versa.

6.4.1 Skaters' calibre impact

The stride length and stride velocity of the high-calibre participants were significantly higher than those of low-calibre skaters (Table 6.2), consistent with Upjohn et al. [7]. Larger strides can help players cover more distance with each push and also require more power for high-calibre skaters, while the skating rhythm (indicated by stance time and contact time) was not significantly different between the calibre-based groups. High-calibre skaters had significantly higher standard deviations in the 3D joint angles of their dominant leg in each repetition of sprint tests, which occurred despite no significant difference in multiscale entropy between these two groups (Table 6.4). A difference in joint angles standard deviation indicated a difference in the variability of joint angles in different strides of their skating trial between high- and low-calibre skaters, whereas similar multiscale entropy values suggest that the complexity or irregularity of the joint angle patterns were not different in both groups. Contrary to Robbins et al. [73], continuous relative phase analysis revealed no significant difference between high- and low-calibre skaters, which might stem from the different definitions of calibre and different levels of participants in their study. This inconsistency further highlights the necessity and rationale behind proposing a more objective clustering method proposed in this study. Only shank-sagittal vs. thigh-frontal coordination was found in our study to be higher in high-calibre skaters. Finally, high-calibre skaters exhibited a greater range of motions, stance peaks, and higher angular velocities (Table 6.3). Higher ranges of motion, stance peaks, and higher segment speed during skating are crucial for executing robust and stable skating movements, efficient weight transfer, and proper push and blades off during skating. Specifically, the hip ranges of motion during skating are crucial for proper stride length and power generation and are essential for generating power and propulsion during skating strides. Also, proper knee flexion range is essential for executing robust and stable skating movements during skating. Therefore, higher ranges of motion in high-calibre skaters result in more efficient weight transfer, higher stride length, and proper push and blades off during skating.

6.4.2 Skating type impact

The biomechanics of hockey and figure skating differ due to the different skate designs and the specialized skill training required for each sport [21, 60]. However, hockey coaches may incorporate figure skating skills, drills, and techniques into their drills [21], and thus, hockey coaches must fully understand the difference between figure and hockey skating biomechanical performance. In this study, it was observed that hockey skaters (height: 172 ± 10 cm, weight: 73 ± 13 kg, stability: 2.7 ± 1.0, balance: 2.6 ± 1.0, fitness: 3.1 ± 0.7, ten male and five female) had higher swing time and stride velocity than figure skaters (height: 163 ± 5 cm, weight: 64 ± 6 kg, stability: 2.6 ± 1.4, balance: 2.4 ± 1.4, fitness: 3.0 ± 0.9, four female). Notably, there was no significant difference between the rated performance of figure and hockey skaters in this study. Additionally, these groups had no significant difference in stride time, stride length, and contact time (Table 6.2). In contrast to the difference between skaters of different calibre, higher multiscale entropy and lower inter-limb coordination values suggest that the irregularity and the coordination of the 3D joint angle were higher in hockey skaters than figure skaters (Table 6.3). Figure skates have been designed to maximize stability and control during intricate movements and have a longer blade with toe picks at the front for a larger surface area for precise movements. Conversely, hockey skates are designed for speed and agility, have shorter blades, and lack toe picks for quicker turns and acceleration [1, 30]. Therefore, the observed differences in inter-limb coordination and variations in skating patterns between figure and hockey skaters were likely attributable to their training and their skate designs. These differences in the performance metrics could have also been estimated prior to measurements on ice using off-ice measurements, such as vertical jump tests.

6.4.3 Effect of lower leg strength

CMJ requires motor coordination and complex lower and upper limb movements [82, 151]. In this study, the CMJ height, as one off-ice measurement, weakly correlated with both stride velocity and stride length, with correlation coefficients of 0.27 and 0.19, respectively, consistent with the results observed in previous studies involving various age groups [82, 84]. The CMJ height also had a moderate correlation (correlation coefficient > 0.4) with lower-body angular velocities. However, the CMJ height showed a stronger correlation (correlation coefficient: 0.59 and 0.61, power > 0.8) with the range of motion and stance peaks in knee flexion (Table 6.4). Therefore, the CMJ height can only predict a few secondary performance metrics with moderate correlation, which supports lower CMJ height dependencies of skating velocity as a primary performance metric. From ice skating physiology, only a few lower-body muscles, such as the Biceps Femoris and hip adductors, are involved during a vertical jump [152]. Consequently, a higher CMJ height may only exhibit a moderate-to-strong correlation with performance metrics that require activation of the same muscle groups. Therefore, the broadened performance metrics introduced in this study can potentially direct research toward identifying more appropriate off-ice measurements. These tests, which target various muscle groups and synergies, could significantly improve the accuracy of predicting on-ice skating performance based on off-ice measurements. Consequently, the correlation of other off-ice tests on these primary and secondary metrics must be further explored.

6.4.4 Limitations

First, a larger sample size can enhance the performance and power of the study analyses. Also, including Olympic-level professional hockey and professional figure skaters will broaden the study's output to a more diverse group of skaters. Second, hockey skaters did not use their hockey sticks while skating, primarily due to constraints posed by the experimental setup and the ice rink's limitations. The absence of hockey sticks could potentially influence their skating patterns. Nevertheless, it facilitated the comparison of skating profiles between figure and hockey skaters, as neither group used hockey sticks. Third, besides the skater's calibre and skating type, the skaters' demographics (such as sex and height) could also impact performance metrics such as stride length and speed, as reported by [4]. Although this is a limitation in our study, our primary goal was to show how the wearable IMUs could show the difference between groups rather than isolating the impact of a skater's calibre or skating type on a single performance metric.

6.5 Conclusions

In this study, we examined the on-ice kinematics measurement of ice skaters using IMUs and studied the difference between the ice skating kinematics as a function of participants' calibre and skating type during an ice skating sprint test. It was discovered that figure skaters skated with lower irregularity and more inter-limb coordination but slower than hockey skaters in ice sprint tests. Although lower body strength seemed to affect a few of the performance metrics, it still could not explain all the overall performance differences of this study population. The outcome of this study can assist coaches in making more informed decisions when selecting figure skating drills for hockey players. Additionally, secondary performance metrics have the potential to facilitate the introduction of more explanatory off-ice tests capable of predicting on-ice test performance by expanding our understanding of ice skating performance. Finally, IMU-based wearable technology has the potential to help us understand the skating of recreational hockey and figure skaters, who are usually overlooked in ice skating studies. Further, this technology has the potential to offer valuable insights and recommendations for enhancing sprint performance while mitigating the risk of injuries.

Chapter 7

Conclusions, recommendations, & future work

This chapter summarizes the results and presents the future directions for this thesis research.

7.1 Main outcomes and original contributions

7.1.1 Development of IMU wearable technology

Employing the technical innovations and novel algorithms presented in this thesis, we developed and validated a wearable sensor technology for measuring temporal and spatial parameters and 3D joint angles for ice skating performance assessment.

Measurement of temporal and spatial parameters using wearable sensors

First, we optimized this technology to measure physiologically relevant lower-limb joint angles and detect temporal and spatial events in ice skating. We implemented 11 methods to detect temporal events in ice skating using IMU readouts. We showed that the proposed algorithms effectively identified skating events with an average one sampling period (0.01 sec) error. Additionally, we introduced four innovative approaches to correct the estimated player position used for stride length estimation, addressing issues of sensor drift and integration of errors. Therefore, we were able to accurately obtain contact time, stride time, length, and velocity for ice skaters and achieve a similar level of accuracy to conventional IMU-based gait analysis.

Assessment of three-dimensional kinematics of high- and low-calibre hockey skaters on synthetic ice

Furthermore, we successfully obtained 3D joint angles of ice hockey skaters using our IMU-based wearable technology and validated its accuracy against a camera-based motion capture system. An intriguing finding from our research was the change in skating patterns observed when skaters used synthetic ice. We showed that synthetic ice alters the skaters' skating patterns such that the on-ice distinctive features could not differentiate low- and high-calibre skaters on synthetic ice. Therefore, understanding the biomechanics of skating on synthetic ice and comparing it to those on ice is crucial, as synthetic ice presents a viable alternative for on-ice skating. Finally, to adapt effectively, we suggest skaters of all levels dedicate time to becoming familiar with synthetic ice through consistent practice. Additionally, skating coaches must understand these differences when they train their players for competitions when monitoring is conducted remotely.

7.1.2 Biomechanical assessment of on-ice skating

The validated 3D skating kinematic measurements are instrumental in developing performance metrics that quantitatively capture skating effectively. The next phases of this thesis research involved on-ice experiments to analyze player performance directly in their natural environment using this validated 3D kinematics.

Variation of kinematic metrics with perceived fatigue

First, we developed a novel algorithm to classify the participants into skill-based groups using the skating videos rated by hockey experts. This algorithm not only proved effective for our study but also has the potential to be a standard classification tool across various sports. Then, nineteen ice skaters were recruited to perform multistage aerobic skating. We showed the relationship between perceived and performance fatigue in skaters of different skill levels, where we showed how our proposed kinematic metrics could also indicate perceived fatigue. In the multistage aerobic skating test, we also showed how machine learning could detect the onset of severe fatigue using a combination of our proposed kinematic metrics. We observed that these kinematic metrics were able to predict severe self-reported fatigue across different skill levels. The concurrent study of perceived and performance fatigue will elucidate the intricate relationships among different fatigue dimensions and thus enhance our understanding of how these dimensions interact and are influenced by various modulating factors.

Assessing ice skating sprint performance using wearable sensors

In the next phase, the ice skater's performance, for the first time, was expressed into two groups of primary and secondary performance metrics. Primary performance metrics, including stride length, stride velocity, stride time, contact time, and swing time, are traditionally regarded as the skater's overall performance metrics in ice sprint tests. Secondary performance metrics, on the other hand, enrich the assessments of ice skaters' performance regarding skating regularity, inter-limb coordination, and segment kinematics and enhance our understanding of the relationship between off- and on-ice measurements. Using the proposed metrics, we discovered that figure skaters skated with lower irregularity and more inter-limb coordination but slower than hockey skaters in ice sprint tests. We also observed that although lower body strength seemed to moderately affect the metrics related to knee flexion, it still could not explain all the differences in the performance metrics of this study population. Therefore, by expanding our understanding of ice skating performance, secondary performance metrics have the potential to facilitate the introduction of more explanatory off-ice tests capable of predicting on-ice performance.

The performance metrics on ice can be predicted through off-ice measurements, saving considerable labour and time. The IMU-measured metrics introduced in this study not only enhance our comprehension of on-ice skating dynamics but also hold promise for identifying off-ice tests that can predict on-ice performance. Furthermore, this investigation will enable the identification of specific on-ice performance metrics that correlate with certain off-ice training activities. Consequently, by utilizing these comprehensive insights, athletes can concentrate on off-ice exercises that are most effective in enhancing their on-ice abilities, thereby improving performance outcomes. This targeted approach to training could also contribute to more effective performance enhancement by ensuring athletes engage in physical preparations that directly benefit their on-ice performance.

7.1.3 Thesis research outcome and significance

The outcome of this thesis research equips skating coaches with precise tools for analyzing and improving their training strategies, enhancing the learning outcomes for their trainees. This wearable IMU technology enables coaches and trainers to monitor skaters' progress with detailed performance assessments, offering the added advantage of remote supervision during their training sessions on ice and synthetic ice. Our research extended its potential benefits to the often-overlooked demographic of recreational hockey and figure skaters, showcasing its broad applicability. Finally, considering the significant financial implications of injuries such as NHL players' concussions, our findings represent an important step towards a more data-centric approach in hockey skating. This approach was an essential step toward understanding fatigue and preventing fatigue-induced injuries, marking a potential giant leap in ice skating health and safety.

7.2 Future work

Objective biomechanical assessment in ice skating can be effectively leveraged for early detection of severe fatigue onset, consequently reducing the risk of fatigue-induced injuries. This wearable technology has the potential to uncover the shortcomings in current training methods, potentially aiding in reducing internal joint forces and moments and analyzing muscle activation during skating. The broader applications and implications of this technology and related methodology warrant further use of this technology for professional matches in future studies.

7.2.1 Expanding applications

This technology's inherent flexibility and adaptability make it an indispensable resource capable of accommodating a variety of skating styles and modalities, including specific adaptations for hockey matches. Additionally, using this IMU wearable technology allows for a more feasible data collection during puck shooting due to its reduced obstruction and more accessibility compared to motion capture systems. Moreover, integrating this wearable technology with cutting-edge machine learning algorithms enhances its accuracy and precision, thereby boosting its marketability. Therefore, this technology's adaptability opens avenues for its application in a wide range of skating disciplines and a promising future for athlete training and skill development.

Another key direction for future work involves addressing the challenges associated with implementing this technology and developing an efficient user interface. Enhancing the user experience through user-friendly interfaces will ensure that athletes, trainers, and coaches can easily access and interpret the data obtained from the wearable technology's output. Making the technology user-friendly will not only increase its adoption in training routines but also maximize its potential to facilitate skating assessments by coaches and trainers.

Finally, expanding the scope of this technology to other winter sports represents a promising opportunity for future work. By adapting and applying the wearable technology developed for ice skating to sports like skiing, snowboarding, and speed skating, researchers can provide more comprehensive biomechanical insights across a broader spectrum of winter athletics. This expansion can further facilitate cross-disciplinary improvements in training methods, injury prevention strategies, and performance optimization in other winter sports.

7.2.2 Expanding biomechanical analysis

Another promising avenue for future research is expanding the biomechanical analysis to estimate joint forces and moments. A comprehensive kinetic analysis of skaters of different calibres can be conducted using a combination of the proposed technology with wearable pressure insoles fitted in the skates. This approach would allow for a more detailed study of the forces exerted by skaters on the ice, providing insights into biomechanical efficiency and potential areas for improvement for junior ice skaters. Such analysis could lead to better-informed decisions regarding training modifications and equipment choices, ultimately enhancing skating performance.

Furthermore, to fully harness the potential of this technology, future research should expand its scope to muscle activity analysis through musculoskeletal modelling or EMG analysis, promising a comprehensive biomechanical skating study. Understanding the variations in muscle activity will enhance the customization of training programs, addressing each athlete's unique physiological and biomechanical needs. This comprehensive approach to skater development promises not only to elevate individual performance but also to contribute significantly to the broader field of sports science.

7.2.3 Expanding insights into fatigue dynamics

Drawing on the findings of this study, IMU-based performance assessments have the potential to offer a strategic advantage in identifying early signs of severe fatigue, thereby minimizing the risk of injuries associated with fatigue. By employing automatic detection of players' fatigue, timely substitutions can be made, thereby decreasing the likelihood of injuries with chronic consequences. Also, coaches and trainers can gain insights into the physical condition of athletes in real time. This data-driven strategy ensures that interventions are not just reactive but also proactive, allowing for adjustments in training intensity, duration, and recovery periods based on objective measures of fatigue. Furthermore, this wearable technology's output can inspire a solution to a pivotal challenge in ice skating training: minimizing impact forces on joints and the upper body during skating. Such technological advancements in sports science can revolutionize how athletes are managed, promoting longer, healthier careers and optimizing performance through enhanced injury prevention strategies.

Finally, our research opens the door to exciting novel studies by illustrating how performance and perceived fatigue interact in ice skating. However, fatigue encompasses a complex interplay of factors that extend beyond mere physical exhaustion, making its assessment during activities like ice skating particularly multifaceted. Thus, we highlight the necessity of a holistic approach to fatigue measurement, combining kinematic metrics obtained by the proposed technology with non-kinematic metrics that provide insight into the physiological and psychological dimensions of fatigue. By integrating these diverse metrics—kinematic, physiological, psychological, and cognitive—future studies can offer a more comprehensive understanding of fatigue in ice skating. Additionally, these future studies will broaden our understanding of the interactions and effects between different dimensions of fatigue. They will set the stage for the development of innovative training and recovery strategies tailored to the complex nature of fatigue, showcasing the transformative potential impact of this line of research in advancing the field of sports science.

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