applied sciences

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Development and Reliability of a Street Skateboarding Notational Analysis Framework and Application

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Abstract: Notational analysis (NA) systems are regularly used to quantify sports performance but have not been adopted in competitive skateboarding. In this study, we aimed to develop an NA application to quantify outcome-related aspects of skateboarding judging criteria (trick selection, obstacle selection, and execution), leveraging known skatepark obstacles and trick classification from public broadcast footage (60 Hz) of the Tokyo 2020 Olympic Men's and Women's semi-finals. We also assessed the intra- and inter-rater reliability of frame selection for key trick attempt events—take-off, event (obstacle interaction) start and end, and landing. Frame selection from 593 trick attempts (male = 324, female = 269) were found reliable (mean absolute difference (MAD) < 3 frames) by a single, experienced rater. Take-off (MAD: intra-rater = 1.43, inter-rater = 3.82 frames) and landing frame (MAD: intra-rater = 1.33, inter-rater = 1.55 frames) were more reliably selected than obstacle interaction (MAD: Inter = 2.04–2.26, Inter = 3.62–4.35 frames), attributed to obstacle and trick type. Generally, trick attempts over longer durations appeared less reliable, but still within useable limits; as such, the NA approach used in this study could be used for describing and understanding performance in elite street skateboarding.

Keywords: sports performance; performance analysis; Olympics; trick classification; video analysis; airtime

Academic Editors: Samo Rauter and Darjan Smajla

Received: 8 March 2025
Revised: 22 April 2025
Accepted: 28 April 2025
Published: 30 April 2025

Citation: Diewald, S.N.; Noth, N.; Mancini, N.; Neville, J.; Cronin, J.; Cross, M.R. Development and Reliability of a Street Skateboarding Notational Analysis Framework and Application. *Appl. Sci.* **2025**, *15*, 5011. https://doi.org/10.3390/app15095011

1. Introduction

Street skateboarding debuted at the Tokyo 2020 Olympic games and is approved for Los Angeles 2028 after its inclusion in the Paris 2024 games [1]. Inclusion into the Olympic programme has accelerated the professionalisation of skateboarding, driving more skaters to train to compete on the world stage [2]. To effectively support athletes navigating the evolving landscape, we need a comprehensive understanding of performance to identify and enhance the capacities that underpin success [3]. A first step to support street skaters in competition is the objective definition and measurement of aspects of performance, before understanding how success is determined.

In competitive street skating, athletes must interact with obstacles in the environment, performing technical tricks through complex board and body movement [4]. In current competition formats, skaters perform isolated tricks on obstacles (best-trick (BT)) and/or a sequence of tricks linked together around the skatepark (RUN) [5]. Success in Olympic competitions is determined by judges who utilise a set of criteria such as trick and obstacle difficulty, variety, and execution, to award an overall impression score for each attempt in order to rank performances in that competition round [6]. Whilst some criteria—like execution quality and style—appear subjective, they may have objective underpinnings (e.g., height, speed, or distance travelled) [6] that could be systematically evaluated. However, the subjective application of these criteria, coupled with impression scoring overall, complicates tying specific judging decisions to measurable, targetable, or trainable performance attributes. Accordingly, coaches and athletes lack understanding of performance metrics upon which to train to perform—a fact which is made even more difficult by diverse and evolving competition formats, and the inherent technical complexity and creative variability of tricks performed [7].

Performance analysis (PA) is a systematic process of examining sports performance [8] to provide insights into tactics and strategies [9]. The goal of PA is to capture factors related to how and why outcomes (e.g., winning) occur [10]. PA could be a useful strategy to identify differences between successful and less successful performances [11]. Yet, despite its adoption in many Olympic sports [12], no researchers have yet explored the application of PA approaches in skateboarding. As the tactical demands of competitive skateboarding remain ambiguous [5], a PA system tailored to the unique context of street skateboarding is warranted.

One PA method by which objective performance data can be captured [13] is notational anlaysis (NA). NA systems are often employed in traditional sports [14] to retrospectively extract spatio-temporal variables to systematically quantify athlete activity from video footage [15]. This method is particularly beneficial when freestyle athlete movement across a large 'field of play' is integral to performance, such as in the board sports surfing [16,17] and snowboarding [18]. Despite relevance, NA has yet to be fully adopted in skateboarding [5]. However, the growing availability of high-quality broadcast footage (e.g., X-Games and Olympics) and recent validation of video-derived temporal trick metrics [19–21], supports the use of an NA approach to use broadcast footage to quantify spatio-temporal performance aspects of trick selection, obstacle selection, and execution judging criteria.

Therefore, the aim of this research was to design an NA system and protocol to capture potential outcome-impacting aspects of competitive street skateboarding performance. Additionally, we aimed to test reliability of the system for measuring style-focused spatio-temporal metrics from broadcast footage, leveraging performances during the semi-finals of the 2020 Tokyo Olympics street skateboarding debut.

2. Materials and Methods

The following section details the design, development, and testing of a custom NA application to quantify aspects of street skateboarding tricks. Although a uniquely built NA tool developed to analyse the Tokyo Olympics street skateboarding competition is described, the overarching NA system and process were designed to be generalisable to other skateboarding competitions and PA software.

A video-based NA application was developed using scatter diagrams, frequency tables, and sequential data collection systems [13] to retrospectively code skateboarding broadcast footage. The construction of an NA system requires consideration of key elements (i.e., player, position, action, time) that are fundamental to all such systems, the intended level of analysis (i.e., team, individual), and how the required information is to be gathered [15]. Therefore, the following sections explore the design of the NA process to record the following key elements: position (obstacle), player (skater), action (trick) and subsequent outcome, and time.

A systematic, mixed-methods approach was used to describe street skateboarding motion. The qualitative approach described by Knudson (2007) was harnessed iteratively—(1) preparation of relevant knowledge using personal experiences, expert opinions, and scientific research, (2) systematic observation, and (3) evaluation of the system to identify weaknesses—and is described in subsequent sections [22].

2.1. Participants

The NA system was designed to be used with any street skateboarding competition video footage. To test the aims, publicly available video footage of the 2020 Tokyo Olympic men's and women's street skateboarding competition (https://olympics.com/, access date: 5 March 2022) was used. The data were high quality (~1080p, 60 frames per s) and formatted for broadcast (e.g., varying camera angles and zoom compiled into a single stream). Only the semi-final round was analysed to capture a consistent range of skill and trick varieties across the men's and women's competitions.

World Skate defines the competition format and rules for Olympic events [6]; however, most street skateboarding competitions follow a similar structure, and as such will be the focus of this paper. Typically, competition format varies by round. In the open qualifier and quarterfinal (preliminary) rounds, skaters often perform only RUNs, taking the best score. In semi-final and final rounds, skaters perform both RUN and BT attempts, with the total number of attempts, score range, and final round score varying depending on the format chosen (e.g., 2-5-4, 2-5-3, etc.). A 2-5-4 format was utilised during the Tokyo 2020 Olympics. In the semi-finals, 4 heats of 5 athletes per sex skated against each other. Skaters performed 2 RUNs of 45 s each, followed by 5 BT attempts, and the top 4 scores (of 7) combined to make the athlete's overall score (2-5-4 format) and ranking for the round. Notably, following the Tokyo Olympics, World Skate transitioned to a 2-5-3 format for street skateboarding, combining the top RUN score and 2 BT scores to form the final round score. Due to it being in its infancy, evolution in the sport is expected; the NA application was designed to accommodate this and any future format changes.

Specific to the Tokyo Olympics, in each heat of the semi-finals, all skaters performed their first RUN before proceeding to their second, followed by a break before beginning the BT attempts in the same fashion. For all RUN and BT attempts, athletes were judged on a point scale from 0.00 to 10.00. Athletes who did not land (bailed) their BT attempt automatically scored a 0.00 for that trick. However, in a RUN, an athlete could bail any number of tricks but continue to attempt to improve their score during the time limit [23]. Demographics and skating characteristics of each skater were retrieved from the World Skate official website (https://www.worldskate.org/skateboarding.html, access date: 5 March 2022).

2.2. Key Elements

The process of breaking street skateboarding skill down into its functional parts is an important first analytical step. For all key elements of tricks, a phased approach was used to divide up the trick (movement) into relevant portions such that attention could be focused on the technique (performance) of each [24]. Three phases were identified based on expert knowledge: take-off (TO), event (obstacle interaction) (IA), and landing (LD). This modified three-phase approach follows traditional sports PA [22], which breaks a skill up into preparation, action, and follow-through phases.

2.2.1. Position (Obstacle)

A scatter diagram was used to capture the skater's position corresponding to discrete obstacles at each TO, IA, and LD phase per trick attempt (TA) (Figure 1). Then, specific obstacle details and type could be defined and attached to each discrete position in the skatepark. Each skatepark is unique; however, there are design features common across competition fields of play by which obstacles can be defined consistently [25]. For example, skateparks are often developed in a mirrored design to equally accommodate goofy and regular stance skaters [26]. In the dataset for this study, the Tokyo 2020 Ariake Urban Sports Park (Figure 1) was coded, and the full list of obstacles and associated details are available online (https://osf.io/n9bjy/). Most obstacles had a mirrored counterpart on each longitudinal side of the park and "bowl-side" (top of centre, Figure 1) and "stand-side" (bottom of centre, Figure 1) were used to distinguish between the two. All "centre" obstacles, without mirrored counterparts, were labelled as such. More broadly speaking, prior to analysing a competition, standard position/obstacle metrics can be pre-defined, including the following: location within the park (e.g., bowl-side, stand-side, etc.), obstacle type (e.g., flat ground, rail, bank, gap, ledge, quarterpipe, etc.) (Figure 1) and a detailed description unique to that obstacle type (e.g., round rail, square rail, coping, bank to flat, A-Frame hubba ledge, etc.). Then, for a specific skatepark, a unique identifier (obstacle number) for each obstacle can be set; associated with standardised metrics (location, type, description), by which subsequent performance can be compared across parks and competitions. However, notably, a degree of subjectivity is inherent when determining obstacle location, type, and description as described above. Nevertheless, notating position is a compromise between accuracy and having manageable data, and the decision was taken to lean towards the latter, with practical implications in mind, the limitations of which are discussed [13].

Figure 1. Image of Ariake Urban Sports Park from the Tokyo 2020 Olympic Games street skateboarding competition. Colours represent the obstacle type, and numbers represent the unique identifier (obstacle number). Some numbers shown on the screen represent unpictured mirrored (#108, #72, #19) obstacles which are not visible (#123, #125, #126). Mirrored obstacles are represented

with those on the top half of the image as "bowl-side" and the bottom half as "stand-side". For example, a visual example of tracking a skater's discrete position throughout the park for each trick attempt (TA) would include the phases of the TA: take-off (TO) (#106), event (obstacle interaction) (IA) (#59), and landing (LD) (#42). Accessed and modified from https://www.skateboarding.worldskate.org/news/1478-tokyo-2020-course-designs.html.

2.2.2. Player (Skater)

Player (skater)-related metrics were coded once per RUN or BT attempt. Demographics and skating characteristics related to the skater in competition included nationality, age, sex, and preferred stance (goofy or regular). The frequency of coding player meta data will depend on the video length and contents specific to the use case.

2.2.3. Action (Trick Attempt)

The most important aspect of defining an action or outcome is ensuring the operational definition of the action is clear and unambiguous [13]. Street skateboarding tricks were grouped to allow for subjective interpretation of style, encompassing athletes' individualisation and nuanced trick variations in a way where trick difficulty and variation could be assessed. Regarding the action, a "trick attempt" (TA) was defined when a skater popped the board to perform a movement with the board and/or obstacle, and then subsequently attempt to land on the board. The NA application allowed for the ability to code a free text trick name (common skateboarding nomenclature) associated with each TA ($trick_{TA}$). All tricks where a skater popped their board (any number of wheels left the ground) were considered TAs; however, kick-turns or reverts alone, such as to change direction, were not considered a TA, but rather a "redirection", coded but removed from any analysis (as noted). Of importance, in skateboarding a redirection is often used to set the skater's position and stance before the next trick, with a matter of intent by the skater. To avoid subjectivity in what TAs to include or not, all movements where any number of wheels left the ground were coded, including potential redirection tricks, such as fundamental stalls often performed on quarterpipe coping (50–50 stalls, rock to fakie) (https://osf.io/n9bjy/). Thus, selected potential redirection tricks could be filtered out during post-processing if desired, ensuring generalisability to suit a practitioner's specific needs.

A best trick (BT) TA was a single trick, and a RUN was made up of consecutive TAs. For this analysis, each TA encompassed the three phases: TO, IA, and LD (Table 1). For each phase, stance (regular, switch, fakie, nollie), skater rotation amount (degrees) and body rotation direction (front-side (FS), back-side (BS)), obstacle approach direction (FS, BS), trick category (fundamental, flip, grind/slide, air/grab/stall, balance, freestyle, or not applicable), and category trick name (e.g., ollie, crooked grind, boardslide, etc.) were recorded (Table 2). The pre-defined lists used for this analysis and all coded TAs from the semi-finals competition are in the online material (https://osf.io/n9bjy/). To note, the three phase approach was selected to encompass the vast majority of street skateboarding tricks at the time [27]. However, as the sport inevitably evolves, this process could accommodate more than three phases, possibly through the inclusion of sub-phases.

Table 1. List and definitions of notational analysis acronyms including phases of trick attempts and a specific example from the Tokyo Olympics.

Trick	Acronym	Description (Example from Tokyo Olympics Semi-Finals)
Trick Attempt	TA	Skater pops board and performs movement(s) to interact with board and/or obstacle. Broken into TO, IA, and LD phases. TA naming aligns with skateboarding nomenclature. (e.g., TA name = Half Cab + FS Noseslide + Varial Heelflip)
Best-Trick Attempt	BT	Single TA; multiple BT TAs are often performed in a competition round. (e.g., 5 BT TAs)
Run Attempt	RUN	Timed attempt, made up of any number of consecutive TAs. Multiple RUNs often performed in a competition round. (e.g., 45-s, 2 RUNs per skater)
Trick Phase—Take-off	TO	Period from pop of board to start of event/interaction (IA) phase. Skaters will not always perform a trick during this period; like when popping the board in a different stance (e.g., nollie). However, to increase trick difficulty, skaters will often rotate or flip into IA phase grinds/slides. (e.g., **Half Cab** + FS Noseslide + Varial Heelflip)
Trick Phase—Event (Interaction)	IA	Period from start to end of 'obstacle' interaction (e.g., grind/slide). In case of a flip trick, this would be the airtime of a flip trick. (e.g., Half Cab + **FS Noseslide** + Varial Heelflip)
Trick Phase—Landing	LD	Period from end of obstacle interaction until landing. Like TO, might only include landing (no tricks), but often skaters will rotate or flip out of event phase grinds/slides. (e.g., Half Cab + FS Noseslide + **Varial Heelflip**)

TA, trick attempt; FS, front-side; BT, best-trick; TO, take-off; IA, event/interaction; LD, landing.

Table 2. List of trick attempt coded features of key elements (action, outcome, position, time) and associated descriptions.

	TA: Associated Feature Name (*Acronym*)	Feature Description	Example
Attempt	Attempt Type	Whether TA occurs during RUN or BT	RUN or BT
	Attempt Number	Sequential order of RUN or BT attempt	RUN = 1 or 2 BT = 1, 2, 3, 4, or 5
Trick Attempt (TA)	TA Number	Sequential order of TAs	RUN = 1, 2, 3, …+ BT = 1
	Trick Name (*trick$_{TA}$*)	Skateboarding nomenclature (common street trick name)	e.g., Half Cab + FS Noseslide + Varial Heelflip

Phase Level—Take-off (TO)	TO Stance *(stance$_{TO}$)*	Stance skater pops board to perform TA	Regular, switch, nollie, fakie
	TO Trick Type *(trick-type$_{TO}$)*	Trick type category describing movement during TO phase	Fundamental, flip, grind, slide, air/grab/stall, balance, freestyle, or not applicable
	TO Trick Name *(trick$_{TO}$)*	Skateboarding nomenclature for trick during TO	e.g., Ollie, Nollie, Half Cab, Cab, BS 180, etc.
	TO Obstacle Number *(obstacle$_{TO}$)*	Obstacle skater pops board from during TO; Predetermined obstacle type *(obst-type$_{TO}$)* and obstacle description *(obst-desc$_{TO}$)* associated	e.g., 1, 2, …131
Phase Level—Event/Interaction (IA)	IA Stance *(stance$_{IA}$)*	Stance during IA phase movement (typically same as TO stance)	Regular, switch, nollie, fakie
	IA Trick Type *(trick-type$_{IA}$)*	Trick type category describing movement during IA phase	Fundamental, flip, grind, slide, air/grab/stall, balance, freestyle, or not applicable
	IA Trick Name *(trick$_{IA}$)*	Skateboarding nomenclature describing movement performed during IA phase	e.g., BS Boardslide, 360 Flip, Tail Stall, etc.
	IA Obstacle Number *(obsaclet$_{IA}$)*	Obstacle skater interacts with (TA on/with/over/etc); predetermined obstacle type *(obst-type$_{IA}$)* and obstacle description *(obst-desc$_{IA}$)* associated	e.g., 1, 2, …131
Phase Level—Landing (LD)	LD Stance *(stance$_{LD}$)*	Stance skater lands in; typically, regular or fakie; if stance$_{TO}$ and stance$_{IA}$ are both switch, stance$_{LD}$ is also switch	Regular, switch, or fakie
	LD Trick Type *(trick-type$_{LD}$)*	Trick type category describing movement during LD phase	Fundamental, flip, grind, slide, air/grab/stall, balance, freestyle, or not applicable
	LD Trick Name *(trick$_{LD}$)*	Skateboarding nomenclature describing additional movement, if any, during LD phase	e.g., kickflip, BS 180, etc.
	LD Obstacle Number *(obstacle$_{LD}$)*	Obstacle skater lands on to end TA; Predetermined obstacle type *(obst-type$_{LD}$)* and obstacle description *(obst-desc$_{LD}$)* associated	e.g., 1, 2, …131

TA, trick attempt; BT, best-trick; TO, take-off; IA, event/interaction; LD, landing; FS, front-side; BS, back-side. The level (attempt, trick attempt, phase) that these features are coded is included to show hierarchy.

2.2.4. Subsequent Outcome(s)

The outcome of a TA was defined as; (1) whether the skater landed or bailed the TA, and (2) the judges' scores (RUN score, BT score, and/or round score). A TA was considered landed when the skater rolled away for at least 1 s following the attempt [23]. If the skater used their hands during the landing but still managed to roll away, this was considered landed, unless otherwise noted by the judges (BT TA scored 0). Moreover, outcome timing was captured as whether a bail occurred during the TO, IA, or LD phase. During a bailed TA, all data that was available up to the bail phase was recorded.

2.2.5. Time

Competition timing was captured for each TA by the skater's heat number, heat order (sequence within the heat), and round. Then, using frame-by-frame video analysis, TAs were identified by where they occurred sequentially (TA number) during a RUN or BT attempt. For each TA, four distinct time points (frames) were coded, as follows: take off (Frame$_{TO}$), event/interaction start (Frame$_{IA\text{-}Start}$), event/interaction end (Frame$_{IA\text{-}End}$), and landing (Frame$_{LD}$) (Table 3). These time points represent the key moments of the start and end of each phase [24]. Then, critical, temporal features were calculated for each timing phase using frame selections: TO time (Time$_{TO}$), IA time (Time$_{IA}$), LD time (Time$_{LD}$), and TA time (Time$_{TA}$) (Table 4, Figure 2). Frame selection and associated time were of particular interest in this study, as the metrics offer insight into estimating skateboarding performance (e.g., airtime, grind time).

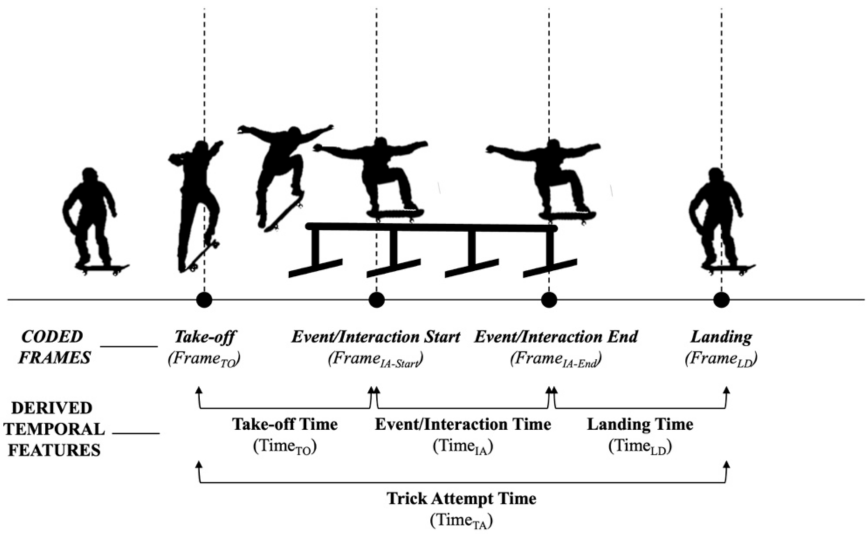

Figure 2. Coded frames (take-off (Frame$_{TO}$), event/interaction start (Frame$_{IA-Start}$), event/interaction end (Frame$_{IA-END}$), and landing (Frame$_{LD}$)) and derived temporal features (take-off time (Time$_{TO}$), event/interaction time (Time$_{IA}$), landing time (Time$_{LD}$), and trick attempt time (Time$_{TA}$)).

Table 3. Definitions and examples of time points per trick attempt to guide frame selection.

obstacle$_{IA}$ and TO - IA Transition [a]	TA Distinct Time Points			
	Take-Off (*Frame$_{TO}$*)	**Event/Interaction Start (*Frame$_{IA-Start}$*)**	**Event/Interaction End (*Frame$_{IA-End}$*)**	**Landing (*Frame$_{LD}$*)**
obstacle$_{IA}$ = Not Applicable: TAs that only interact with obstacles during TO and LD (not IA) (e.g., fundamental, flip, air/grab, balance, etc.)	Frame prior to board completely leaving ground (no contact of wheels with ground)	Same as *Frame$_{TO}$*	Same as *Frame$_{LD}$*	First frame, all wheels contact ground
obstacle$_{IA}$ = Applicable; Clear TO - IA TAs that interact with obstacle (other than air) during IA phase (e.g., grind, slide, stall)		Frame before first contact of board (wheels/trucks) with obstacle (typically start of grind/slide)	Frame before last contact of board (wheels/trucks) with obstacle (typically end of grind/slide)	
obstacle$_{IA}$ = Applicable; NOT Clear TO - IA	Frame before board	Frame before first contact of	Frame before last contact of	First frame, all wheels contact

TAs that interact with obstacle (other than air) during IA phase, but with no clear frame where IA phase starts/stops; typically involves redirection or potential redirection tricks like quarterpipe "coping tricks" (e.g., BS/FS 50–50 stall, FS 5–0, Fakie Tail Stall, Rock to Fakie, etc.)	appears to rotate or first set of wheels goes over coping	board (wheels/trucks) with obstacle (typically first contact of trucks with quarterpipe coping)	board (wheels/trucks) with obstacle (typically last contact of trucks with quarterpipe coping)	ground (quarterpipe transition)

TA, trick attempt; TO, take-off; IA event/interaction; LD, landing; BS, back-side; FS, front-side; [a] Frame selection guided by classification of obstacle$_{IA}$ and visibility of transition from TO phase to IA phase.

2.3. Procedures

2.3.1. Data Preparation and Notational Analysis

To capture potential outcome-related aspects of street skateboarding, a custom NA application was designed using MATLAB (MathWorks Inc. (2021b). MATLAB version: 9.11.0 (R2021b), Natick, MA, USA: The MathWorks Inc.) (Figure 3). Importantly, the NA framework we present is independent from this particular software, and the system could be implemented using other platforms or tools. Broadcast footage was clipped into separate videos for each BT and RUN, and subsequently loaded into the application, featuring two video viewing windows, each displaying the video selected (A) from the file selection panel (B) and the trick selection panel (C), respectively. The trick selection panel was accompanied by buttons for frame selection (D), and a panel for trick and obstacle classification (E). The application included buttons for TA tagging (F) and an athlete details panel (G). Attributes related to that BT or RUN clip were entered (skater and select action attributes). Then, each individual TA was tagged (as above) (F), and a trimmed video clip (H) was created capturing one second before and after the TA frame. A rater could then label each TO, IA (start and end), and LD phase, respectively, capturing action (E), position (J), and outcome metrics (K) to identify that TA. For intra-rater reliability, one rater (R1) coded all video clips on two occasions ($R1_1$ and $R1_2$), at least two weeks apart. For inter-reliability, three raters (R1, R2, and R3) coded all video clips in a different order. Specifically, raters coded TAs in alphabetical order by skater first name (or reverse alphabetical order). Thus, each coded all TAs from an individual skater before moving on to another skater.

Trick classification was conducted independently by two authors, who were experienced in classifying skateboarding tricks, skaters themselves for at least 5 years, and were familiar with skating terminology. The reliability of trick naming and coding was not assessed; however, any disagreements in trick classification or TA outcome (e.g., whether hand drag during RUN TA was landed or bailed) were discussed together and final decisions and underpinning reasonings were provided in Section 4.

2.3.2. Post-Processing and Feature Engineering

All TAs and associated coded attributes were exported (as csv) (each TA as a row, with position, action, and outcome attributes as columns) and imported into R Statistical Software (RStudio Team (2020). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL) to calculate select features (e.g., trick type grouping features) (Table 4). Derived features were selected to encompass trick and obstacle difficulty and variety.

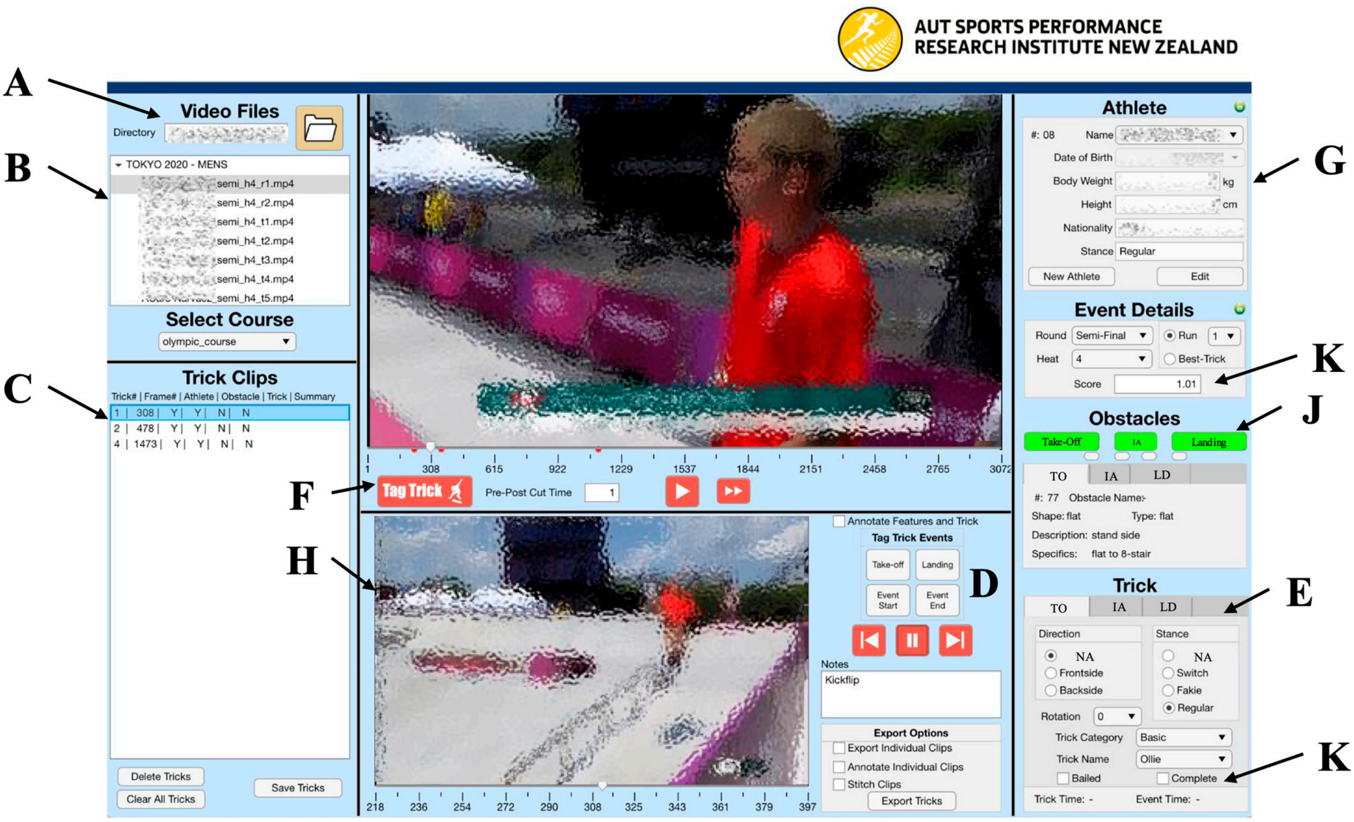

Figure 3. Example of the custom MATLAB notational analysis application to code street skateboarding trick attempts.

Table 4. Derived trick attempt feature definitions and associated acronyms.

	Derived Features (Acronym, if Applicable) *(Variable Type)*	Description	Equations and Associated Coded Attributes [b]
TA Features	TA Trick Type (trick-type$_{TA}$) *(Factor)*	Combination of all phase trick types (trick-type$_{TO}$, trick-type$_{IA}$, trick-type$_{LD}$) to create unique TA; if phase trick type was 'not applicable', it was removed [a]	trick-type$_{TA}$ = trick-type$_{TO}$ + trick-type$_{IA}$ + trick-type$_{LD}$
	Combination Trick *(Boolean)*	Whether skater combines more than one trick through flipping or rotating (body and/or board) into and/or out of grind (>180 degrees), slide, air/grab/stall, balance, freestyle trick-type$_{IA}$	IF trick-type$_{TA}$ contains "+" → Combination Trick = TRUE
	Flip In and/or Out (Flip In/Out) *(Boolean)*	Whether skater flips board into and/or out of grind, slide, balance, freestyle, air/grab/stall trick (e.g., combination trick)	IF [trick-type$_{TO}$ ∣ trick-type$_{L}$ = flip AND trick-type$_{IA}$ = grind ∣ slide ∣ balance ∣freestyle∣ air/grab/stall] → Flip In/Out = TRUE

TA Phase (TO, IA, LD) Obstacle Features	Obstacle Type (obst-type$_{TO, IA, LD}$) *(Factor)*	Stair, flat, rail, bank, gap, ledge, bank, or quarterpipe	Predetermined by obstacle$_{TO}$, obstacle$_{IA}$, obstacle$_{LD}$
	Obstacle Description (obst-desc$_{TO,TA/IA, LD}$) *(Factor)*	Detailed description related to obstacle type: Rail: round rail, square rail, etc. Stair: 12-stair, 5-stair, etc. Bank: banked hip, bank to gap, etc. Ledge: A-frame hubba, inclined hubba, etc. Quarterpipe: coping, transition, etc.	obst-desc$_{TA}$ = obst-desc$_{IA}$ (predetermined by obstacle$_{TO}$, obstacle$_{IA}$, obstacle$_{LD}$)
	Park Side (obst-side$_{TO, A/TA, LD}$) *(Factor)*	Side of skatepark obstacle is located: stand-side (mirrored) OR bowl-side (mirrored) OR centre (not-mirrored)	obst-side$_{TA}$ = obst-side$_{A}$ (predetermined by obstacle$_{TO}$, obstacle$_{IA}$, obstacle$_{LD)}$
	Mirrored Obstacle Number *(Factor)*	If obstacle is located on stand-side or bowl-side (not centre), a mirrored obstacle number is created to reflect same obstacle on opposite side (e.g., # - #)	Predetermined by obstacle$_{TO}$, obstacle$_{IA}$, obstacle$_{LD}$
TA Temporal Features	Take-off Time (Time$_{TO}$) *(Numeric)*	Time from board pop to start of IA phase; time to reach obstacle; typically 'air-time (in)'	Time$_{TO}$ = Frame$_{IA\text{-}Start}$ − Frame$_{TO}$ If trick-type$_{IA}$ is aerial based trick (not grind, slide, or stall) → Time$_{TO}$ = not applicable
	Event/Interaction Time (Time$_{IA}$) *(Numeric)*	Time on obstacle; 'air-time' (for aerial tricks), 'grind/slide/stall time', 'manual time', etc.	Time$_{IA}$ = Frame$_{IA\text{-}End}$-Frame$_{IA\text{-}Start}$
	Landing Time (Time$_{LD}$) *(Numeric)*	Time from last interaction with obstacle to landing; Corresponds to 'air-time (out)' (e.g., if skater flips out of grind/slide/stall, Time$_{LD}$ is air-time related to that flip trick)	Time$_{LD}$ = Frame$_{LD}$-Frame$_{IA\text{-}End}$ If trick-type$_{IA}$ is aerial based trick (not grind, slide, stall) → Time$_{LD}$ = not applicable
	Trick Attempt Time (Time$_{TA}$) *(Numeric)*	Time from board pop to landing	Time$_{TA}$ = Time$_{LD}$ − Frame$_{TO}$ If TA is not a Combination Trick and trick-type$_{TA}$ is fundamental, air (not grab), flip, balance, or mannual → Time$_{TA}$ = Time$_{IA}$

TA, trick attempt; TO, take-off; IA, event/interaction; LD, landing; obst, obstacle; [a] Ollie, nollie, and switch ollie were not considered fundamental trick types and were removed; for example, the trick type of a Nollie Kickflip is “Flip”, not “Fundamental + Flip Trick”. [b] Coded attributes from custom notational analysis application including pre-determined obstacle metrics (obstacle type, obstacle description, and park-side) for TA phases (TO, IA, LD)

2.4. Analysis

All statistical analyses were performed using R. Notably, we used *tidyverse* [28], *easystats parameters* [29], and the *boot* package [30]. For all analyses, redirection tricks were removed (acid drop (1 male TA, 1 female TA), kick-turns (24 male TAs, 22 female TAs)). Unless otherwise noted, potential other redirection tricks such as coping tricks (e.g., BS 50-50 stalls) were included for consistency. Descriptive frequency analysis was used to present a high-level summary of the data, using derived TA temporal features from a single rater (R1).

The intra-rater and inter-rater reliability of both TA coded frame selection ($Frame_{TO}$, $Frame_{IA\text{-}Start}$, $Frame_{IA\text{-}End}$, $Frame_{LD}$) and derived temporal features were quantified ($Time_{TO}$, $Time_{IA}$, $Time_{LD}$, $Time_{TA}$) (e.g., $Time_{TO}$ could be influenced by the choice of two separate frames, $Frame_{TO}$ and/or $Frame_{IA\text{-}Start}$). Specifically, intra- and inter-rater reliability of coded frame selection were assessed using mean absolute differences (MAD) overall and broken into different group comparisons based on sex (male, female), obstacle type ($obst\text{-}type_{TO,\ TA,\ LD}$), and trick selection (grind vs. slide, combination vs. non-combination) (Table 4). Groupings based on preferred stance (regular, goofy), $stance_{TO}$, obstacle location ($obst\text{-}side_{TO,\ TA,\ LD}$), and obstacle descriptions ($obst\text{-}desc_{TA}$) for rails (square, round) and ledges (A-frame hubba, hubba) were explored but not presented here due to uneven sample sizes. Bootstrapped (1000 samples) confidence intervals (CI) (95%) were also calculated. To calculate MAD for inter-rater reliability between three raters, the process involved spreading each metric across different raters (R1, R2, R3) to enable pairwise comparisons. The absolute differences between raters (R2-R1, R3-R1, R3-R2) was calculated for each TA. MAD was then computed by averaging the absolute differences between each pair. The approach for intra-rater reliability was the same, but for two rater timepoints ($R1_1$–$R1_2$). Using TA times from previous literature [21], based off a static ollie airtime of 0.38 s (0.18 m), MADs < 3 frames (0.05 s at 60 Hz) were considered ‘acceptable’ for TA coded frames (<15% of a static ollie). This level of granularity was presumed essential for capturing subtle performance differences in skateboarding tricks, as even small timing variations can significantly impact execution [31].

The intra- and inter-rater reliability of derived temporal features were assessed using intraclass correlation (ICC) (Table 4, Figure 2). Adopting a two-way, single measurement/rater, absolute agreement and consistency models, with random and mixed effects, respectively [32]. Values of ICC > 0.9 were interpreted as high variable reliability for derived temporal features, with attention paid to the lower bound of the 95% CI (e.g., ≥0.7).

Bland–Altman (BA) analyses were used to assess intra-rater and inter-rater consistency for both coded frame selection and derived temporal features. BA mean differences (MD) and 95% limits of agreement (LoA) were used to evaluate agreement and consistency between pairs of raters (R2-R1, R3-R1, R3-R2) and rater timepoints ($R1_1$-$R1_2$), respectively.

3. Results

3.1. Descriptive Analysis

Forty skaters (20 males, 20 females) competed in the semi-finals, representing 18 different countries. The average age was 22.9±5.2 years (male = 24.2 ± 4.3, female = 21.5 ± 5.7). There were 19 regular (male = 11, female = 8, total = 366 TAs) and 21 goofy (male = 9, female = 12, total = 434 TAs) stance skaters. TAs were popped in all stances: 83% regular, 6.12% fakie, 5.5% nollie, and 5.38% switch ($\text{stance}_{\text{TO}}$).

Skaters attempted 27 different $\text{trick-type}_{\text{TA}}$ (https://osf.io/n9bjy/), of which 20 were combination tricks (4 flip-in, 5 flip-out). Slides (327 TAs) and grinds (221 TAs) encompassed 68.5% of TAs. Seven $\text{trick-type}_{\text{TA}}$ were only attempted once and sixteen $\text{trick-type}_{\text{TA}}$ were attempted five or less times. Moreover, 13 $\text{trick-type}_{\text{TA}}$ were attempted by a single skater only. Skaters interacted with 101 out of the possible 131 labelled obstacles in the park (Figure 2).

The semi-finals encompassed 80 RUN and 200 BT attempts. After removing selected redirection tricks, 800 TAs (male = 426, female = 374) remained for the descriptive analysis of performance. After further removing 196 bailed TAs, 604 TAs (BT = 94, RUN = 510) remained, from which reliability was evaluated. The nature of broadcast footage meant some TA key events went partially or completely unobserved, leading to data missing not at random [33]. Subsequently, for reliability analyses, listwise deletion was utilised, identifying 44 TAs (Frame_{TO}), 38 TAs ($\text{Frame}_{\text{IA-Start}}$), 38 TAs ($\text{Frame}_{\text{IA-End}}$), and 44 TAs ($\text{Frame}_{\text{LD}}$) missing frames, respectively. As such, sample sizes varied. After listwise deletion, 593 TAs (male = 324, female = 269) remained. Specifically, this included 98 coping TAs, including 22 (3.7%) (male = 13, female = 9) potential redirection coping tricks (e.g., axel stalls). Summary statistics for derived temporal features are provided in Table 5.

Table 5. Summary statistics of derived temporal features (Time_{TO}, Time_{IA}, Time_{LD}, Time_{TA}) from landed trick attempts (TA) during the semi-finals round of the Tokyo 2020 Olympics street skateboarding competition.

Derived Temporal Features	**Summary Statistics [a]**	
	Coping Tricks *Included* [b] (*n* = 593)	**Coping Tricks *Excluded* [c] (*n* = 495)**
Time_{TA}	0.843 ± 0.217	0.815 ± 0.188
Time_{TO}	0.355 ± 0.119	0.385 ± 0.105
Time_{IA}	0.316 ± 0.146	0.302 ± 0.12
Time_{LD}	0.23 ± 0.085	0.215 ± 0.061

TA, trick attempt; TO, take-off; IA, event/interaction; LD, landing; [a] Values are presented as mean ± standard deviation (number of TAs). [b] Coping tricks (kick-turns) were removed, but additional assumed redirection tricks (e.g., axel stalls) are included. [c] All coping tricks and potential redirection tricks have been removed.

3.2. Reliability

Intra-rater frame selection was reliable (MAD < 3 frames, ICC > 0.7), whilst inter-rater reliability varied (MAD = 1.55 to 4.35 frames, ICC = 0.38 to 0.96). Only Frame_{LD} selection was acceptable for inter-rater reliability. However, overall, inter-rater consistency was higher than agreement, particularly for Time_{IA} (Table 6). Based on ICC thresholds, only Time_{TA} was found to be reliable between raters (consistency and agreement). BA results for inter-rater and intra-rater reliability are presented in Table 7.

Table 6. Intra- and inter-rater reliability (agreement and consistency) of coded frames ($Frame_{TO}$, $Frame_{IA\text{-}Start}$, $Frame_{IA\text{-}End}$, $Frame_{LD}$) and derived temporal features (seconds) ($Time_{TO}$, $Time_{IA}$, $Time_{LD}$, $Time_{TA}$) during the semi-finals round of the Tokyo 2020 Olympics street skateboarding competition.

Coded Temporal Frames	**MAD [95% CI [a]]**	
	Intra-Rater	**Inter-Rater**
$Frame_{TO}$	1.43 [1.29, 1.56] (*n* = 586)	3.82 [3.66, 3.97] (*n* = 489)
$Frame_{IA\text{-}Start}$	2.26 [2.08, 2.46] (*n* = 586)	4.35 [4.07, 4.63] (*n* = 489)
$Frame_{IA\text{-}End}$	2.04 [1.85, 2.24] (*n* = 586)	3.62 [3.4, 3.85] (*n* = 489)
$Frame_{LD}$	1.33 [1.21, 1.47] (*n* = 586)	1.55 [1.45, 1.68] (*n* = 489)

Derived Temporal Features	**ICC [95% CI] (*n* = # TAs) [b]**			
	Intra-Rater		**Inter-Rater**	
	Agreement	**Consistency**	**Agreement**	**Consistency**
$Time_{TA}$	0.97 [0.96, 0.98] (*n* = 586)	0.97 [0.97, 0.98] (*n* = 586)	0.91 [0.65, 0.96] (*n* = 488)	0.96 [0.95, 0.97] (*n* = 488)
$Time_{TO}$	0.87 [0.84, 0.89] (*n* = 443)	0.87 [0.85, 0.89] (*n* = 443)	0.62 [0.56, 0.68] (*n* = 376)	0.64 [0.59, 0.68] (*n* = 376)
$Time_{IA}$	0.87 [0.84, 0.89] (*n* = 408)	0.87 [0.85, 0.89] (*n* = 408)	0.63 [0.38, 0.77] (*n* = 355)	0.73 [0.69, 0.77] (*n* = 355)
$Time_{LD}$	0.73 [0.66, 0.78] (*n* = 448)	0.74 [0.7, 0.78] (*n* = 448)	0.38 [0.26, 0.48] (*n* = 378)	0.43 [0.37, 0.49] (*n* = 378)

TO, take-off; IA, event/interaction; LD, landing; MAD, mean absolute differences; ICC, intra-class correlation coefficient; CI, confidence interval; Values *include* all coping tricks (e.g., potential redirection tricks such as axel stalls), but *exclude* redirection tricks (e.g., kick-turns). [a] Bootstrapped confidence interval (n = 1000 samples). [b] Number of TAs may vary derived features due to missing data from raters and specific trick type nuances.

Table 7. Intra-rater and inter-rater Bland–Altman analysis of coded frames ($Frame_{TO}$, $Frame_{IA\text{-}Start}$, $Frame_{IA\text{-}End}$, $Frame_{LD}$) and derived time features ($Time_{TA}$, $Time_{TO}$, $Time_{IA}$, $Time_{LD}$) from landed trick attempts during the semi-finals round of the Tokyo 2020 Olympics street skateboarding competition.

Coded Frames and Derived Temporal Features	**BA Mean Difference (frames/seconds) [95% LoA] (*n* = # TAs) [a]**			
	Intra-Rater	**Inter-Rater**		
	$R1_1$-$R1_2$ [b]	**R2-R1 [c]**	**R3-R1**	**R3-R2**
$Frame_{TO}$	−0.55 [−6.75, 5.65] (*n* = 586)	−4.72 [−10.53, 1.09] (*n* = 489)	−5.04 [−9.56, −0.53] (*n* = 489)	−0.32 [−5.21, 4.57] (*n* = 489)
$Frame_{IA\text{-}Start}$	−0.14 [−6.62, 6.34] (*n* = 586)	−3.55 [−17.29, 10.19] (*n* = 489)	−3.48 [−10.38, 3.42] (*n* = 489)	0.07 [−14.78, 14.92] (*n* = 489)
$Frame_{IA\text{-}End}$	−0.14 [−6.75, 5.65] (*n* = 586)	2.71 [−9.19, 14.61] (*n* = 489)	1.52 [−6.57, 9.61] (*n* = 489)	−1.19 [−11.77, 9.39] (*n* = 489)
$Frame_{LD}$	0.23 [−3.79, 4.26] (*n* = 586)	0.97 [−4.46, 6.39] (*n* = 489)	−0.35 [−4.61, 3.9] (*n* = 489)	−1.32 [−6.34, 3.71] (*n* = 489)
$Time_{TA}$	0.01 [−0.08, 0.11] (*n* = 586)	0.09 [−0.04, 0.23] (*n* = 488)	0.08 [−0.03, 0.18] (*n* = 488)	−0.02 [−0.13, 0.09] (*n* = 488)
$Time_{TO}$	0.01 [−0.1, 0.12]	0 [−0.23, 0.24]	0.03 [−0.09, 0.16]	0.03 [−0.21, 0.27]

	(*n* = 443)	(*n* = 376)	(*n* = 376)	(*n* = 376)
$Time_{IA}$	−0.01 [−0.15, 0.14] (*n* = 408)	0.14 [−0.12, 0.4] (*n* = 355)	0.07 [−0.11, 0.25] (*n* = 355)	−0.07 [−0.36, 0.21] (*n* = 355)
$Time_{LD}$	0.02 [−0.1, 0.13] (*n* = 448)	−0.05 [−0.2, 0.1] (*n* = 378)	−0.04 [−0.19, 0.12] (*n* = 378)	0.02 [−0.13, 0.17] (*n* = 378)

TO, take-off; IA, event/interaction; LD, landing; BA, Bland–Altman; LoA, limits of agreement. Values *include* all coping tricks (e.g., potential redirection tricks such as axel stalls), but *exclude* redirection tricks (e.g., kick-turns). Intra-rater reliability was assessed between two timepoints (denoted with subscript) by a single rater (R1), and inter-rater reliability was assessed between two different raters of three individuals (R2-R1, R3-R1, and R3-R2). [a] Number of TAs may vary across grouping and derived features due to missing data from raters and specific trick-type nuances. [b] Intra-rater (R1) time points (1 and 2). [c] Inter-rater individual raters (1, 2 and 3). R1 is the same as the intra-rater.

3.2.1. Intra-Rater Reliability

There was strong intra-rater consistency across all frame selections (BA: MD < 1 frame, LoA < ±7 frames) (Table 7). Intra-rater reliability of frame selection for all groups was high (MAD 95% upper limit < 3 frames) (Table 8). Of all frame selections, sex differences in reliability were highest for $Frame_{TO}$, and were slightly less reliable for male TAs (MAD = 1.67 [1.48, 1.85]) than female TAs (MAD = 1.12 [0.95, 1.33]), and less consistent (BA MD [95% LoA]: male = −1 [−5.35, 3.34], female = 0.01 [−3.77, 3.79]). All frame selections were least reliable for quarterpipe/coping obstacle interactions (obst-$type_{TO}$, obst-$type_{IA/TA}$, obst-$type_{LD}$). $Frame_{IA\text{-}End}$ selection was less reliable for grinds (MAD = 2.38) than slides (MAD = 1.43).

Table 8. Intra-rater reliability of coded frames ($Frame_{TO}$, $Frame_{IA\text{-}Start}$, $Frame_{IA\text{-}End}$, $Frame_{LD}$) from landed trick attempts during the semi-finals round of the Tokyo 2020 Olympics street skateboarding competition.

Grouping		**MAD [95% CI] [a] (*n* = # TAs) [b]**			
		$Frame_{TO}$	**$Frame_{IA\text{-}Start}$**	**$Frame_{IA\text{-}End}$**	**$Frame_{LD}$**
Sex	Male	1.67 [1.48, 1.85] (*n* = 322)	2.42 [2.16, 2.65] (*n* = 322)	2 [1.75, 2.28] (*n* = 322)	1.43 [1.27, 1.61] (*n* = 322)
	Female	1.12 [0.95, 1.33] (*n* = 264)	2.06 [1.79, 2.36] (*n* = 264)	2.08 [1.81, 2.38] (*n* = 264)	1.21 [1.02, 1.43] (*n* = 264)
Trick Type [d]	Grind	1.4 [1.13, 1.7] (*n* = 174)	2.44 [2.1, 2.8] (*n* = 174)	2.38 [1.99, 2.8] (*n* = 174)	1.16 [0.93, 1.39] (*n* = 174)
	Slide	0.97 [0.83, 1.13] (*n* = 214)	1.94 [1.71, 2.17] (*n* = 214)	1.43 [1.24, 1.66] (*n* = 214)	0.98 [0.85, 1.11] (*n* = 214)
	Combination	1.27 [1.04, 1.5] (*n* = 131)	2.08 [1.73, 2.5] (*n* = 131)	2 [1.57, 2.48] (*n* = 131)	1.18 [0.97, 1.39] (*n* = 131)
	Non-Combination	1.47 [1.31, 1.65] (*n* = 455)	2.31 [2.09, 2.54] (*n* = 455)	2.05 [1.84, 2.28] (*n* = 455)	1.38 [1.22, 1.55] (*n* = 455)
Obstacle Type [c]	Ledge	–	1.98 [1.69, 2.27] (*n* = 120)	2 [1.63, 2.43] (*n* = 120)	–
	Stair	–	1.46 [0.96, 2.04] (*n* = 26)	0.88 [0.5, 1.42] (*n* = 26)	–
	Quarterpipe	2.97 [2.56, 3.48] (*n* = 102)	3.72 [3.13, 4.36] (*n* = 102)	3.63 [2.93, 4.4] (*n* = 102)	2.56 [2.09, 3.05] (*n* = 98)
	Rail	–	2 [1.77, 2.21] (*n* = 219)	1.59 [1.39, 1.81] (*n* = 219)	–

Bank	1.19 [1.01, 1.35] (*n* = 243)	1.45 [1.08, 1.84] (*n* = 49)	1.53 [1.18, 1.94] (*n* = 49)	1.26 [1.05, 1.47] (*n* = 143)
Gap	–	2.93 [1.8, 4.31] (*n* = 45)	2.13 [1.33, 3.07] (*n* = 45)	–
Flat	0.94 [0.78, 1.11] (*n* = 212)	0.96 [0.57, 1.35] (*n* = 23)	1.74 [1.22, 2.48] (*n* = 23)	0.98 [0.85, 1.1] (*n* = 324)
Roll	1.59 [1.1, 2.07] (*n* = 29)	–	–	1.57 [1.1, 2.14] (*n* = 21)

TA, trick attempt; TO, take-off; IA, event/interaction; LD, landing; Values presented by skateboarding specific groupings: sex, grind or slide, combination trick, and obstacle type and *includes* all coping tricks (e.g., potential redirection tricks such as axel stalls), but *excludes* redirection tricks (e.g., kick-turns). Corresponding obstacle types determined for respective coded frame selection are as follows: $Frame_{TO}$ ~ $obstacle_{TO}$, $Frame_{IA\text{-}Start/End}$ ~ $obstacle_{IA/TA}$, $Frame_{LD}$ ~ $obstacle_{LD}$. [a] Bootstrapped confidence interval (1000 samples). [b] Number of TAs may vary across grouping and derived features due to missing data from raters and specific trick type nuances. [c] Obstacle type, corresponds to the TA phase (e.g., $Frame_{TO}$ ~ $obstacle_{TO}$, $Frame_{IA\text{-}Start}$ ~ $obstacle_{IA}$, etc.). [d] Only grind and slide trick types were included to encompass the majority of TAs involving an obstacle interaction.

3.2.2. Inter-Rater Reliability

Frame selection inter-rater reliability for all groups had a MAD 95% upper limit greater than the 3-frame threshold. Only $Frame_{LD}$ was acceptable, and was the most consistent across all rater combinations; however, this was not the case when involving quarterpipes (MAD Upper CI < 2 frames) (Table 9). Additionally, of all the groups, $Frame_{IA\text{-}Start}$ onto a ledge, and $Frame_{IA\text{-}End}$ off stairs or rails, and out of slides (MAD Upper CI < 3.1 frames) were reliable. The lowest consistency occurred during $Frame_{TO}$ and $Frame_{IA\text{-}Start}$ selection between R3-R1 and R2-R1 (BA MD ranged from −3.48 to −5.04); however, consistency between R2-R3 was much higher (BA MD < 1 frame) (Table 7). The reliability of $Frame_{IA\text{-}Start}$ and $Frame_{IA\text{-}End}$ was better for female TAs (MAD = $Frame_{IA\text{-}Start}$: 3.68 [3.43, 3.95], $Frame_{IA\text{-}End}$: 3.04 [2.82, 3.28]) than male TAs (MAD = $Frame_{IA\text{-}Start}$: 4.95 [4.5, 5.41], $Frame_{IA\text{-}End}$: 4.15 [3.82, 4.54]). In addition, selecting $Frame_{IA\text{-}Start}$ was more reliable for non-combination tricks (MAD = 3.92 [3.7, 4.17]) than combination tricks (MAD = 5.84 [4.94, 6.8]), and most reliably selected when on a ledge (obst-$type_{IA/TA}$) (MAD = 2.61 [2.22, 3.04]). Alternatively, selecting $Frame_{IA\text{-}End}$ was more reliable off a rail (MAD = 2.38 [2.2, 2.57]) compared to a ledge (MAD = 3.35 [3.03, 3.68]).

Table 9. Inter-rater reliability of coded temporal frames ($Frame_{TO}$, $Frame_{IA\text{-}Start}$, $Frame_{IA\text{-}End}$, $Frame_{LD}$) from landed trick attempts during the semi-finals round of the Tokyo 2020 Olympics street skateboarding competition.

Grouping		**MAD [95% CI]** [a] (***n*** **= # TAs)** [b]			
		$Frame_{TO}$	**$Frame_{IA\text{-}Start}$**	**$Frame_{IA\text{-}End}$**	**$Frame_{LD}$**
Sex	Male	3.45 [3.25, 3.65] (*n* = 256)	4.95 [4.5, 5.41] (*n* = 256)	4.15 [3.82, 4.54] (*n* = 256)	1.68 [1.53, 1.83] (*n* = 256)
	Female	4.22 [4, 4.43] (*n* = 233)	3.68 [3.43, 3.95] (*n* = 233)	3.04 [2.82, 3.28] (*n* = 233)	1.42 [1.26, 1.59] (*n* = 233)
Trick Type [d]	Grind	3.91 [3.67, 4.16] (*n* = 151)	3.45 [3.04, 3.89] (*n* = 151)	3.8 [3.46, 4.13] (*n* = 151)	1.47 [1.28, 1.68] (*n* = 151)
	Slide	3.65 [3.44, 3.87] (*n* = 187)	3.92 [3.42, 4.46] (*n* = 187)	2.15 [2.01, 2.31] (*n* = 187)	0.97 [0.87, 1.09] (*n* = 187)

	Combination	3.2 [2.93, 3.45] (*n* = 108)	5.84 [4.94, 6.8] (*n* = 108)	3.67 [3.11, 4.25] (*n* = 108)	1.16 [1, 1.33] (*n* = 108)
	Non-Combination	3.99 [3.82, 4.16] (*n* = 381)	3.92 [3.7, 4.17] (*n* = 381)	3.61 [3.38, 3.83] (*n* = 381)	1.67 [1.54, 1.8] (*n* = 381)
Obstacle Type [c]	Ledge	–	2.61 [2.22, 3.04] (*n* = 102)	3.35 [3.03, 3.68] (*n* = 102)	–
	Stair	–	3.82 [2.42, 5.58] (*n* = 19)	2.11 [1.65, 2.61] (*n* = 19)	–
	Quarterpipe	4.03 [3.61, 4.42] (*n* = 78)	5.79 [5.13, 6.44] (*n* = 78)	7.23 [6.34, 8.24] (*n* = 78)	3.61 [3.24, 4.04] (*n* = 75)
	Rail	–	4.16 [3.68, 4.64] (*n* = 197)	2.38 [2.2, 2.57] (*n* = 197)	–
	Bank	4.03 [3.81, 4.25] (*n* = 209)	5.52 [4.86, 6.29] (*n* = 43)	3.19 [2.6, 3.81] (*n* = 43)	1.71 [1.47, 1.96] (*n* = 118)
	Gap	–	5.48 [4.67, 6.4] (*n* = 31)	4.86 [4.05, 5.74] (*n* = 31)	–
	Flat	3.49 [3.27, 3.7] (*n* = 180)	5.92 [4.75, 7.33] (*n* = 17)	3.69 [2.82, 4.65] (*n* = 17)	0.95 [0.86, 1.03] (*n* = 280)
	Roll	3.73 [3.09, 4.42] (*n* = 22)	–	–	1.42 [1.08, 1.75] (*n* = 16)

TA, trick attempt; TO, take-off; IA, event/interaction; LD, landing. Values presented by skateboarding specific groupings: sex, grind or slide, combination trick, and obstacle type, *including* all coping tricks (e.g., potential redirection tricks such as axel stalls), but *excluding* redirection tricks (e.g., kick-turns). Corresponding obstacle types determined for respective coded frame selection: $Frame_{TO}$ ~ $obstacle_{TO}$, $Frame_{IA\text{-}Start/End}$ ~ $obstacle_{IA/TA}$, $Frame_{LD}$ ~ $obstacle_{LD}$. [a] Bootstrapped confidence interval (1000 samples). [b] Number of TAs may vary across grouping and derived features due to missing data from raters and specific trick-type nuances. [c] Obstacle type corresponds to the TA phase (e.g., $Frame_{TO}$ ~ $obstacle_{TO}$, $Frame_{IA\text{-}Start}$ ~ $obstacle_{IA}$, etc.). [d] Only grind and slide trick types were included, to encompass the majority of TAs involving an obstacle interaction.

4. Discussion

A NA system and protocol were designed to capture outcome-impacting aspects of competitive street skateboarding performance and applied it to broadcast footage from the Tokyo Olympics. Overall, intra-rater reliability for the expert rater was good, with no notable differences in reliability across groupings (trick and obstacle types, or time durations). Frame selection and derived temporal feature reliability varied with obstacle types (rails, ledges, quarterpipes) and trick types (grinds/slides, combination/non-combination). Specifically, the reliability of obstacle interaction frames ($Frame_{IA\text{-}Start}$, $Frame_{IA\text{-}End}$) and associated performance times ($Time_{IA}$, $Time_{TO}$, $Time_{LD}$) were the most impacted, with longer durations being less reliable.

Overall, the PA approach and associated NA system developed demonstrated acceptable reliability of key TA event frame selection (MAD < 2 frames) by a single, experienced rater. In contrast, inter-rater reliability was considerably lower, albeit better when judged as consistency versus agreement; for example, the lower bounds of total trick attempts and interaction time increased to 0.95 (from 0.65) and 0.69 (from 0.38), respectively, when using a consistency model. Acceptable intra- and inter-rater reliability had been observed in technical sports previously, such as with jump height from 2D video footage of gymnastics vaulting [34]. This might suggest that the extra complexity of the skater–skateboard–obstacle interaction with the inconsistency of broadcast footage potentially impacts reliability. Also, more experience and familiarity with the NA system might improve reliability, with a single, experienced rater being preferable in practice.

However, insights can be provided from the inter-rater reliability results as to what specifically may impact a rater's ability to reliably code skateboarding metrics.

Building on these observations, a more detailed breakdown of reliability reveals important nuances between frame selection and timing measurements. Take-off and landing frames were more reliably selected than frames influenced by obstacle interaction. Moreover, trick time, derived from take-off to landing, exhibited the highest reliability. A possible explanation is that movements occurring over shorter durations, such as the pop, provide less room for variability in frame selection. The clear definitions and nature of these movements, typically starting from flat or inclined ground, make it easier to distinguish the frame when wheels leave the ground. Thus, temporal features derived from broadcast footage of tricks in the transition should be limited to interaction time, to avoid using unreliable take-off and landing frames.

In contrast, identifying the start and end of obstacle interactions, such as with rails or ledges, was less reliable. Initial contact of the board or wheel trucks was visually less distinct, and longer durations between take-off and the obstacle interaction further decreased reliability. This is likely due to more complex movements of the board and skater, such as combination tricks, which tend to be more dynamic and create visually complex scenarios that make pinpointing the start of the obstacle interaction more difficult. These limitations could possibly be mitigated by utilising a 'zoom' feature or higher resolution footage (e.g., sharper videos).

Obstacle interaction reliability also decreased with longer interaction times. This relationship appears to be influenced by aspects of trick difficulty and variety. The duration of obstacle interaction often equates to the grind/slide time, and skaters increase this via distance along the obstacle and/or by decreasing speed. Although obstacle length was not controlled, it is postulated that reduced speeds (e.g., increased interaction time) confounded selecting the point of clearing an obstacle. For example, if females performed more grinds than slides, on more ledges than rails, and at reduced speeds, this might explain the reduced reliability of the selected end interaction frame from grinds and ledges, compared to slides and rails. Differences in skateboarding performance metrics is an interesting topic for future study. Nevertheless, practitioners should exercise caution when attempting to use temporal performance metrics derived from broadcast video [35], particularly when comparing tricks of different difficulties and obstacle varieties.

The raters in this study were familiar with PA, but the primary rater was extremely habituated in the use of the NA system for skateboarding applications. Ultimately, the accurate identification and consistent classification of street tricks require attuned skateboarding-specific knowledge. This necessity poses a limitation for future research, as the interpretation and classification of complex tricks may vary between raters with different levels of expertise. Moreover, the current approach employs both subjective (trick names and types) and objective (rotation amount and direction) classification of tricks. Notably, in this study, the reliability of trick naming and coding was not assessed, which is a crucial element of an NA system [36]. This is likely a topic for future researchers and ultimately practitioners to explore. Given the multitude of variables captured by the system, if a similar system is desired to be used reliably, it is essential to apply skateboarding-specific knowledge to select the most relevant aspects of performance for analysis. The authors believe a transition from subjective trick naming to more objective trick attributes will be critical for advancing efficient and practical PA. An aligned, evidence-based approach to grouping may help reduce time costs and move towards an objective end of trick classification continuum. For example, it is suggested that future NA users define standardised trick types to group together tricks of similar style, difficulty, and execution. This approach will ensure the data collected provides meaningful and ecologically valid insights into competitive performance.

Using this NA application, 800 TAs were coded from the Tokyo Olympics. Of these, 595 were analysed, and thus would have feasibly been useable for other purposes (e.g., in practice in quantifying aspects of performance). It is important to note that some trick attempts were excluded due to footage limitations. This represents a limitation of relying on public broadcast footage for detailed PA and could signal a challenge for practitioners. However, the NA approach developed is not limited to broadcast footage, and reliability may improve with other methods of video collection. For example, an additional 'side-on' camera view may improve the visibility and reliability of obstacle interaction frame selection, as opposed to an aerial view. More to this point, this analysis also revealed that frame selection and derived time metrics for quarterpipe and coping tricks were not reliable, likely due to the lack of a clearly visible pop and landing. The lack of clarity in determining these events using this NA system challenges utility in overall trick counts, particularly when considering the impact on judges' overall impression. Similar issues have been addressed in snowboarding and surfing [17,18] and might provide useful insights for refining the NA system in skateboarding, such as consolidating the metrics coded; for example, removing obstacle IA time phases, and replacing them with a system to directly measure the vertical or horizontal speed of movement.

Limitations and Future Recommendations

A rater's ability to use the application to accurately capture and quantify performance elements (critical aspects of trick selection, obstacle selection, and execution) is directly related to experience and familiarity with skateboarding. The selection of raters in this research meant the interpretations were somewhat limited. A more homogenous sample of raters familiar with street skateboarding may be useful for future research exploring reliability of such a system. In street skateboarding, tricks are given names depending on the movements performed by the skater and board interacting with an obstacle. However, naming tricks is nuanced in the community, such that the same trick can have many names (e.g., treflip vs. 360 flip). In addition, many tricks appear very similar (nosegrind vs. crooked grind) and are potentially only distinguishable by the intention of the rider. Therefore, to understand if tricks can be consistently and reliably identified across raters, future research should investigate the validity of trick classification.

To provide effective and practical insight into strategy, it is essential to capture events in enough detail to replicate the interacting elements that could affect each action and outcome [9]. However, to ensure the NA process can be conducted efficiently and reliably between raters, future research should look to consolidate the number of coded metrics and standardise trick classification prior to extracting specific key performance differentiators (rather than the current approach of trick naming and subsequent feature engineering of performance related metrics). One such solution could be to explore trick families to reduce the number of trick types. Additionally, the system should be used on other competitions of various skill levels and skateparks to ensure its generalisability. However, when doing so, particular attention should be given when categorising obstacles to ensure consistency and applicability across skate parks.

5. Conclusions

This study evidenced the successful implementation of a PA approach within skateboarding that facilitates uniquely defining skateboarding trick attempts. Accordingly, this approach allows users to quantify performance aspects of judging criteria, including subjective elements of style, without sacrificing skateboarding nomenclature. Whilst the approach shows promise, caution should be used when extracting temporal features from broadcast footage. Future researchers should look to leverage this PA method to understand the technical and tactical demands of street skateboarding before understanding the underlying physical capacities required to be successful.

Author Contributions: Conceptualization, S.N.D., N.M., M.R.C. and J.N.; Methodology, S.N.D., N.M., M.R.C. and J.N.; Software, S.N.D., N.M. and J.N.; Validation, S.N.D., N.M., M.R.C., J.N. and J.C; Formal Analysis, S.D, N.M. and M.R.C.; Investigation, S.N.D., N.M., N.N. and M.R.C.; Data Curation, S.N.D. and N.M.; Writing—Original Draft Preparation, S.N.D., M.R.C. and N.N.; Writing—Review and Editing, S.N.D., J.C., N.N., J.N., N.M. and M.R.C.; Supervision, M.R.C., J.C. and J.N. All co-authors have contributed in a meaningful way to the published work and agree to its publication in Applied Sciences. All authors have read and agreed to the published version of the manuscript.

Funding: The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The New Zealand Sports Foundation Charitable Trust (NZSFCT), via High Performance Sport New Zealand (HPSNZ), provided funding for this research through a scholarship, provided to the primary author (SD).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data generated or analysed during this study are included in this published article and available on OSF at https://osf.io/n9bjy/.

Acknowledgments: The research results do not constitute an endorsement by the authors or the journal.

Conflicts of Interest: Author Nick Mancini was employed by the company Skatesense. Author John Cronin was employed by the company Athlete Training and Health. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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