HOW GEOMETRY SHAPES TRICK OPPORTUNITIES IN OLYMPIC PARK SKATEBOARDING: A MODELLING STUDY OF THE TOKYO 2020 AND PARIS 2024 PARK COURSES

ALEXIS-JOHN VILLAMIL DE LOS REYES

Abstract. This project asks whether the geometry of the Tokyo 2020 and Paris 2024 Olympic park skateboarding courses favours certain trick families, using a simple geometry-based model. From a small reconstructed dataset of obstacle depths, hips and extensions, I define feasibility for four trick families and compare how many "good spots" each course offers. Paris has a slight but non-significant advantage, and deeper obstacles are much more likely to be big-air-feasible, suggesting that park design shapes trick opportunities.

Keywords. Sports analytics, geometric modeling, trick feasibility, course design bias
GitHub Repo. https://github.com/ofthekings/olympic-skateboard-performance-modeling/

1. Introduction

Park skateboarding, introduced at the Tokyo 2020 Olympics, takes place on non-standardized concrete bowls whose geometry can vary from event to event. Different tricks depend on specific geometric conditions such as depth, radius and the presence of hips or extensions. As a result, course design may influence which tricks are feasible and therefore shape competitive performance. However, detailed obstacle measurements and trick-attempt datasets are rarely available publicly, making it difficult to evaluate.

Despite the lack of (publicly available) data, I still choose to tackle the following research question: *Can a geometry-based model of park-style skateboarding courses be used to estimate how the layouts of the Tokyo 2020 and Paris 2024 Olympic park courses could advantage or penalize different trick families, and to quantify the resulting design-induced performance bias?*

My working hypotheses are that (i) the Paris course will offer at least as many feasible opportunities as the Tokyo course for each trick family, and (ii) across both courses, greater obstacle depth will be positively associated with trick feasibility. The broader aim is to assess, through this case study, whether such a geometry-based framework can provide a useful quantitative lens on design-induced bias in park skateboarding.

2. Literature reviews

Although skateboarding entered the Olympics only recently, quantitative scholarly work examining it, whether in Tokyo 2020 and/or Paris 2024, remains *very* limited. Diewald et al. (2025) analyzed street skateboarding performance, using notational analysis of Tokyo 2020, to quantify trick selection and obstacle usage [3]. It demonstrated that objective data can be extracted from footage, but it did not consider spatial layout or obstacle geometry as variables. Complementing this, Diewald et al. (2024) conducted a study that further identified the sport's physical, technical, and tactical demands [4]. These studies establish the analytical foundation for performance measurement but underscore a major research gap: no study yet connects trick mechanics to the geometric features of competition courses, much less the Olympics..

Non-academic and industry sources help explain how Olympic street courses were designed. World Skate (2021) described the Tokyo 2020 course as "meticulously designed to let athletes maximize creativity, flow, speed, and technical variety" [7]. Reports from Inside the Games (2021) and NBC

Olympics (2024) show that both the Tokyo and Paris courses were custom-built with very different layouts: Tokyo's was compact and symmetrical [6], while Paris featured 18 distinct obstacles spread across a larger plaza [12]. Together, these sources show that course geometry is a carefully planned design element with potential effects on performance that have not yet been measured.

However, I decided to look beyond the current scholarship around skateboarding and see what is done when no data is available. Papers like "Synthetic Data for Sharing and Exploration in High-Performance Sport" (2025) illustrate the creation of synthetic athlete monitoring data, to overcome data scarcity in sport science [11]; while "An approximate simulation model for initial luge track design" (2011) builds a simulation model for luge sled motion along a track, using geometric parameters [5], demonstrating hope that the same is feasible for my project.

In summary, current scholarship has analyzed what tricks are performed and how they are executed, but not where or why certain tricks are more feasible depending on course design. These studies and insights support the notion that geometry affects performance, yet no published model links obstacle dimensions and spatial layout to trick-level feasibility or performance bias in Olympic street skateboarding. This project addresses that gap by developing a quantitative, geometry-based compatibility model to simulate how course design may advantage specific trick categories, specifically in park skateboarding.

3. Data

Because no public dataset exists regarding Olympic park geometry to trick feasibility, the dataset used was reconstructed from official course materials for the Tokyo 2020 and Paris 2024 park events, as well as any skatepark measurements that I could find.

I started with the park design courses for the Tokyo 2020 and Paris 2024 Olympics.[7][12] The Tokyo course illustrates the overall layout and intent of the Ariake Urban Sports Park bowls and emphasizes that the design is "almost twice the size of a standard competition skatepark."[9] For Paris 2024, I used the World Skate article "New Forms: How the Paris 2024 Olympic Skateboard Street and Park Designs Were Created", which explains footprint, heights and certification constraints for the Paris course[13], together with NBC's course preview, which describes how the terrain was designed to be "fair and equal" and explicitly compares it to the more intimidating Tokyo features.[12]

From these diagrams and descriptions, I identified ten visually distinct obstacles per course (i.e., deep pockets, shallow walls, hips, extensions, waterfall-like sections) to use as the basis of my reconstructed geometry, with which I created three custom datasets:

(1) **Reconstructed Obstacle Geometry:** Exact construction blueprints for the Tokyo and Paris Olympic bowls are not publicly available, so obstacle depths and radii were not measured directly. Instead, I assigned metric values by mapping 3 qualitative categories (shallow/medium/deep) into ranges that are consistent with documented bowl depths in real parks.

For example, the official layout for Ocean Bowl Skate Park in Maryland specifies a pool with a 5-ft shallow end and an 8.5-ft deep end [10]. The SK8 Charleston facility description lists a pro bowl with an 11.5-ft deep end and a 6-ft shallow end, and an intermediate bowl with a 7-ft deep and 5-ft shallow end [1]. The Kensington Skateboard Park in Vancouver is described as a pool-style bowl "9.5 feet at the deep end … and 5 feet deep at the shallow end" [2]. These examples show that real park bowls commonly use shallow ends around 5–6 ft (1.5–1.8 m) and deep pockets around 9–12 ft (2.7–3.7 m). With these I set shallow obstacles in my reconstruction to approximately 1.5–1.8 m, medium walls to

2.0–2.2 m, and deep pockets to 2.4–3.0 m. The ordering of which obstacles on each course were treated as shallow, medium or deep was then determined visually from the official Tokyo 2020 and Paris 2024 course diagrams and broadcast course-walkthrough footage (Relative comparisons only. No measurement from video).

(2) **Trick-Family Requirement:** A second dataset defines four trick families (because there are just too many tricks to if not): big-air, lip-trick, coping-grind, and hip-transfer. For each family, I specify a minimum depth threshold (in metres) and simple binary structural requirements (e.g. needs coping, needs a hip, needs an extension) as a modelling choice informed by standard descriptions of park skating. Lip tricks and coping grinds are performed on the lip / coping of ramps and bowls and therefore naturally require coping in the model.[1] Hip-transfer require 2 faces to be separated by an edge. Big-air style tricks are associated with larger, steeper transitions that generate more speed and airtime. So the big-air family is given a higher minimum depth and benefits from extensions. To keep these thresholds realistic, all minimum depths are chosen to lie within the 1.5–3.5 m.[8]

(3) **Course-Trick Compatibility:** The analytical dataset consisted of 20 obstacles × 4 trick families = 80 obstacle–trick pairs, each labelled compatible (1) or not compatible (0) based on whether the obstacle geometry satisfied the trick-family requirements. This table forms the basis of the statistical testing that follows.

4. Methodology

This study evaluates whether the geometry of the Tokyo 2020 and Paris 2024 Olympic park skate courses influences trick feasibility. The constructed dataset contains all obstacle-trick-family pairings. For each pairing, a rule-based feasibility model assigns compatible = 1 or compatible = 0, based on the geometric requirements defined for each trick family (depth, hip presence, extension). Using this, 5 tests were done to address 2 main hypotheses:

4.1. Feasibility scores.

For each course c and trick family t, the feasibility score is defined as

$$\text{Feasibility}(c,t) = \sum \text{compatible}_{c,t}, \tag{4.1}$$

i.e. the number of obstacles on course c that are geometrically compatible with trick family t. This yields a course × trick-family matrix of counts for Tokyo and Paris.

4.2. Bias index.

To compare opportunity directionally between the two courses, a simple bias index is defined for each trick family t as

$$\text{Bias}(t) = \big(\#\text{ compatible obstacles in Tokyo}\big) - \big(\#\text{ compatible obstacles in Paris}\big). \tag{4.2}$$

Interpretation is purely deterministic:

- $\text{Bias}(t) > 0$: Tokyo offers more compatible obstacles than Paris;
- $\text{Bias}(t) < 0$: Paris offers more compatible obstacles than Tokyo;
- $\text{Bias}(t) = 0$: both parks offer the same number of compatible obstacles (no bias).

4.3. t-test: depth vs. compatibility.

For each trick family, a t-test is used to check whether obstacles marked compatible differ in depth from those marked non-compatible. Let $\bar{x}_1$ and $\bar{x}_2$ denote the sample means of obstacle depth in the compatible and non-compatible groups, respectively; s_1^2 and s_2^2 the corresponding sample variances; and n_1, n_2 the group sizes. The test statistic is

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}}}. \tag{4.3}$$

The hypotheses are

$$H_0 : \bar{x}_1 = \bar{x}_2, \qquad H_A : \bar{x}_1 \neq \bar{x}_2, \tag{4.4}$$

[1]Coping is the circular metal pipe along the top edge that skaters grind / stall on.

so the test evaluates whether mean obstacle depth differs between "compatible" and "not compatible" obstacles for each trick family.

4.4. **Fisher test.** For each trick family, a 2×2 contingency table is constructed to examine the association between course and compatibility. It uses Odds Ratio (OR) to compare the odds of compatibility on Tokyo vs. Paris:

$$\text{Odds Ratio} = \frac{\text{odds}_{\text{Tokyo}}}{\text{odds}_{\text{Paris}}} = \frac{\frac{\text{compatible}_{\text{Tokyo}}}{\text{non-compatible}_{\text{Tokyo}}}}{\frac{\text{compatible}_{\text{Paris}}}{\text{non-compatible}_{\text{Paris}}}} = \frac{\text{compatible}_{\text{Tokyo}} \cdot \text{non-compatible}_{\text{Paris}}}{\text{non-compatible}_{\text{Tokyo}} \cdot \text{compatible}_{\text{Paris}}} \tag{4.5}$$

- Odds Ratio > 1: Tokyo has higher odds of compatibility than Paris;
- Odds Ratio < 1: Paris has higher odds of compatibility than Tokyo;
- Odds Ratio $= 1$: No difference in odds.

Because the sample size is small, Fisher's exact test is used on this table to obtain an exact p-value for the null hypothesis of no association between course and compatibility.

4.5. **Logistic regression: depth effect on feasibility.** To quantify how depth affects feasibility within each trick family, a logistic regression is fit with obstacle depth (in metres) as predictor and compatibility as outcome. For each family, the model is

$$\log\left(\frac{P(\text{compatible} = 1)}{P(\text{compatible} = 0)}\right) = \beta_0 + \beta_1 \,\text{depth}_m. \tag{4.6}$$

The depth coefficient β_1 is reported in terms of its odds ratio:

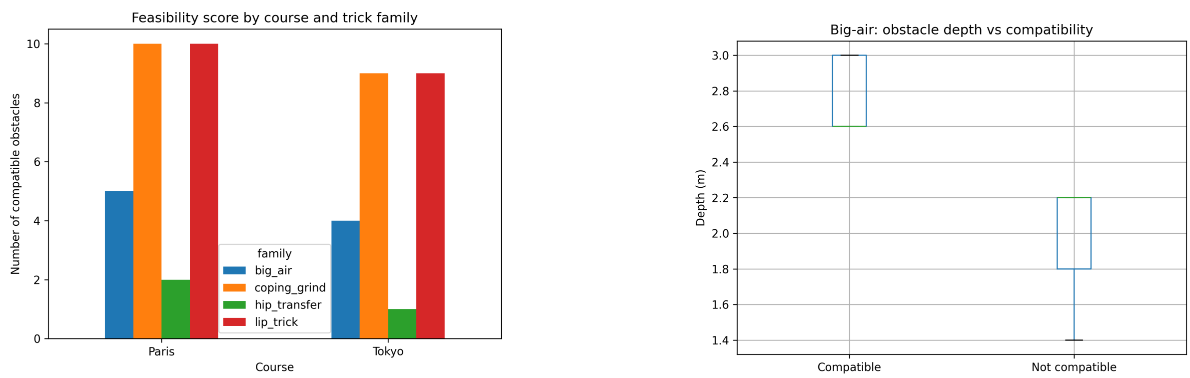
$$\text{OR}_{\text{depth}} = e^{\beta_1},$$

- Odds $\text{Ratio}_{\text{depth}} > 1$: deeper obstacles increase the odds of an obstacle being compatible;
- Odds $\text{Ratio}_{\text{depth}} < 1$: deeper obstacles decrease those odds of an obstacle being compatible.

A 95% confidence interval for OR_{depth} is obtained from the standard errors of β_1, to quantify the uncertainty around the depth effect.

5. Results

Across the 80 obstacle–family pairs, 50 were labelled compatible. Compatibility counts were almost symmetric between courses: Paris (5,10,2,10) vs. Tokyo (4,9,1,9) for big-air, coping-grind, hip-transfer, lip-trick. So the bias index is –1 for every family, implying only a one-obstacle advantage for Paris. (See Figure 1a) Depth was clearly linked to big-air feasibility: compatible big-air obstacles were much deeper (2.73 m vs. 1.98 m; t $\approx$ 7.06, p $<$ 0.001) (See Figure 1b), while hip-transfer showed virtually no depth difference (2.33 m vs. 2.32 m; p $\approx$ 0.93); for coping-grind and lip-trick, the non-compatible class contained only one obstacle, so depth effects are statistically inconclusive rather than absent.



(A) Feasibility counts by course and family

(B) Big-air depth: compatible vs. non-compatible.

FIGURE 1. Summary of feasibility scores and depth effect for big-air.

Fisher's exact tests on course × compatibility tables gave p = 1.000 for all families, providing no evidence that feasibility differs between Tokyo and Paris. Finally, logistic regressions (and the extended synthetic model) suffered from complete separation, with compatibility perfectly predicted by the rule-based features and odds-ratio confidence intervals of the form $(0,\infty)$; at this data scale, the regression adds no information beyond the deterministic feasibility rules.

6. Discussion

This project is limited by reconstructed geometry and simplified feasibility rules, resulting in near-deterministic labels, very small data, and preventing meaningful logistic inference on the original data. The exploratory synthetic extension, however, showed that when small realistic variation is introduced, logistic models converge and depth becomes a strong predictor of feasibility (and hip presence for hip-transfers), demonstrating that a geometry-based model is viable but contingent on richer data. (see final_project.ipynb). While the results do not establish that Tokyo or Paris truly advantaged specific trick families, they illustrate how geometry can be used to formalize design-induced bias. With measured obstacle data and trick outcomes, such models could provide fairness monitoring, evidence-based course design, and course-scouting tools for skateboarders and coaches deciding which lines best suit their strengths and flow.

7. Conclusion

In conclusion, this project examined whether the Tokyo 2020 and Paris 2024 park geometries favour specific trick families and whether a geometry-based model can quantify such bias. The reconstructed dataset showed no significant course advantage, although depth was strongly related to big-air feasibility. Synthetic extensions demonstrated that geometry-driven logistic models become informative with richer data, suggesting future potential for quantitative course-scouting.

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