

Utilizing Categorical Data Analysis Methods to Quantify Grasping Kinematics

Felicia Tassone and Nathaniel Goldstein

Department of Psychology, York University

PSYC 6136: Categorical Data Analysis

Dr. Michael Friendly

April 20th, 2026

Introduction

Reach-to-grasp is one of the most studied actions in motor neuroscience, yet previous work has only focused on single timepoints or on summary metrics of the grasping trajectory: most notably the Maximum Grip Aperture (MGA), movement time, and the velocity profile at a single moment (Jeannerod, 1984; Smeets & Brenner, 1999). Past approaches have produced important insights, but ignore the spatiotemporal organization of the full trajectory. For instance, it is less understood how grip aperture unfolds across the full grasping trajectory, how the trajectory may change when grasping various objects, and whether those relationships are structurally intact or disrupted. The present project addresses this limitation by applying categorical data analysis (CDA) graphical methods alongside machine learning classification and Dynamic Time Warping (DTW) to two distinct grasping datasets to demonstrate what becomes visible when trajectory-level and model-based analyses complement discrete timepoint measurements.

Part 1 asks which kinematic features most strongly distinguish monocular and binocular grasping in healthy young adults. It applies CDA graphical methods to inform the classification structure of kinematic behaviour. Using Random Forest classification and binomial logistic regression with Monte Carlo cross-validation, followed by effect plots and fourfold displays, we characterize how viewing condition modulates grasping behaviour across the full movement.

Part 2 extends this trajectory-level framework to patients with limb apraxia, which is a neurobehavioural consequence of stroke affecting approximately 30–50% of patients with left hemisphere damage (Buchmann et al., 2019; Rounis & Binkofski, 2023). Despite this higher-level disruption of skilled movement planning, basic reach-to-grasp has been considered relatively spared when patients use their ipsilesional (less-affected) hand (Hermsdörfer et al., 1999; Ietswaart et al., 2006; Poizner et al., 1990). Part 2 challenges this idea by applying DTW to derive a Kendall's Tau correspondence score that indexes how systematically grip aperture trajectories are organized across object sizes.

The unifying methodological contribution to make model outputs interpretable across Parts 1 and 2 is the application of CDA graphical methods, including effect plots, fourfold displays, mosaic displays, and spineplots (Fox, 2003; Friendly, 1994, 2016). These tools do not replace statistical models, but they can reveal the shape, direction, and structure of predictor-outcome relationships in ways that coefficient tables and accuracy scores alone cannot. Together, the two parts argue that trajectory-level analyses combined with CDA graphical methods can reveal information from grasping kinematics that standard approaches may miss.

Part 1: Using Categorical Methods to Distinguish Monocular vs. Binocular Grasping in Healthy Young Adults

Methods

Participants and Task

Thirty healthy, right-handed participants (M age = 22.17 ± 3.95 years) completed a reach-to-grasp task in which they grasped 3D-printed white discs varying in size (35, 45, and 55 mm diameter), reach distance (near: 180 mm from midline; far: 360 mm), and viewing modality (binocular; monocular dominant eye). Each participant completed 180 trials (3 sizes \times 2 distances \times 2 viewing modalities \times 15 repetitions). For each trial, three-dimensional positions of the thumb, index finger, wrist, and object were recorded using six OptiTrack motion capture cameras.

Kinematic Features

From each trial, a range of kinematic features were extracted. These features were sensitive to grasping aperture, timing, and spatial trajectory. Selected features are described in Table 1. This yielded an aggregated dataset with one row per trial for classification analyses.

Table 1. Selected kinematic features used in Random Forest and logistic regression analyses.

Variable	Description
MGA	Maximum grip aperture (peak thumb-to-index finger distance)
Change in grip aperture (10–30%, 40–60%, 70–90%)	Mean aperture change across 20% increments of total movement time
Grasping time	Duration from movement initiation to object contact
Time to MGA; % movement time to MGA	Timing of peak aperture
Max wrist velocity; % movement time to max velocity	Peak wrist speed and its temporal location
Wrist velocity (10–30%, 40–60%, 70–90%)	Mean wrist speed across 20% increments of movement
Index finger/wrist location (x, y, z) (10–30%, 40–60%, 70–90%)	Mean spatial position along each axis across 20% increments of movement

Statistical Approach

A Random Forest classifier (Breiman, 2001) was trained to predict viewing modality (binocular vs. monocular) from the kinematic feature set. Model performance was evaluated using Monte Carlo Cross-Validation (MCCV; Xu & Liang, 2001) across 250 resamples of an

80/20 training–testing split, with performance quantified as the macro-averaged F1 score (chance = 0.50). Variable importance scores identified the strongest predictors. The five highest-importance features were then used to fit a binomial logistic regression model under the same 250-iteration MCCV procedure to allow for a direct comparison of the two approaches. In accordance with CDA graphical methods, object size and grasping distance were included as discrete factors in the models. Effect plots and fourfold displays were then used to visualize the classification structure (Fox, 2003; Friendly, 1994).

Results

Random Forest Classification

The Random Forest classifier achieved approximately 75% average macro-F1 accuracy across the 250 MCCV iterations, well above the chance baseline of 50% (Figure 1A). The four highest-importance predictors were: wrist velocity at 70–90% of movement, movement time, percentage of movement time to MGA, percentage of movement time to peak velocity, and wrist velocity at 40–60% of movement (Figure 1B). These late-movement velocity and timing features consistently distinguished binocular from monocular trials, which suggests that the kinematic consequences of depth cue manipulation are most pronounced in the deceleration phase of grasping rather than during the initial reach.

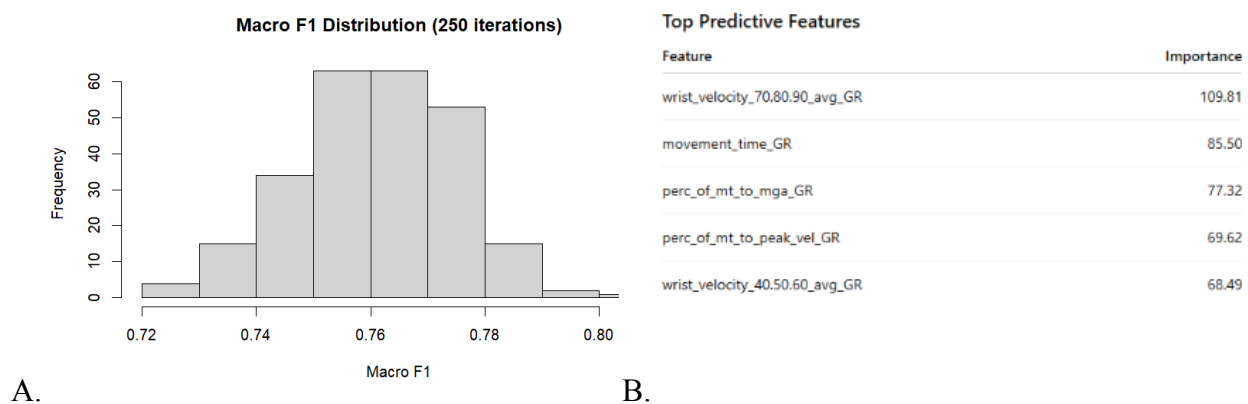


Figure 1 (A). Histogram portraying the Macro-F1 (accuracy) distribution of distinguishing monocular and binocular trials in the testing set, across 250 cross-validation iterations (training/testing splits). On average, accuracy was around 75%. **(B).** The top 5 features that carry predictive value for distinguishing monocular and binocular grasping profiles.

Logistic Regression and CDA Graphical Methods

The logistic regression model using the top five Random Forest predictors plus object size and distance as factors achieved approximately 65% average macro-F1 across the same 250 MCCV iterations. This was slightly lower than the Random Forest but substantially above chance (Figure 2). The reduction in accuracy reflects a well-known trade-off: Random Forest captures complex non-linear interactions among predictors, while logistic regression imposes a linear structure. Though the loss in accuracy is modest, the gain in interpretability is substantial.

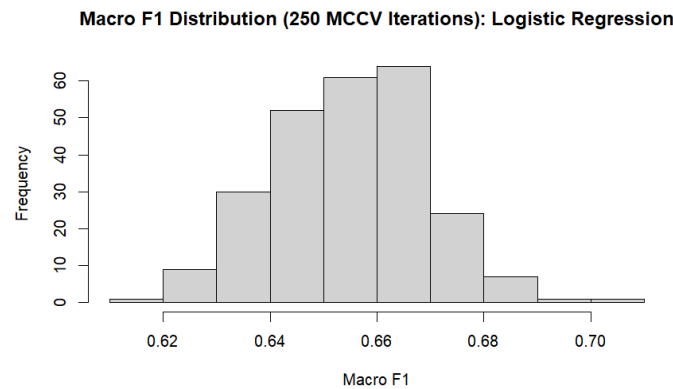


Figure 2. As was done with the Random Forest classification, a histogram portraying the Macro-F1 (accuracy) distribution of distinguishing monocular and binocular trials in the testing set, across 250 cross-validation iterations (training/testing splits). Classification accuracy was slightly lower using this method.

To compare the two models' classification structure directly, fourfold displays were produced for both (Figure 3). The Random Forest showed larger sector areas in the diagonal cells, which is an indication of fewer misclassifications. Both models showed correct predictions in the majority of cases, with the logistic regression showing slightly more off-diagonal weight, consistent with its lower F1 score. The fourfold display makes the relative accuracy of the two models easily interpretable visually, and allows the reader to evaluate differences in classification accuracy without needing to interpret a confusion matrix numerically.

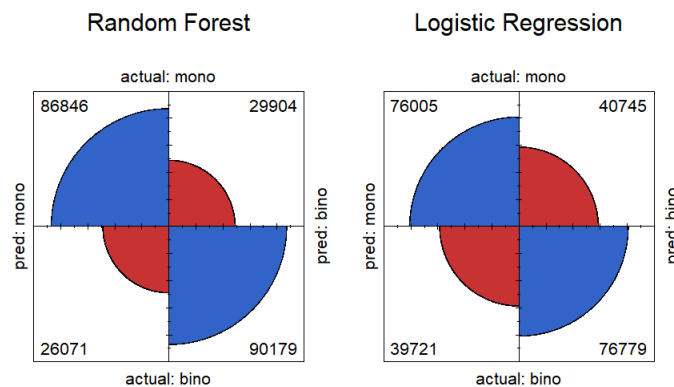


Figure 3. A 2x2 confusion matrix style fourfold plot, which graphically displays the association between actual class and predicted class. Note that for both models there are larger counts in the diagonal cells, which is an indication of correct predictions. In simplified terms, a model that is "more accurate" is said to result in a larger diagonal area (blue colours).

Effect plots were then produced for each of the top five predictors in the logistic regression model, showing the predicted probability of binocular classification as a function of each predictor with 95% confidence bands, holding other predictors at typical values (Figure 4). For all continuous predictors except grasping time, the relationship was positive. As the predictor increased, the probability of binocular classification increased. Movement time showed the opposite pattern, where longer movement times were associated with higher probability of monocular classification. This suggests that the absence of binocular depth information produces

slower and less efficient grasping. These plots reveal the directional structure of each predictor's contribution, which is a level of detail unavailable from methods traditionally conducted.

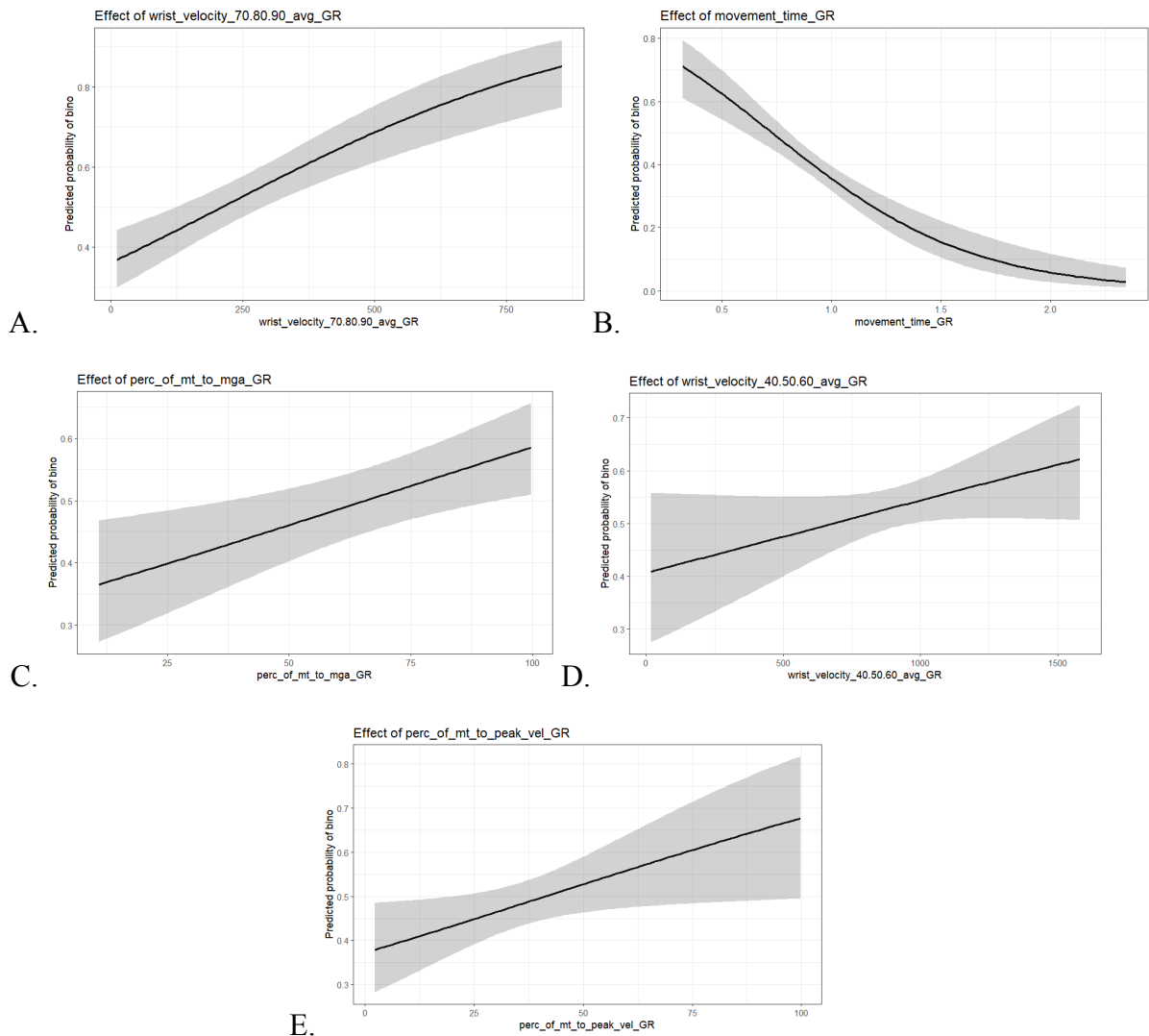


Figure 4. Effect plots for each of the respective variables that held the highest importance for Random Forest classification. This visualization provides the following insight: for all continuous variables not including grasping movement time (Figure 4B), as the variable increases on its respective scale, the likelihood of the trial being classified as binocular is higher.

Discussion

Part 1 demonstrated that binocular and monocular grasping are distinguishable from kinematic features at well-above chance accuracy. The strongest predictors were concentrated in late-movement velocity and timing, which suggests that binocular depth information primarily modulates the deceleration and contact phase of reaching rather than the initial object grasping and transport. This is consistent with the view that binocular vision contributes most to the fine-tuning of grip closure rather than to the overall reach trajectory (Watt & Bradshaw, 2000). CDA graphical methods, specifically fourfold displays and effect plots, made the structure of this classification interpretable. Through these methods, it is made apparent not simply that models

succeeded in their classification above chance, but precisely how each kinematic feature contributed to that classification.

Interim Discussion: Bridging Healthy and Clinical Populations

Part 1 established that the kinematic structure of a grasp encodes systematic information about viewing conditions, and that CDA graphical methods make this structure interpretable in ways that accuracy scores alone cannot. Part 2 aims to extend this logic by asking whether the same trajectory-level framework can detect impairment in populations where the motor system itself is disrupted. We address this question in the context of post-stroke limb apraxia, focusing specifically on the ipsilesional hand. DTW is used as a trajectory-level measure and combined with CDA graphical methods to interpret model outputs.

Part 2: Using Categorical Methods to Characterize Ipsilesional Grasping Impairment in Post-Stroke Limb Apraxia

Methods

Participants

The dataset included 21 apraxic stroke patients (ipsilesional hand and contralesional hand where available; M age = 59.6, SD = 10.5) and 17 right-handed controls (M age = 61.0, SD = 10.1).

Task and Kinematic Measures

Participants completed an Efron block width-scaling task, reaching to grasp rectangular blocks varying in width across four levels (20, 25, 30, and 35 mm) for 40 trials. Kinematic data were recorded using the OptiTrack motion capture system, which tracked three-dimensional positions of the thumb, index finger, and wrist throughout each trial. Three standard metrics were extracted: (1) MGA; (2) Movement Time; and (3) Percent of Movement Time to MGA.

Dynamic Time Warping (DTW) Analysis

Dynamic Time Warping (DTW) is an algorithm that measures similarity between time series by computing their optimal temporal alignment, originally developed for comparing acoustic signals in speech recognition (Sakoe & Chiba, 1978). For each participant, grip aperture trajectories were extracted for each trial. DTW distances were computed between all pairwise combinations of trajectories across the four object sizes, which yielded a 4×4 mean-distance matrix per participant. This matrix was then correlated with an ideal size-based model matrix using Kendall's Tau. Higher tau scores indicate that movement trajectories are more systematically organized by object size (i.e., same-size trajectories are more similar to each other than trajectories from different size conditions). Since tau is derived from a 4×4 rank matrix, it takes only a limited number of discrete values.

Statistical Approach

Group differences in MGA, Movement Time, and Kendall's Tau were tested using Welch's t -test, Mann–Whitney U (appropriate for the discrete tau variable), and permutation tests (10,000 iterations). Effect sizes are reported as Cohen's d . Three binomial logistic regression models were compared: (1) tau only; (2) standard kinematics (MGA, Movement Time, Percent Time to MGA); and (3) a full model combining all predictors. Model comparison used AIC and a

likelihood ratio test. A proportional odds model extended the binary comparison to a three-level ordinal outcome: Control RH → Stroke IPSI → Stroke CONTRA, ordered by theoretical degree of sparing. CDA graphical displays were then produced.

Results

Descriptive Statistics

Table 2. Descriptive statistics for the analysis sample (Control RH vs. Stroke IPSI).

Group	N	Age M (SD)	Tau M (SD)	MGA M (SD)	MT M (SD)
Control RH	17	61.0 (10.1)	0.867 (0.039)	71.8 (8.2)	0.769 (0.121)
Stroke IPSI	21	59.6 (10.5)	0.836 (0.062)	76.5 (4.8)	0.944 (0.151)

Exploratory Kinematic Comparisons

Figure 5 shows all three kinematic variables for the primary comparison: Control RH ($N = 17$) versus Stroke IPSI ($N = 21$). Three distinct findings emerge.

Movement Time showed the clearest separation. Stroke IPSI patients moved significantly more slowly than controls ($M = 0.944$ s vs. 0.769 s), Welch's $t(36.9) = -3.996$, $p < .001$, $d = 1.25$. This is a large effect, confirming that the ipsilesional hand is not spared with respect to movement execution speed.

MGA was significantly higher in Stroke IPSI (76.5 mm) than Control RH (71.8 mm), $t(24.3) = -2.082$, $p = .048$, $d = 0.72$. Patients opened their grips wider on average, consistent with a compensatory strategy: by increasing overall grip amplitude, patients can overcome the consequences of disrupted trajectory organization. Still, this does not contradict previous aperture scaling literature, as mean MGA level and the slope of MGA scaling across object sizes are distinct quantities.

DTW Kendall's Tau was lower in Stroke IPSI ($M = 0.836$, $SD = 0.062$) than Control RH ($M = 0.867$, $SD = 0.039$). This difference had a medium effect size and was consistent across three independent tests: Welch's $t(35.7) = 1.908$, $p = .064$; Mann–Whitney $p = .065$; permutation $p = .097$; $d = 0.58$. With only five discrete tau values and $N = 38$, statistical power for a medium effect is substantially reduced and warrants further future investigation.

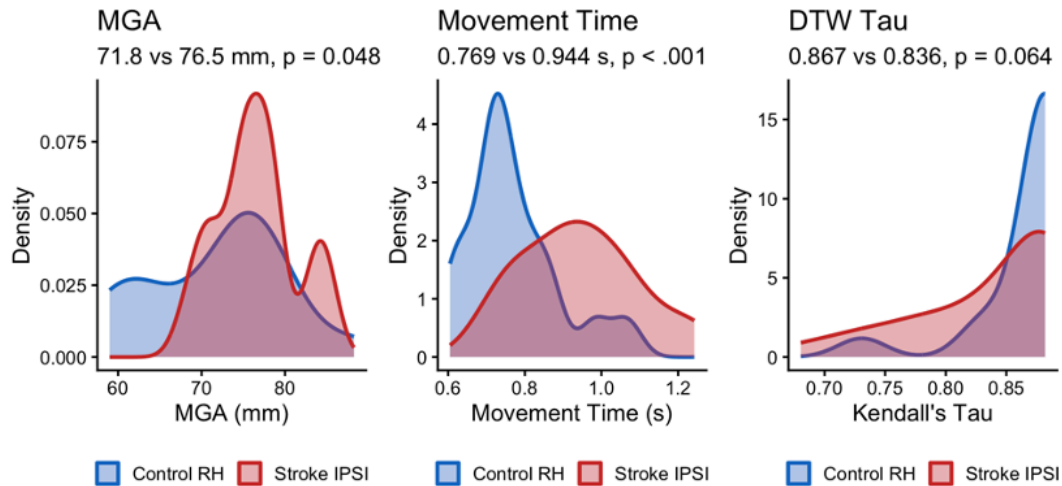


Figure 5. MGA, MT, and DTW Tau distributions for Control RH ($N = 17$) versus Stroke IPSI ($N = 21$).

Logistic Regression

Three logistic regression models were compared to examine the independent contribution of DTW tau beyond standard kinematic predictors. As shown in Table 3, the kinematics-only model (Model 2) had the lowest AIC ($AIC = 45.00$), followed by the full model ($AIC = 46.93$) and the tau-only model ($AIC = 53.89$). A likelihood ratio test confirmed that adding DTW tau to the kinematics model did not significantly improve fit, $\Delta G^2(1) = 0.145$, $p = .703$. The driving predictor in the kinematics model was Movement Time ($OR = 18,846$, $p = .007$).

The tau-only model shows extreme intercept inflation ($OR = 189,919$), a symptom of quasi-complete separation arising from tau's narrow range (0.68–0.88) and only five discrete values. Raw odds ratios for this model are therefore unreliable, making the effect plot a more faithful representation. The failure of tau to add beyond movement time does not indicate biological irrelevance; both variables index the same underlying ipsilesional impairment and cannot be separated at this sample size. Model accuracy for the tau-only model (63.2%) was modest relative to the kinematics model (86.8%), both compared against a majority-class baseline of 55.3%.

Table 3. AIC comparison across three logistic regression models. Lower AIC = better fit.

Model	df	AIC
Model 2: Kinematics only (MGA, MT, %TtoMGA)	4	45.00
Model 3: Full (Tau + Kinematics)	5	46.93
Model 1: DTW Tau only	2	53.89

Effect Plots

Figure 6 shows effect plots for DTW tau (Model 1, left) and Movement Time (Model 2, right). The tau plot shows a downward slope: as tau decreases, predicted $P(\text{Apraxic})$ increases, with a wide confidence band reflecting the discrete tau range and high-tau overlap between groups. Critically, the lowest tau values (0.680, 0.731) are exclusively apraxic: low tau is a

reliable signal for apraxia even though high tau is shared by both groups. The movement time plot shows a steeper, more precise relationship with a narrow confidence band, which is consistent with its stronger and more reliable group separation.

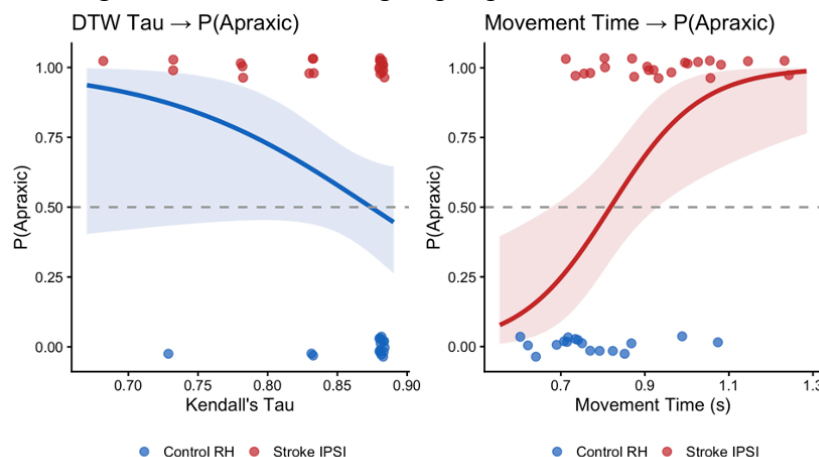


Figure 6. Effect plots for DTW tau (left) and Movement Time (right).

CDA Displays

Figure 7 shows three CDA displays operating on model outputs. The fourfold display for the tau model shows overlapping 95% confidence rings, with modest discrimination (accuracy = 61.5%). The mosaic display reveals the residual structure: the tau model correctly predicts most controls but misclassifies 11 of 21 apraxic patients as controls. These errors are concentrated in the high-tau apraxic observations where both groups overlap. The spineplot makes this asymmetry explicit: at the two highest tau levels (0.832, 0.882) both groups are represented; only at the lowest values (0.680, 0.731) is the composition exclusively apraxic. This structure, invisible in a single accuracy score, is a key contribution of categorical data analysis methods.

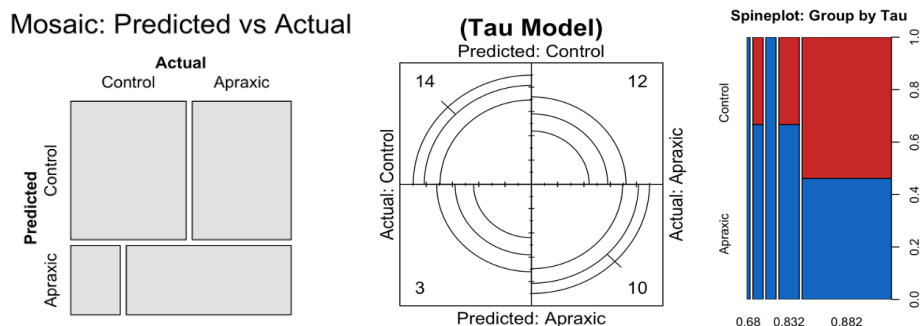
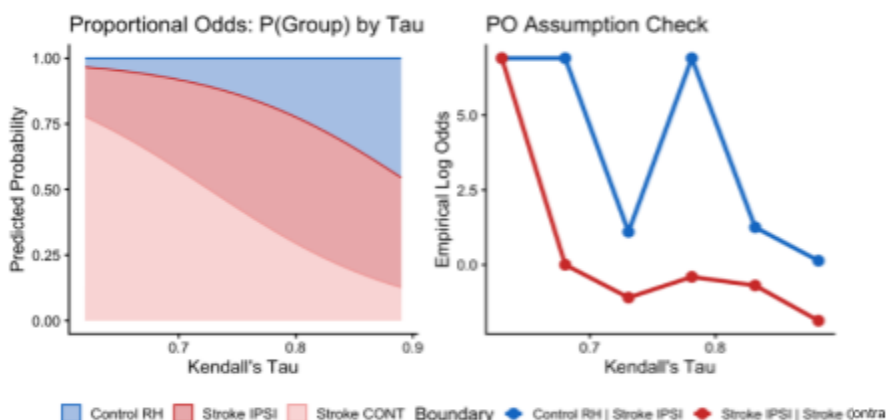


Figure 7. CDA contributions: Mosaic display (left), fourfold display (middle), spineplot (right).

Proportional Odds Model

To situate the ipsilesional finding within the broader impairment gradient, a proportional odds model was fit to a three-group ordinal outcome: Control RH \rightarrow Stroke IPSI \rightarrow Stroke CONTRA, ordered by theoretical degree of sparing (fully intact \rightarrow partially spared \rightarrow most impaired). Higher tau was associated with lower odds of being in a more impaired group (OR per 0.10-unit increase = 0.308). Note that Wald confidence intervals for this estimate are unreliable due to quasi-complete separation in the data and are not reported. The effect plot and predicted probability gradient (Figure 8) provide a more faithful representation of the relationship. Figure 8 shows the stacked predicted probabilities: as tau decreases, probability shifts from Control RH

toward Stroke IPSI and then to Stroke CONTRA. The empirical cumulative logit lines are roughly parallel, supporting the proportional odds assumption: Tau's effect is consistent across both group boundaries.



General Discussion and Conclusion

Together, the two parts of this project make the unified argument that categorical data analysis methods are invaluable tools to quantify reaching and grasping kinematics. We demonstrate, both in healthy adults and in stroke patients, that CDA methods can provide insights into aspects of movement that traditional statistical approaches generally miss.

In Part 1, binocular and monocular grasping were distinguishable at well-above chance accuracy using kinematic features extracted across the full movement trajectory. CDA methods were used to complement traditional findings that binocular trajectories were more efficient than monocular ones, by showing how the direction and shape of various predictors change with viewing conditions. Furthermore, fourfold displays and effect plots made the relative structure of Random Forest and logistic regression more visible.

In Part 2, the same trajectory-level logic exposed ipsilesional grasping deficits that peak metrics had missed. Three converging findings characterize the ipsilesional hand as not fully spared, with CDA displays being essential to characterizing this trend. The spineplot revealed that only the lowest tau values are exclusively apraxic, showing where in the measurement space the signal concentrates, while the fourfold display and mosaic showed where the model succeeded and failed.

Across two distinct experimental contexts, this project demonstrated that CDA graphical methods add substantial interpretive value to the analysis of grasping kinematics. These methods represent a generalizable framework for communicating the categorical structure of continuous kinematic data.

Statement of AI Use

During the preparation of this work, the authors used Claude (Anthropic) and ChatGPT (OpenAI) to help develop parts of their analysis scripts and aid with figure creation. All outputs were manually reviewed and the authors take full responsibility for the content of their outputs.

Acknowledgments

We would like to thank our graduate supervisor, Dr. Erez Freud, for his research insights and guidance, and to Dr. Michael Friendly for his outstanding contributions to the field of categorical data analysis!

References

- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32.
<https://doi.org/10.1023/A:1010933404324>
- Buchmann, I., Dangel, M., Finkel, L., Jung, R., Makhkamova, I., Binder, A., Dettmers, C., Herrmann, L., Liepert, J., Möller, J. C., Richter, G., Vogler, T., Wolf, C., & Randerath, J. (2019). Limb apraxia profiles in different clinical samples. *The Clinical Neuropsychologist*, 34(1), 217–242. <https://doi.org/10.1080/13854046.2019.1585575>
- Fox, J. (2003). Effect displays in R for generalised linear models. *Journal of Statistical Software*, 8(15), 1–27. <https://doi.org/10.18637/jss.v008.i15>
- Friendly, M. (1994). Mosaic displays for multi-way contingency tables. *Journal of the American Statistical Association*, 89(425), 190–200.
<https://doi.org/10.1080/01621459.1994.10476460>
- Friendly, M., & Meyer, D. (2016). *Discrete data analysis with R: Visualization and modeling techniques for categorical and count data*. CRC Press.
- Hermisdörfer, J., Ulrich, S., Marquardt, C., Goldenberg, G., & Mai, N. (1999). Prehension with the ipsilesional hand after unilateral brain damage. *Cortex*, 35(2), 139–161.
[https://doi.org/10.1016/S0010-9452\(08\)70791-3](https://doi.org/10.1016/S0010-9452(08)70791-3)
- Ietswaart, M., Carey, D. P., & Della Sala, S. (2006). Tapping, grasping and aiming in ideomotor apraxia. *Neuropsychologia*, 44(7), 1175–1184.
<https://doi.org/10.1016/j.neuropsychologia.2005.10.003>
- Jeannerod, M. (1984). The timing of natural prehension movements. *Journal of Motor Behavior*, 16(3), 235–254. <https://doi.org/10.1080/00222895.1984.10735319>
- Poizner, H., Mack, L., Verfaellie, M., Rothi, L. J. G., & Heilman, K. M. (1990). Three-dimensional computergraphic analysis of apraxia. *Brain*, 113(1), 85–101.
<https://doi.org/10.1093/brain/113.1.85>
- Rounis, E., & Binkofski, F. (2023). Limb apraxias: The influence of higher order perceptual and semantic deficits in motor recovery after stroke. *Stroke*, 54(1), 30–43.
<https://doi.org/10.1161/STROKEAHA.122.037948>
- Sakoe, H., & Chiba, S. (1978). Dynamic programming algorithm optimization for spoken word recognition. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 26(1), 43–49. <https://doi.org/10.1109/TASSP.1978.1163055>
- Smeets, J. B. J., & Brenner, E. (1999). A new view on grasping. *Motor Control*, 3(3), 237–271.
<https://doi.org/10.1123/mcj.3.3.237>
- Watt, S. J., & Bradshaw, M. F. (2000). Binocular cues are important in controlling the grasp but not the reach in natural prehension movements. *Neuropsychologia*, 38(11), 1473–1481.
[https://doi.org/10.1016/S0028-3932\(00\)00065-8](https://doi.org/10.1016/S0028-3932(00)00065-8)
- Xu, Q.-S., & Liang, Y.-Z. (2001). Monte Carlo cross validation. *Chemometrics and Intelligent Laboratory Systems*, 56(1), 1–11. [https://doi.org/10.1016/S0169-7439\(00\)00122-2](https://doi.org/10.1016/S0169-7439(00)00122-2)