Impact of Dynamic Alignment Cluster Preservation on Early Clinical Outcomes in Navigated Total Knee Arthroplasty Under Controlled Load

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INTRODUCTION: Conventional radiographic alignment classes (neutral/varus/valgus) are static snapshots that do not reflect limb behavior under load across the flexion arc in total knee arthroplasty (TKA). Despite advances in navigation and robotics, intraoperative alignment and soft-tissue decisions still vary widely, and a uniform “neutral” goal has not consistently translated into superior function for every patient. In a tibia-first surgical workflow, where the tibial resection is performed before femoral cuts, we use a force-controlled intra-articular distractor integrated with computer-assisted orthopaedic surgery (CAOS) system to acquire dynamic hip-knee-ankle (dHKA) alignment throughout motion under a quasi-constant distraction force with neutral manipulation (no varus/valgus stress). We then apply unsupervised machine learning (ML) to dHKA data to discover data-driven clusters of dynamic alignment. With those clusters defined, we ask whether preserving a patient’s pre-cut cluster after femoral cuts (“cluster preservation”) relates to improvement in KOOS Jr. within a single senior surgeon’s practice.

METHODS: We assembled a multi-surgeon training dataset (11 surgeons and 1890 primary tibia-first TKAs) of pre-cut dHKA acquired with a force-controlled intra-articular distractor integrated with CAOS system under neutral manipulation across the flexion arc. “Pre-cut” was defined as the acquisition after the tibial resection and before any femoral cuts. We applied unsupervised ML model (K-means clustering) to these pre-cut dHKA data and used internal model-selection procedures to automatically determine the optimal feature space, the number of clusters, and the cluster boundaries. The resulting centroids and boundaries (summarized in Figure 1) were then held fixed and applied, without retraining to post-cut dHKA, defined as the repeat acquisition after femoral cuts (and trialing per workflow) under the same loading and neutral conditions, enabling boundary-consistent labeling from pre-cut to post-cut. From all cases, we identified one surgeon with available KOOS Jr., yielding N = 141 consecutive TKAs for outcomes analysis. The primary endpoint was KOOS Jr. improvement, defined as the difference between 1-year postoperative KOOS Jr. and preoperative KOOS Jr. We first compared KOOS Jr. improvement between cluster matched cases (same cluster at pre-cut and post-cut) and cluster shifted cases (different clusters at pre-cut and post-cut). To examine cluster specific effects while avoiding unstable estimates, we then performed within precut cluster comparisons of the matched transition (same cluster at both time points) against each specific shift (change from the pre-cut cluster to a specified, different post-cut cluster), restricting tests to subgroups with $n \geq 10$. The Welch’s t-test was used with statistical significance set at 0.05.

RESULTS SECTION: Figure 1 reports the K-means training results (selected feature space, chosen clusters, and centroids). The model selected an 8-dimensional feature space of dHKA (varus valgus at flexion 10°, 20°, 30°, 45°, 60°, 75°, 90°, 105°) and four clusters as optimal. Based on cluster centroids and dHKA profiles, cluster 1 was characterized as valgus and neutral, cluster 2 as neutral, cluster 3 as low to moderate varus, and cluster 4 as moderate to high varus. Figure 2 shows the surgeon’s pre-cut to post-cut transition profile using Sankey diagram and cluster transition matrix. Transitions occurred predominantly between adjacent clusters and 72.3% (102/141) of cases preserved their pre-cut cluster after femoral cuts. Figure 3 presents KOOS Jr. comparisons overall and stratified by pre-cut cluster. Although the mean KOOS Jr. improvement was higher with cluster preservation than with a change in cluster (32.0 ± 19.5 vs 27.2 ± 14.7), the difference was not statistically significant ($p = 0.117$). Given the single-surgeon cohort, we interpret this as a likely sample-size/power limitation despite a directionally favorable effect. In stratified analyses limited to $n \geq 10$ per subgroup, a cluster-dependent signal emerged: for knees pre-cut in a low-to-moderate varus pattern, preserving that cluster post-cut was associated with significantly larger KOOS Jr. gains than shifting to a more varus pattern (3 to 3: 34.8 ± 17.4, $n = 36$ vs 3 to 4: 22.1 ± 15.0, $n = 10$; $p = 0.036$). For neutral pre-cut knees, improvement was similar whether preserved or shifted to the adjacent cluster (2 to 2: 29.8 ± 20.5, $n = 34$ vs 2 to 3: 28.0 ± 20.1, $n = 10$; $p = 0.808$). For the remaining clusters, only preserved transitions met the $n \geq 10$ threshold (1 to 1: $n = 15$; 4 to 4: $n = 17$), precluding within-cluster hypothesis tests.

DISCUSSION: We employed an unsupervised K-means model on force controlled, tibia-first intraoperative dHKA data to learn data driven phenotypes on pre-cut measurements and then applied the same fixed boundaries to post-cut measurements without retraining. This framework enabled an outcomes analysis based on phenotype match, asking whether keeping the same dHKA phenotype from pre-cut to post-cut relates to KOOS Jr. improvement. Overall, cases with a phenotype match showed a higher mean KOOS Jr. improvement, although the difference was not statistically significant in this single surgeon cohort. In stratified testing limited to subgroups with at least 10 cases, we observed a significant advantage for the phenotype commonly aligned with what we label as cluster 3, whereas results for the phenotype commonly aligned with cluster 2 showed no difference between match and shift. These findings illustrate how unsupervised ML derived dHKA phenotypes can structure intraoperative decisions and postoperative evaluation in a way that is patient specific rather than tied to a single neutral target. The study is limited by sample size and by inclusion of one surgeon. As more one-year outcomes accrue across additional patients and multiple surgeons, it will be possible to compare effects across phenotypes with adequate power, incorporate covariate adjustment, and test generalizability and durability over longer follow up.

SIGNIFICANCE/CLINICAL RELEVANCE: A force-controlled, tibia-first TKA workflow coupled with unsupervised ML derived dHKA phenotypes provides real-time, patient-specific alignment targets to guide intraoperative decisions.

IMAGES AND TABLES:

Figure 1: dHKA clustering results (N=1890)

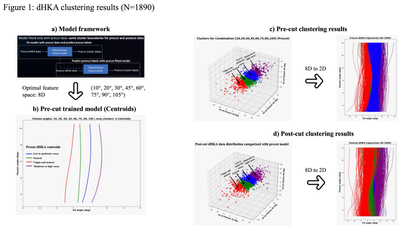
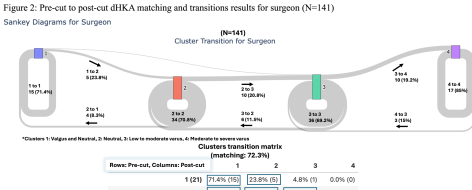


Figure 2: Pre-cut to post-cut dHKA matching and transitions results for surgeon (N=141)



Clusters transition matrix (matching: 72.3%)

Rows: Pre-cut, Columns: Post-cut	1	2	3	4
1 (21)	71.4% (15)	23.8% (5)	4.8% (1)	0.0% (0)
2 (48)	8.3% (4)	70.8% (34)	20.8% (10)	0.0% (0)
3 (52)	0.0% (0)	11.5% (6)	69.2% (36)	19.2% (10)
4 (20)	0.0% (0)	0.0% (0)	15.0% (3)	85.0% (17)

*Clusters 1: Valgus and Neutral, 2: Neutral, 3: Low to moderate varus, 4: Moderate to severe varus

Figure 3: KOOS Jr. improvement by clustering matching. Overall comparison (top) and stratified by pre-cut cluster (bottom)