AI-Driven Analysis of Processor Feedback Enables Personalized Training for Tissue Recovery Technicians:

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Background: Tissue recovery quality depends on technician proficiency. While individualized, data-informed training based on processor feedback is utilized in many recovery agencies, the consistency, depth, and scalability of these efforts vary across organizations. This variability highlights an opportunity to further standardize and enhance how performance data is translated into actionable, ongoing training. We hypothesized that artificial intelligence (AI)-driven analysis could address this gap by automating pattern detection across tissue categories, surfacing insights otherwise missed, and generating data-driven training recommendations at scale. This proof-of-concept study evaluated an AI-driven platform designed to augment current training workflows by analyzing processor feedback to identify technician-specific error patterns across cardiovascular (CV), musculoskeletal, and skin tissue recoveries.

Methods: A proof-of-concept study was conducted using synthetic datasets modeled on real-world recovery scenarios with intentionally elevated error rates to stress-test the AI model's pattern detection capabilities. The CV dataset consisted of 300 entries spanning 4 tissue types (Aortic Arch, Femoral Vessels, Pulmonary Arteries, Saphenous Veins) and 8 error categories. The musculoskeletal/skin (MS/Skin) dataset consisted of 500 entries spanning 17 tissue types bones (Hemipelvis, Whole Femur, Whole Tibia, Whole Fibula, Humerus without Cuff), enbloc (Knee, Ankle), tendons (Achilles, Gracilis, Semitendinosus, Anterior Tibialis, Posterior Tibialis, Peroneus Longus, Fascia Lata), and skin (Full-Thickness, Split-Thickness) and 8 error categories. Both datasets were distributed across 10 simulated technicians, recording tissue type, laterality, error classification, and anatomical location. It should be noted that certain error categories, such as tendons recovered too short, may reflect anatomical limitations rather than technician error; real-world implementation would require distinguishing technician-attributable errors from non-modifiable factors. An AI model analyzed the combined 800-entry dataset to identify error patterns by technician and tissue type.

Results: The CV dataset showed an overall error rate of 77.3% (232/300), with technician error rates ranging from 66.7% to 86.7%. The most frequent CV error was recovery laceration (70 occurrences, 30.2%), followed by transection (41, 17.7%) and insufficient length (34, 14.7%). The MS/Skin dataset showed an error rate of 66.0% (330/500), with technician rates from 52.0% to 74.0%. The top MS/Skin error was recovered too short (167, 50.6%), followed by laceration (51, 15.5%). Tissues with the highest error rates included Achilles Tendon (25/31, 80.6%), Hemipelvis (24/31, 77.4%), and Whole Tibia (32/45, 71.1%). These rates are intentionally elevated above real-world levels to validate the model's detection sensitivity; actual error rates in practice are expected to be significantly lower. The AI model identified technician-specific patterns, such as recurring errors on specific tissues despite overall proficiency, and generated individualized dashboards with targeted training recommendations (see Table 1).

Conclusions: AI-driven analysis can augment existing processor feedback practices by automating pattern detection across technician performance data and generating personalized training recommendations at scale. By integrating with existing recovery feedback workflows,

the platform adds analytical capability without additional operational burden. A known challenge is the feedback lag for MS tissues, which may be evaluated months after recovery; future work will explore strategies to reduce this delay. Additional future work includes validation with real-world data at representative error rates, refinement of error attribution to distinguish technician-modifiable errors from anatomical limitations, and integration of assessment tracking to measure technician progression over time.

Keywords: tissue recovery, personalized training, artificial intelligence, allograft quality

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Tab 1. Summary of synthetic dataset analysis across tissue categories.

Category	Entries	Tissue Types	Error Categories	Error Rate*	Top Error
Cardiovascular	300	4	8	77.3% (232/300)	Recovery laceration (n=70)
MS/Skin	500	17	8	66.0% (330/500)	Recovered too short (n=167)
Combined	800	21	16	70.3% (562/800)	Recovered too short (n=167)

**Error rates reflect intentionally elevated synthetic data designed to test model sensitivity. Real-world rates are expected to be significantly lower.*

AI-DRIVEN ANALYSIS OF PROCESSOR FEEDBACK FOR PERSONALIZED TISSUE RECOVERY TECHNICIAN TRAINING

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Background

Processors supply technician-level data used by agencies for individualized training, yet pattern detection stays manual. DonorIQ applies AI to processor feedback, detecting technician-specific error patterns across tissue categories and generating individualized training recommendations at scale, augmenting existing workflows without added operational burden.

Hypothesis

Can AI analysis of processor feedback:

- Detect technician-specific error patterns
- Surface patterns manual review misses at scale
- Generate individualized training at scale

Methods

- Synthetic data with elevated error rates, to stress-test detection
- CV (300 entries / 4 types) + MS/Skin (500 / 17 types); 8 error categories each
- 800 entries across 10 technicians; analyzed by technician and tissue; errors not adjudicated as anatomical vs. technician-modifiable

Results

- CV error rate 77.3% (232/300); technicians 66.7–86.7%
- MS/Skin 66.0% (330/500); technicians 52.0–74.0%
- Combined 70.3% (562/800), 21 tissue types
- Top errors: recovery laceration (CV, n=70); recovered too short (MS/Skin, n=167)
- Highest-error tissues: Achilles 80.6%, Hemipelvis 77.4%, Whole Tibia 71.1%
- AI flagged technician-specific patterns → individualized training dashboards

Intentionally elevated synthetic data tests detection sensitivity; real-world rates are expected to be far lower. Some categories, such as recovered too short, may reflect anatomy rather than technician error.

Conclusions

AI analysis augments existing processor feedback practices, automating pattern detection across technician performance and generating personalized training at scale, without added operational burden.

Future work: validate on real-world data at representative rates, refine error attribution (technician-modifiable vs. anatomical), reduce analysis-to-training latency once processor feedback is received, and add progression tracking over time.

