**Analysis for Step 4**

**Global Model Accuracy**

In the random selection strategy, the global model reached a final accuracy of 20.03 percent by Round 20, with a peak accuracy of 22.06 percent in Round 10. The average accuracy across all rounds was approximately 15.2 percent. In contrast, the smart selection approach resulted in a slightly lower final accuracy of 17.53 percent but achieved a significantly higher peak accuracy of 26.83 percent in Round 18. The average accuracy was slightly better at around 15.8 percent.

**Training Efficiency**

When comparing training efficiency, smart selection had a longer actual training time of 85.03 seconds compared to 71.40 seconds in random selection, representing a 19 percent increase. However, it improved simulation round time from 182.25 seconds to 160.38 seconds, which is a 12 percent gain in efficiency. The client selection time slightly increased from 0.0044 to 0.0172 seconds, which is negligible in the overall performance.

Smart selection also showed more consistent training durations across rounds, reducing bottlenecks caused by slow clients. Random selection showed a high variance in simulation times, ranging from 160 to 257 seconds per round.

**Client Selection Patterns**

In the random strategy, inefficient clients such as CID3, which has only 216 samples and 12 minibatches, were selected 6 times out of 20. This caused unnecessary slowdowns and introduced noisy updates. On the other hand, the smart selection method selected CID3 only once, in the final round, and consistently preferred efficient clients such as CID0, CID8, CID9, CID10, CID1, and CID5. It also avoided clients with less than 500 samples, focusing on better data quality.

**Key Observations**

Smart selection showed several improvements, including a higher peak accuracy (26.83 percent versus 22.06 percent), faster round completion, and fewer training delays by avoiding inefficient clients. It also provided more stable simulation times across rounds.

However, there were also drawbacks. The final accuracy was slightly lower at 17.53 percent, and total training time was longer by about 19 percent. Additionally, there was greater instability in round-to-round accuracy.

**Root Cause Analysis**

These mixed results suggest that while the smart selection strategy improved efficiency and avoided poor-performing clients, it may have been too aggressive. By prioritizing efficiency too heavily, it excluded small but potentially useful clients. This led to instability in convergence and lower final performance.

**Recommendations for Improvement**

To address these issues, the strategy should better balance efficiency and data diversity. Reducing the efficiency weighting from 40 percent to 25 percent and softening penalties for small clients can help. Adding convergence stability metrics and dynamically adjusting weights based on the model’s current performance would also improve outcomes.

The fact that smart selection achieved a peak accuracy 35 percent higher than random selection shows its strong potential. With better tuning, this approach can provide both efficient training and improved overall model accuracy.