Activity 4: End-to-End Flow Explanation

Mentor Matching & Intervention Recommendation System

1. Introduction

Activity 4 translates analytical insights derived from previous modules into actionable mentoring decisions. This module integrates:

- Student performance scores
- ML-based cluster segmentation
- Similarity-based mentor matching
- Operational constraints (availability and capacity)
- Intervention recommendation rules
- High-risk alert generation

The objective is to ensure that each student receives a structured, personalized mentoring assignment aligned with their needs.

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2. Input Layer

2.1 Student Scores & Clusters

The system takes as input the processed student dataset containing:

- APS (Academic Performance Score)
- WWS (Wellness & Wellbeing Score)
- PTMS (Productivity & Time Management Score)
- CRS (Career Readiness Score)
- SRI (Student Readiness Index)
- Cluster_Label (ML-based student segmentation)

These values represent student academic, wellness, productivity, and career dimensions.

2.2 Mentor Dataset (mentors.csv)

The mentor dataset includes:

- Mentor ID and Name
- Expertise Domain (Academic / Wellness / Career)
- Specialization

- Mentoring Style (Structured / Supportive / Strategic)
- Experience Years
- Availability (hours per week)
- Capacity constraints (max_students and current_load) This dataset models realistic

mentoring operations.

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3. Student Need Identification

Based on cluster classification, student needs are derived:

Cluster Type	**Identified Need**
At-Risk Students	Academic & Wellness Support
Career-Confused Students	Career Guidance
High Performers	Advanced Growth Mentorship

This step converts ML insights into mentoring domains.

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4. ML-Assisted Mentor Matching (Similarity Modeling)

4.1 Feature Representation

Students are represented as normalized feature vectors using:

- APS
- WWS
- PTMS
- CRS

Mentors are encoded using domain-aligned vectors corresponding to student dimensions.

4.2 Cosine Similarity Computation

Cosine similarity is calculated between the normalized student feature vector and mentor expertise vector.
To ensure operational and behavioral alignment, the similarity score is combined with:

- Mentoring style compatibility bonus
- Availability-based weighting
  The final mentor matching score is computed as:

Final Score = Cosine Similarity + Style Bonus + Availability Weight

Mentors are ranked based on this final score, ensuring both technical alignment and operational feasibility.

All student features are normalized using MinMax scaling prior to similarity computation.

4.3 Mentoring Style Compatibility

Each cluster type is mapped to a preferred mentoring style:

Cluster	**Preferred Style**
At-Risk	Supportive
Career-Confused	Strategic
High Performers	Structured

If a mentor's style matches the preferred style, a compatibility bonus is added to the final matching score.

A fixed bonus weight of **0.10** is added when mentoring style matches the preferred cluster style.

This ensures psychological and communication alignment.

4.4 Availability Weighting

Mentors with higher availability hours receive a weighted boost in their final score to ensure:

- Faster engagement
- Realistic scheduling
- Operational efficiency

Availability hours are normalized across mentors and contribute up to **0.15 weight** to the final matching score.

4.5 Capacity Constraint Enforcement

Before assigning a mentor:

- Mentors exceeding max capacity are excluded
- Only eligible mentors are considered
- The mentor with the highest final score is selected

After assignment, the mentor's current load is updated dynamically to ensure balanced workload distribution across future assignments. This ensures practical feasibility and workload balance.

5. Intervention Recommendation Engine

After mentor assignment, intervention types are mapped based on cluster classification:

Cluster	**Suggested Intervention**
At-Risk Students	Immediate Academic & Wellness Intervention
Career-Confused Students	Career Planning & Skill Alignment
High Performers	Advanced Leadership & Growth Mentorship

This step converts segmentation into structured mentoring actions.

6. High-Risk Alert Simulation

The system generates alerts based on:

- Low SRI threshold
- High-risk cluster classification Alert Categories:
- High Risk – Immediate Action Required
- Monitor Closely
- Stable

This ensures proactive mentoring intervention.

7. Final Output Generation

The final recommendation table includes:

- Student ID
- Cluster Label
- SRI
- Assigned Mentor
- Matching Score (Final Mentor Selection Score)
- Recommended Intervention
- Alert Status

The Matching Score represents the combined similarity, behavioral compatibility, and operational feasibility of the assigned mentor.

This output is saved as:

outputs/student_mentor_recommendations.csv and is ready for

operational deployment or dashboard integration.

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8. System Architecture Summary

Activity 4 integrates:

- Rule-Based Intelligence (scoring & SRI)
- Unsupervised ML (clustering)
- Similarity-Based Matching (cosine similarity)
- Style Compatibility Modeling
- Availability Weighting
- Capacity Constraints
- Final Score–Based Mentor Ranking with Explainability
- Dynamic Mentor Load Updating
- Intervention Rules Engine This hybrid design ensures:
- Interpretability
- Operational realism
- Scalability
- Personalized mentoring decisions

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9. Conclusion

The Mentor Matching & Intervention module successfully translates analytical student insights into structured, real-world mentoring assignments.

By combining ML-based similarity modeling with rule-based intervention logic and operational constraints, the system ensures that mentoring decisions are:

- Data-driven
- Context-aware
- Interpretable
- Actionable

Operationally optimized through workload balancing and availability-aware assignment.

This completes the actionable intelligence layer of the HEPro AI+ mentoring framework.