INTERNSHIP PROPOSAL

Development of a Personalized Learning Recommendation Model
for Skill Gap Fulfilment Using ITS and SFIA

Prepared for:

Radya Labs

Prepared by:

Sarah Aiko Sitompul
Software Engineering Student
The University of Sydney

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I. Introduction

Learners in digital training programs have different skill levels and competency gaps based on their education history and learning speed. Personalized learning aims to recommend learning paths based on a learner's current level and required target skills. By identifying the gap between existing competencies and desired skill levels (learning goals), a learning system can guide learners through the most relevant content to improve efficiency and learning outcomes.

This project focuses on developing a personalized learning model that recommends adaptive learning paths based on learner levels and identified skill gaps. The model applies Intelligent Tutoring System (ITS) principles to track learner progress that will be used for decision making, while using the Skills Framework for the Information Age (SFIA) to define skill levels and target competencies.

In designing the proposed model, several key personalization factors will be considered to ensure meaningful output. Time-related factors will include learner focus duration, expected time required for learning materials, and variations in learning speed across different study phases. Understanding-related factors will account for the learner's educational background, estimated mastery level, engagement behaviour, and patterns of errors observed in assessments. Content-related factors will consider learning difficulty, structured learning maps (learning objectives), and appropriate content formats. Finally, the decision-making logic will be designed to accommodate multiple valid next learning steps, allowing learners to explore alternative recommendations or continue on the related topic, and adapt learning paths.

II. Problem Statement

The main challenges addressed in this project are:

- Learning sequences are mostly static or minimally personalized.
- Personalization often relies heavily on scores as the primary indicator. This narrow focus overlooks other important factors such as learner engagement, interaction patterns, time used on tasks, and error behaviours, which are critical for understanding actual learning progress and mastery.
- Learners are frequently given recommendations without clear explanations or visibility into alternative learning paths.
- Repetitive content, fixed difficulty levels, and score-focused evaluation can lead to a reduction in learners' motivation and do not always reflect the true understanding, especially when partial mastery is not captured well.

- Many existing systems do not explicitly mapthe learner progress to standarized competency, making it difficult to systematicall identify the skill gaps that will be used to define learner goals, and ensure the learning outcomes align with related competencies.

III. Objectives and Key Questions

1) Main Objective
   Develop a personalized learning model that suggests a learning path based on learner levels and identified skill gaps.

2) Specific Objectives and Key Questions
   - Develop a model that generates personalized learning paths by integrating several factors (time, learner's understanding, content, decision-making logic).
     Key question: How can the learner's performance and mastery levels be used to dynamically adjust the sequence of learning modules to better address skill gaps?

   - Design a learner model that combines results, engagement, interaction, and learning behaviour to represent learner knowledge and progress more accurately.
     Key question: How can engagement metrics, interaction data, and learner goals be integrated to improve recommendation accuracy?

   - Implement a mechanism that continuously updates learning paths as new learner data becomes available.
     Key question: Does dynamically adapting the learning path lead to better learning outcomes than a (semi) static one?

   - Develop an explainable recommendation logic that allows learners to understand why specific learning paths are recommended and evaluate the effectiveness of the model.
     Key question: How can the model provide interpretable and actionable explanations for learning path recommendations? How can the effectiveness of personalized learning be measured in terms of mastery gain, engagement, and completion rate?

IV. Scope and Limitations

This internship project focuses on the design and development of a personalized learning model with the following scope:

- Development of a learning path recommendation based on learner levels and skill gaps.

- Integration of several factors (performance, engagement, interaction, and learning progress).
- Application of Intelligent Tutoring System (ITS) principles to guide personalization logic and adaptive decision-making.
- Use of the Skills Framework for the Information Age (SFIA) to define target skills and support structured skill gap identification.

The project is subject to the following limitations:

- The implementation will be limited to a prototype and will not include full production deployment.
- Skill mapping using SFIA will focus on selected skills and proficiency levels relevant to the learning context.
- Model evaluation will rely on existing/sample data and may not include real-time data.
- Real-time system integration and large-scale performance optimization are outside the scope of this project.

V. Project Overview

This project proposes the development of a personalized learning model that recommends adaptive learning paths based on learner levels and skill gaps. The solution integrates learner data, skill frameworks, and adaptive decision logic:

1) System Overview
    - Learner model: represents learner knowledge, mastery level, engagement, and interaction behaviour based on assessment results and learning activity data.
    - Skill model (SFIA-aligned): defines the learning modules based on target skills and proficiency levels using selected SFIA skill categories to enable structured skill gap identification.
    - Personalization and decision engine: applies adaptive logic to identify skill gaps and recommend learning paths that prioritize relevant modules based on learner needs.
    - Recommendation output: produces an ordered and explainable learning path, including alternative modules to give a chance for the learner to explore different topics.

2) Key Personalization Factors
    - Time-related factors: consider learner focus time, expected duration of learning materials, and observed learning speed across different study phases.
    - Understanding-related factors: consider learner educational background, estimated mastery level, engagement behaviour, and patterns of mistakes identified through assessments.

- Content-related factors: consider learning difficulty, prerequisite relationships, structured learning maps, and content formats suitable for different learning needs.
- Decision-making logic factors: support multiple valid next learning steps, allow exploration of alternative recommendations, maintain continuity in specified topics, and adapt recommendations based on learner progress over time.

3) Personalization Logic and Algorithms
   - Baseline personalization (related algorithm: *Rule-Based Logic*)
     Rule-based logic serves as the foundation of a personalization system. It applies a predefined mastery threshold, prerequisite relationship, and progression rules to check whether the quantitative score meets the standard or not.
   - Learner knowledge and mastery modelling (related algorithms: *Bayesian Knowledge Tracing* and *Multiple Perceptron*)
     To model learner knowledge progression over time, knowledge tracing techniques are needed. BKT is used to estimate concept-level mastery in an interpretable manner, which supports clear identification of skill gaps aligned with skill levels in SFIA. In parallel, the MLP model is used to predict learner mastery and learning outcomes by integrating multiple signals (performance, engagement, and interaction).
   - Learner segmentation and similarity (related algorithms: *K-Means Clustering*, *DBSCAN*, and *TD-IDF*)
     To capture diverse learning behaviours, K-Means clustering is used to identify common learner behaviour, and DBSCAN to detect irregular or outlier learning behaviours that might require different consideration. Besides, TD-IDF with cosine similarity is used as a baseline for content similarity.
   - Adaptive path optimization (related algorithm: *Reinforcement Learning*)
     As an exploratory component, RL is an important part of the decision-making process to give a recommendation for the learner. The system optimizes long-term objectives such as mastery improvement, engagement, and completion.

VI. Methodology

This project focuses on developing and evaluating a personalized learning path recommendation model by following:

1) Problem understanding and data exploration
   To build a model, understanding the structures and factors is needed. A data exploration together with analysis will be conducted to identify relevant factors (performance, engagement, and progression) with other personal learners' background factors, such as education history and learning capability.

2) Learner and skill representation

   The existing/sample data will be transformed into structured representations that capture:
   - Performance and mastery indices
   - Engagement and interaction behaviour
   - Skill coverage and gaps

   Learning content and skills will be mapped using predefined competency levels (ITS concepts and SFIA-aligned skills).

3) Personalization logic

   The personalization logic defined in the previous section (Project Overview), and each approach is developed as an independent experiment to assess its contribution to learning path recommendations:
   - Baseline progression using rule-based logic
   - Learner mastery estimation and prediction
   - Learner behaviour segmentation and content similarity
   - Exploratory adaptive path optimization

4) Evaluation and analysis

   Each model is evaluated and compared against the baseline personalization logic. Evaluation focuses on skill mastery progression, learner engagement and completion behaviour, and relevant recommendations.

5) Iteration and refinement

   Information from evaluation will be used to define learner representations, personalization rules, and modeling strategies. The methodology follows an iterative cycle of trial and error, analysis, and improvement throughout the internship period.

VII. Expected Outcomes

By the end of the internship, the following outcomes are expected:

- A personalized learning path recommendation model that applies ITS principles and SFIA-aligned skill levels to identify learner skill gaps and recommend a learning path.
- A structured comparison of baseline and data-driven personalization strategies, highlighting their strengths, limitations, and practical trade-offs for adaptive learning.
- A documented approach for representing learner performance, engagement, and progression in relation to SFIA skills, supporting future personalization and learning analytics efforts.

- An evaluation summary covering mastery progression, engagement, and recommendation decision-making, providing evidence-based insights into the effectiveness of the adaptive learning paths.
- Actionable recommendations for extending personalized learning implementation.

Best-Case Scenario:

The internship successfully produces a robust personalized learning path recommendation model aligned with ITS principles and SFIA skill levels. Data-driven personalization approaches demonstrate measurable improvements over the baseline rule-based logic in terms of learner mastery progression, engagement, and completion rates. The learner model effectively integrates performance, engagement, and interaction, enabling accurate identification of skill gaps and readiness for upcoming progression. As a result, selected components and the insights are suitable for further development, internal testing, or implementation within Radya Labs's projects.

Worst-Case Scenario:

The internship still delivers a validated SFIA-aligned baseline personalization framework, supported by structured learner-skill mappings and clearly defined progression rules within the ITS framework. Although an adaptive learning path may not demonstrate significant visible output, the analysis provides valuable insights into learner behaviour, data limitations, and system constraints. These findings will help future R&D directions by detecting which approaches are feasible, what data improvements are required, and how adaptive learning can be implemented in the future.

Personal Learning Goals:

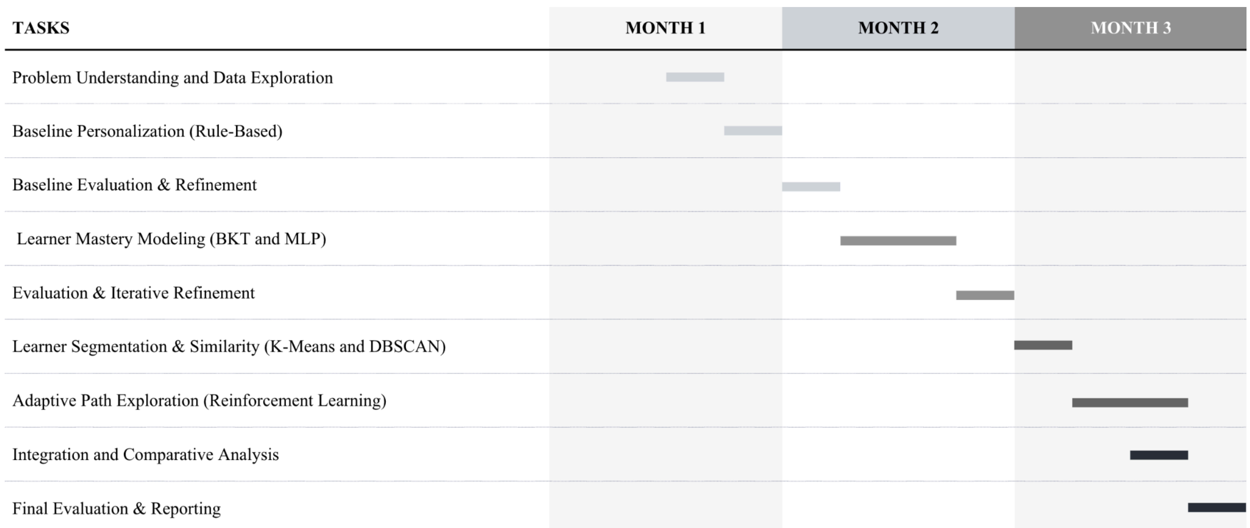
In addition to contributing to Radya Labs's research and development objectives, this internship is a learning opportunity to deepen practical and research-oriented skills in an adaptive learning system. Through this internship, I aim to:

- Develop applied expertise in ITS
  Gain hands-on experience designing learner models, mastery estimation, and adaptive learning paths using ITS principles.
- Apply machine learning in an educational context
  Strengthen the ability to evaluate and compare machine-learning approaches for personalized learning implementation.
- Understanding skill framework integration
  Learn how competency frameworks such as SFI can be operationalized within learning systems to support structured skill development and gap analysis.
- Improve research and experimentation skills
  Enhance skills in experimental design, evaluation, and result interpretation in research and development.

- Develop professional communication skills
  Improve the ability to document and communicate technical findings and present insights clearly.

VIII. Work Plan

Gantt chart:



Iteration 1:

- Week 1: Problem Understanding and Data Exploration
  Focuses on reviewing the SFIA skill list and learning content structure, identifying available learner performance and engagement data, and exploring data analysis to understand learner behaviour.
- Week 2: Baseline Personalization (Rule-Based)
  Focuses on implementing SFIA-aligned rule-based personalization logic, defining mastery thresholds, and prerequisite relationships, and generating baseline learning paths as a reference point.
- Week 3: Baseline Evaluation and Refinement
  Focuses on evaluating baseline learning paths, identifying gaps, limitations, and improvement opportunities, and refining rules, thresholds, and prerequisites.

Iteration 2:

- Week 4-5: Learner Mastery Modelling (BKT and MLP)
  Focuses on implemented learner mastery estimation models, integrating performance, engagement, and interaction features, and comparing mastery models against baseline rules.

- Week 6: Evaluation and Iterative Refinement
  Focuses on evaluating mastery predictions and learning path adjustments, refining learner representations and feature selections, and updating personalization logic based on findings.

Iteration 3:

- Week 7: Learner Segmentation and Similarity (K-Means and DBSCAN)
  Focuses on applying clustering and similarity techniques, analyzing learner groups, and alternative learning paths.
- Week 8-9: Adaptive Path Exploration (Reinforcement Learning)
  Focuses on exploring adaptive decision-making mechanisms, simulating adaptive learning path adjustments, and evaluating the feasibility and impact of adaptive approaches.

Iteration 4:

- Week 9: Integration and Comparative Analysis
  Focuses on integrating segmentation insights into personalization logic with a comparison analysis of each approach.

- Week 10: Final Evaluation and Reporting
  Focuses on conducting final comparative evaluation across approaches, analyzing, and preparing the deliverable prototype and final report of findings and recommendations.

IX. Conclusion

This proposal outlines an internship project to explore and develop a personalized learning path recommendation model aligned with ITS principles and SFIA skill levels. Through an iterative R&D approach, the internship aims to evaluate a combination of multiple personalization strategies, identify learner skill gaps, and generate actionable insights for adaptive learning design. The expected outcome include a validate baseline personalization framework, comparative analysis of data-driven models, and practical recommendations for future development.