TransitionIQ: An Explainable Learning Analytics Prototype for Cross-Discipline Transfer Readiness

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Abstract

Students increasingly choose interdisciplinary academic paths. However, most Learning Analytics systems focus on performance instead of supporting transitions between disciplines. This paper explores how clear, competency-based analytics can help learners understand which skills they can transfer to a new discipline and where they need to improve. We present TransitionIQ, a prototype explainable analytics system that assesses cross-discipline readiness. It uses a mixed framework that combines the ETH Competency Model with the Dreyfus Skill Acquisition stages. Learners evaluate their current and target domain skills. The system then calculates a weighted readiness score, identifies transferable skills, points out gaps, and displays these results on an explainable dashboard. All scoring methods, skill mappings, and suggestions are shared with the learner, following the principles of transparency, personal choice, and Explainable Learning Analytics. This work offers a model and prototype that shows how Learning Analytics can shift from tracking performance to providing clear, skill-focused insights that effectively support interdisciplinary learning paths.

Keywords

Explainable Learning Analytics, Skill Transfer, Interdisciplinary Education, LMS Integration, Dreyfus Model, ETH Competency Framework, Artificial Intelligence

1. Introduction

Interdisciplinary learning is becoming crucial for preparing students to tackle complex real-world problems that cross different fields [1, 2]. However, many learners find it hard to identify which of their existing skills can transfer to a new discipline and which skills they need to develop from scratch [3, 4]. This issue is especially evident in higher education, where programs are often divided into separate subject areas, making transitions between fields challenging to navigate [5, 6].

Explainable Learning Analytics (XLA) offers a promising solution by focusing on clarity, learner involvement, and understandable feedback [7, 8]. Unlike traditional learning analytics systems, which mainly emphasize tracking performance and predicting outcomes, XLA seeks to clarify how learning happens, why certain skills are important, and how students can effectively address skill gaps [9, 10]. This approach supports responsible data use and helps learners make informed choices about their educational paths.

In this work, we present *TransitionIQ*, a tool integrated within LMS that uses XLA to assist in transferring skills across disciplines and assessing readiness but our future goal is that this framework should be integrated as a tool in any LMS. TransitionIQ integrates a self-assessment process based on the Dreyfus model of skill acquisition with evaluations for both domain-specific and general competencies [1, 3]. Through this setup, the system pinpoints transferable skills, identifies areas for improvement, and creates personalized learning plans to guide learners during interdisciplinary transitions. For instance, a student shifting from Mathematics to AI in Education might bring strong analytical skills but need to

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develop programming, data management, or applied machine learning knowledge. Similarly, a student transitioning from Computer Science to Quantum Computing or Quantum Technology may possess solid foundations in algorithms and software development but must acquire new competencies in quantum mechanics, linear algebra for quantum systems, and quantum-specific programming paradigms.

This work contributes three key points:

1. A new XLA-based framework for modeling and visualizing transferable skills across academic fields.
2. A privacy-conscious LMS integration showing how explainable analytics can function within current institutional systems.
3. A complete and structured process explaining how TransitionIQ helps learners find and address interdisciplinary skill gaps.

Overall, TransitionIQ promotes learner-focused analytics for interdisciplinary education and gives institutions a clear, ethically sound system to support academic transitions. TransitionIQ is presented as a design-driven, theory-informed prototype rather than a validated predictive system. The contribution of this paper lies in explicating the conceptual mechanisms, explainability design, and computational logic that underpin cross-discipline transition readiness, not in reporting empirical learning outcomes.

2. Related Work

Cross-discipline learning and skill transfer have been the subject of much study in education research. Traditional approaches often emphasize curriculum design and teaching strategies to help students move between different areas [5, 2]. However, these methods usually depend on instructor guidance and do not provide individual analytics for learners.

Learning Analytics (LA) has emerged as a data-driven method to understand and improve student learning outcomes [11, 12]. Standard LA techniques focus on tracking performance, making predictions, and visualizing learning behaviors [8, 7]. While these methods work well for assessment, they often do not offer clear insights into skill transfer, leaving learners unsure about how to apply their existing skills in new areas [9].

Explainable Learning Analytics (XLA) builds on LA by highlighting understandability, transparency, and learner involvement [10, 4]. XLA frameworks aim to clarify and make actionable the reasoning behind learning recommendations. This supports learners in recognizing which skills they can transfer and how to gain new ones. Recent studies in XLA have looked into personalized dashboards, guidance on micro-tasks, and metrics for transfer readiness to aid interdisciplinary learning [3, 1, 6].

Many tools and systems have tried to facilitate skill transfer across different fields. For instance, competency mapping frameworks align skills across various disciplines and provide structured pathways for learners [1]. Plugins integrated into Learning Management Systems (LMS) have also been considered, using built-in assessments and analytics to assist student learning [7]. However, few existing solutions integrate understandability, actionable advice, and privacy-friendly AI systems at the same time.

TransitionIQ builds on these ideas by combining a skill assessment framework inspired by Dreyfus, domain-specific self-assessments, and clear analytics to deliver personalized, actionable insights for learners. Unlike earlier systems, it focuses specifically on skill transfer, micro-task roadmaps, and a score for transfer readiness to help learners navigate between fields, ensuring ethical and transparent use of learner data.

3. Theoretical Foundations

3.1. ETH Competency Framework

The theoretical foundation of TransitionIQ is based on the ETH Zurich Competency Framework. This framework offers a structured model to describe learner abilities across various disciplines [13]. It identifies four dimensions of competence: *subject-specific*, *method-specific*, *personal*, and *social*. Subject-specific competencies cover disciplinary knowledge, conceptual understanding, and technical skills relevant to a particular field. Method-specific competencies include general skills like analytical reasoning, data literacy, and problem-solving. Personal competencies involve self-regulation, adaptability, and reflective practice. Social competencies focus on collaboration, communication, and effective teamwork.

TransitionIQ uses this complete model as a conceptual foundation but focuses only on two dimensions: subject-specific and method-specific competencies for computation and readiness scoring. These two dimensions were chosen for two main reasons. First, they provide the clearest indicators of how well a learner's current skills match the academic expectations of a new discipline. Subject-specific competencies highlight potential gaps in domain knowledge. In contrast, method-specific competencies show transferable skills that can aid learning across different fields. Second, by limiting the quantitative assessment to these dimensions, we ensure that the resulting metrics remain understandable for learners. This avoids the complexities of measuring personal and social competencies, which tend to be more qualitative and context-dependent. The broader ETH framework still guides the system's design by placing the assessed competencies within a recognized model of interdisciplinary skill development.

3.2. Dreyfus Skill Acquisition Model

TransitionIQ adapts the Dreyfus Skill Acquisition Model. This model views learning as a progression through five stages: novice, advanced beginner, competent, proficient, and expert [14]. In the original model, each stage reflects higher levels of independence, contextual awareness, and intuitive decision-making. We use this framework to structure how learners report their familiarity with competencies and progress through transition bands (see Table 1).

Table 1
Adapted Dreyfus Skill Levels, Numeric Score Ranges, and Readiness Bands in TransitionIQ

Dreyfus Stage	Score Range (0–100)	Readiness Band	Operational Meaning in System
Novice	0–20	Starter	Learner relies on explicit rules with minimal contextual understanding; requires step-by-step guidance.
Advanced Beginner	21–40	Emerging	Shows basic familiarity and can follow structured tasks; beginning to recognize patterns but needs reinforcement.
Competent	41–60	Building	Can plan and execute small tasks with support; applies methods in familiar situations; considered partially transferable.
Proficient	61–80	Ready Soon	Demonstrates growing independence, handles sequenced tasks, and adapts strategies; weighted strongly in readiness scoring.
Expert	81–100	Transition-Ready	Displays intuitive mastery and fluid performance; regarded as a transferable strength suitable for advanced tasks.

To implement the model for quantitative analysis, TransitionIQ collects two types of learner inputs: (1) domain familiarity ratings for both the current and target fields and (2) competency ratings spanning subject-specific and method-specific skills. Each item is answered on a 1–5 Likert scale aligned with the five Dreyfus stages. These values function as more than numeric inputs; they are used to create an aggregate score that represents the learner's overall readiness for moving to a new discipline. The cumulative score is then mapped onto the readiness bands in our prototype. These bands turn theoretical stages into practical categories that learners can easily understand.

The readiness bands range from *Starter* to *Transition-Ready*, with each defined by a specific score interval (0–100) based on the sum of Likert responses across key competency areas. For instance, scores in the 0–20 range match the *Starter* band, reflecting traits similar to the Novice stage. In contrast, scores of 81–100 correspond to the *Transition-Ready* band, which closely aligns with the Expert stage's intuitive mastery. The band labels also guide the wording of AI-generated self-assessment questions, ensuring the questions fit the expected behaviors of each readiness level.

Table 1 summarizes how the Dreyfus stages inform our operational scale, the associated score ranges, and the readiness bands used in TransitionIQ.

The numeric score ranges presented in Table 1 are derived from a linear mapping of Likert-scale responses to a 0–100 scale, which reflects the learner's overall competency levels. It is important to note that the original Dreyfus model is qualitative and does not specify numeric thresholds. These ranges were therefore defined within TransitionIQ to operationalize the model for computational assessment, enabling learners to see their readiness in clearly defined bands. Each band—from *Starter* to *Transition-Ready*—provides an interpretable indicator of current skills, highlights areas for improvement, and aligns with the expected behaviours of the corresponding Dreyfus stage, supporting transparent, explainable learning analytics.

4. System Design

TransitionIQ operates through a three-stage workflow that begins with secure learner onboarding, followed by structured competency assessment, and concludes with an explainable readiness analysis and personalized transition roadmap. Beginning with secure user onboarding and LMS integration and progressing through assessment, analytics, and explainable personalization. Learner readiness is computed through competency aggregation, skill gap analysis, and Dreyfus band mapping, which then informs a local AI–driven personalized learning roadmap. Privacy, consent, and explainability mechanisms are embedded across all stages to ensure transparent and trustworthy decision-making. All computation occurs on institutionally hosted servers, ensuring transparency, privacy, and full data control.

4.1. User Onboarding

The onboarding stage introduces learners to the system and establishes a secure connection with the institutional LMS through OAuth2. TransitionIQ retrieves only minimal enrollment metadata—such as course and module names—to contextualize domain-specific assessments. No grades, submissions, or personal identifiers beyond the learner's explicit inputs are accessed. This stage also explains the system's ethical design: all AI processing remains within the university's computing environment, and no data is transmitted to external services. Learners then complete a brief profile that is used solely to personalize competency questions and subsequent roadmap recommendations.

4.2. Assessment

The assessment stage collects structured self-evaluations rooted in the ETH Competency Framework and interpreted through the adapted Dreyfus model. Learners first provide familiarity ratings for their current and intended disciplines, using a Likert-style input that guides the calibration of later questions. This prevents the assessment from becoming too advanced for novices or too shallow for experienced learners.

Subsequent items ask learners to rate their subject-specific and method-specific competencies in both the source and target fields. These items distinguish conceptual understanding (e.g., theories, principles) from practical methodological skills (e.g., workflows, tools) and are generated dynamically based on LMS-derived domain metadata. All responses are interpreted using the score ranges and readiness bands defined in Table 1. Although the original Dreyfus model is qualitative, TransitionIQ operationalizes each stage into numeric ranges on a 0–100 scale to support consistent and transparent interpretation within a digital assessment context. In the current prototype, each competency is assessed using a single calibrated self-report item aligned with the adapted Dreyfus scale, allowing transparent interpretation while supporting future extension to multi-item measures.

4.3. Analysis and Feedback

The analysis stage converts the learner's self-assessment data into an interpretable measure of transfer readiness. TransitionIQ computes two parallel representations: (1) a numerical Transfer Readiness Score and (2) an interpretable readiness band derived from the adapted Dreyfus ranges in Table 1. Both representations draw directly from the ETH competency categories.

TransitionIQ does not assume that all competencies contribute equally to cross-discipline transitions. Instead, the system distinguishes between transfer-enabling competencies and domain-constraining competencies. Method-specific competencies (e.g., analytical reasoning, procedural thinking, tool usage) are treated as primary transfer enablers, as they tend to generalize across domains. Subject-specific competencies function as alignment constraints that indicate where additional domain learning is required. The readiness score therefore reflects not only overall competence level but also the balance between transferable strengths and domain-specific gaps.

All competency ratings are collected using a five-point Likert scale aligned with the adapted Dreyfus stages (1 = Novice, 5 = Expert). First, the system aggregates the learner's ratings into two competency areas in each domain: subject-specific and method-specific competencies. Let $\mathrm{Avg}_{\mathrm{sub,current}}$ and $\mathrm{Avg}_{\mathrm{meth,current}}$ denote the averaged ratings for the current discipline, and $\mathrm{Avg}_{\mathrm{sub,target}}$ and $\mathrm{Avg}_{\mathrm{meth,target}}$ the corresponding averages for the target discipline. TransitionIQ quantifies required development by computing a competency gap for each area:

$$\mathrm{Gap}_i = \mathrm{Avg}_{i,\mathrm{target}} - \mathrm{Avg}_{i,\mathrm{current}},$$

Positive values indicate required development, while near-zero or negative values indicate transferable competencies. Method-specific competencies are weighted more heavily in this interpretation, as these typically generalize across disciplines more reliably than subject-specific knowledge. Method-specific competencies are weighted more heavily in this interpretation, as these typically generalize across disciplines more reliably than subject-specific knowledge.

To analyze overall preparedness, TransitionIQ derives a numerical readiness value from the learner's current-domain competencies:

$$R = \frac{\mathrm{Avg}_{\mathrm{sub,current}} + \mathrm{Avg}_{\mathrm{meth,current}}}{2}.$$

This value is normalized using standard min max normalization to a 0–100 range through a linear transformation, where the denominator 4 is obtained by max - min, in our case 5 - 1,

$$R_{\%} = 100 \times \frac{R-1}{4},$$

The constants derive from min–max normalization of the Likert scale, where 1 is the minimum and 5 1 = 4 is the range. This ensures that the minimum level on the Likert scale maps to 0% and the maximum maps to 100%. Although inspired by the qualitative structure of the Dreyfus model, this operationalization provides a transparent, quantitative representation the learner can interpret without ambiguity.

The resulting percentage is then mapped to the Dreyfus-aligned readiness bands shown in Table 1. These bands—Starter, Emerging, Building, Ready Soon, and Transition-Ready—provide an accessible explanation of what the learner's numerical readiness signifies in terms of independence, transfer potential, and expected ability to navigate tasks in the target field. By grounding these bands in explicit score ranges, TransitionIQ offers learners a clear rationale for the system's judgments and how incremental changes in their ratings affect their progression.

To ensure interpretability, TransitionIQ exposes multiple explanation layers to learners: The framework includes readiness bands that translate numerical scores into clear semantic stages, along with explicit visualizations that highlight competency gaps between source and target domains. It provides visibility into how method-specific factors are weighted versus subject-specific ones, and offers a personalized roadmap that connects identified gaps directly to recommended learning actions. Inline tooltips are also included to explain how individual ratings contribute to overall readiness.

The system then synthesizes the competency gaps, weighted interpretations, and readiness band to identify (1) transferable competencies, where current skills meet or exceed target expectations, and (2) developmental areas requiring targeted learning. These insights feed directly into the personalized roadmap generator, which proposes sequenced learning tasks, module recommendations, and short practice activities aligned with the learner's progression toward higher readiness bands. Because the analysis is recalculated whenever the learner updates their ratings, TransitionIQ supports iterative self-reflection and transparent skill growth. The Personalized Roadmap in the TransitionIQ prototype presents a sequence of learning modules arranged along a simple timeline, where each module is displayed as a labeled block with its estimated duration and point contribution, alongside an overall progress indicator and target completion date, providing a clear, high-level view of the learner's structured path toward transition readiness.

4.4. Explainability, Privacy design and Institutional logging

TransitionIQ focuses on explainability, transparency, and privacy so learners understand how their data is used and how insights are created. The system displays all readiness calculations and skill mappings through intuitive tooltips and explanations. This allows users to see how their self-assessment inputs affect their Transition Readiness Score. This approach reflects educational XAI research, which emphasizes the need for clear reasoning to build trust and support ethical decision-making [15, 16].

When learners first use the system, they see a clear consent banner. This banner details what data is collected, how it will be used, and what controls they have, including the option to opt out. This ensures informed consent and respects learner autonomy, following established guidelines for responsible analytics in education.

To build trust further, all AI-driven processing, such as generating personalized statements or task descriptions, happens on locally hosted models within the institution's own infrastructure. This avoids dependence on external services and keeps sensitive data completely under institutional control [15]. Integration with the LMS is kept minimal and limited to non-sensitive metadata like course and module names. It excludes grades, submissions, or any identifying information to reduce privacy risks. By combining explainable scoring, local AI processing, secure LMS integration, and clear user consent, TransitionIQ establishes a trustworthy and privacy-sensitive environment. This encourages honest learner engagement and supports ethical, long-term use of AI in education.

4.5. System Design Limitations

TransitionIQ has an initial-stage student dashboard that has not yet been integrated into an LMS with a teacher dashboard, which limits its direct applicability for instructors and institutional workflows. The whole system design and its workflow is shown in Figure 1. This prototype shows how Explainable Learning Analytics (XLA) can go beyond just tracking performance. It uses the adapted Dreyfus framework to model learning readiness across different fields. This helps learners and mentors understand the gaps that exist, why they come up, and how to tackle them. However, the current prototype has some limitations affecting its practicality. TransitionIQ depends on learners assessing their own abilities to gauge their subject-specific and method-specific skills. This can lead to bias since what learners believe they can do may not match their true performance. While this subjectivity is acceptable in early development, it limits how accurately we can estimate readiness. While the system provides explainable outputs, learners may still require initial scaffolding to interpret readiness bands in relation to real-world transition decisions. In TransitionIQ, readiness bands are therefore paired with concrete roadmap actions to reduce abstraction and support sense-making.

Another limitation is that most learning systems don't keep organized records of skill levels that fit the Dreyfus-inspired framework. This makes it hard to verify or cross-check the skills learners report. As a result, the system relies entirely on information provided by users instead of institutional

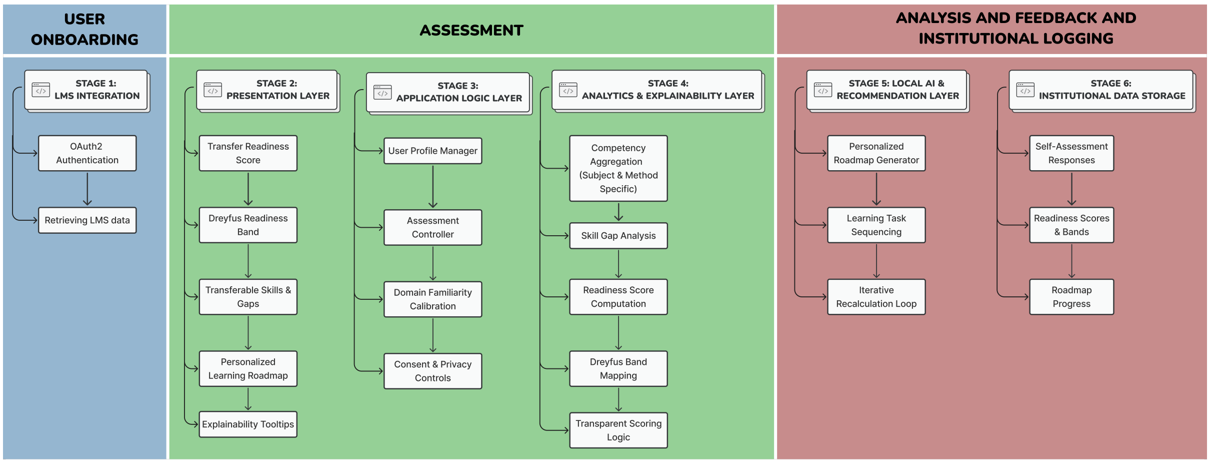

Figure 1: System architecture of TransitionIQ illustrating a six-stage workflow from secure user onboarding to analysis, feedback, and institutional data storage. The process begins with User Onboarding, where learners authenticate via OAuth2 and provide consent for retrieving LMS data. Stage 1: LMS Integration manages authenticated access and LMS data retrieval. Stage 2: Presentation Layer supports learner self-assessment through transfer readiness scores, Dreyfus readiness bands, and the identification of transferable skills and gaps, supported by explainability tooltips. Stage 3: Application Logic Layer handles user profile management, assessment control, domain familiarity calibration, and consent and privacy controls. Stage 4: Analytics and Explainability Layer aggregates subject- and method-specific competencies, performs skill gap analysis, computes readiness scores, maps learners to Dreyfus bands, and exposes transparent scoring logic. Stage 5: Local AI Recommendation Layer generates personalized learning roadmaps through learning task sequencing and an iterative recalculation loop. Finally, Stage 6: Institutional Data Storage securely stores self-assessment responses, readiness scores and bands, and longitudinal readiness progress to support institutional analysis and feedback. Explainability and privacy-by-design principles are integrated across all stages.

proof. The numeric readiness bands—0–20, 21–40, 41–60, 61–80, and 81–100—were defined by the authors for quantitative analysis and have not yet been validated with users. This method used to weigh different fields in the readiness calculations is based on heuristics and needs future checks with experts to confirm its educational value. Additionally, even though TransitionIQ creates personalized learning plans, these pathways come from static algorithms and don't currently adjust in real time to changes in learner progress or skill levels. Despite these issues, TransitionIQ shows how transparency, clear explanations, and ethical data use can boost learner agency, improve mentorship efficiency, and aid institutions in creating better interdisciplinary transitions.

5. Future Work

TransitionIQ is currently a design concept that will undergo systematic validation in future studies. Several extensions can enhance its value and confirm its impact across its key stakeholders, including students, teachers, and universities. First, a multi-university usability study will evaluate how clear and understandable the dashboard is, and how much users can trust it. This study aligns with recommendations for learner-centered evaluation in explainable dashboard research [17]. It will include an examination of how well the Dreyfus-based transitions convey competence development.

Second, future work will look into adaptive question generation using local LLMs. Instead of using fixed prompts, the system could customize examples and explanations based on each learner's background, discipline, and target field, improving personalization without compromising privacy.

Another research direction involves expanding the readiness model to other areas like biology, economics, and design. This expansion will help find out whether the Dreyfus progression remains easy to understand and whether different fields need adjusted transition rules.

Finally, we envision long-term integration within LMS ecosystems. TransitionIQ could act as a standard module for transfer-readiness analytics. It would support academic advising, career paths, and lifelong learning scenarios while strictly following XAI and privacy guidelines.

6. Conclusion

TransitionIQ presents a clear and understandable method for learning readiness analytics that helps students as they move between different fields. Unlike performance-focused dashboards, this system uses a Dreyfus-based progression model, competency mapping, and explainable scoring. These features help learners understand not only where they stand but also why they are at that level. By including structured self-assessments, transfer analysis, and personalized development roadmaps, TransitionIQ promotes both learner independence and advisor effectiveness.

The prototype shows that it is possible to evaluate cross-domain readiness without intrusive data collection. Instead, it focuses on local computation, understandable feedback, and minimal LMS metadata. Dashboards may boost confidence and clarity when navigating academic transitions. Overall, TransitionIQ adds to a new category of ethical and understandable learning analytics tools that protect privacy while promoting movement between disciplines.

TransitionIQ offers a new approach to learning analytics by modeling how learners transfer skills across different subjects. It goes beyond just analyzing performance in a specific field. The system features clear dashboards that include understandable scores, Dreyfus-level mappings, and tooltip explanations. This addresses known issues with current skill-visualization tools [18, 19]. By encouraging ongoing self-assessment and clear weighting methods, TransitionIQ gives learners more control. It helps them understand, question, and shape their own development paths. Finally, the system supports the larger goals of the LAK and XAI-Ed communities by providing an explainable, practical, and ethical approach to educational decision-making.

Overall, TransitionIQ positions learning readiness as an interpretable, ethically grounded analytic capability extending the vision of learning analytics to support smooth interdisciplinary transitions and empowering learners with actionable insights.

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Declaration on the Use of Generative AI

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