LAURA: An Awareness-Oriented Explainable AI Framework for Academic Stress in Higher Education

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***Abstract*—Academic stress represents a significant challenge in higher education, especially for students navigating unfamiliar academic environments. In such contexts, difficulties in understanding expectations, feedback, and performance standards can affect engagement, participation, academic performance, and decision-making. Despite significant advances in learning analytics and artificial intelligence, current educational systems remain limited in their ability to support students' sense-making of their academic conditions. Existing systems predominantly focus on prediction and performance monitoring, offering limited support for interpretation and awareness, which are essential for understanding academic stress, particularly in complex or unfamiliar learning environments. To address this limitation, this study introduces the LAURA framework (Learning Context Modeling, Academic Stress Assessment, Understanding-Oriented Explanation, Reflection Support, and Adaptive Awareness Feedback), an awareness-oriented framework designed to support students in understanding their academic stress through interaction. Unlike traditional AI approaches that prioritize prediction, LAURA conceptualizes academic stress as an interpretive process and positions explainable AI as a mechanism to support students' awareness. The framework integrates transparent modeling, explanation, and structured reflection within a unified interaction cycle, enabling students to interpret academic signals, examine contributing factors, and develop a more informed understanding of their conditions. Grounded in appraisal-based stress theory and principles of human-centered AI, LAURA extends existing approaches by embedding explanation and reflection as core components of system design rather than auxiliary features. In this way, it shifts the role of explainable AI from revealing model behavior to supporting meaning-making processes within educational contexts. The proposed framework contributes a new perspective on AI-supported educational systems by emphasizing awareness as the primary outcome. It provides a conceptual and design foundation for developing student-facing systems that not only analyze academic conditions but also support students in making sense of them, particularly in diverse and complex educational environments. As a conceptual framework, LAURA provides a foundation for future implementation and empirical validation in educational settings.**

***Keywords*—Explainable Artificial Intelligence (XAI); academic stress; student awareness; interpretable models; human-centered AI; higher education**

I. Introduction

Academic stress is a well-established challenge in higher education, influencing students' well-being, engagement, and academic performance. While a certain level of stress can support motivation, prolonged or poorly managed stress may negatively affect students' learning experiences and academic decision-making [1]. In response, universities have increasingly adopted data-driven approaches, including learning analytics and artificial intelligence (AI) systems, to monitor and understand students' academic conditions [2].

These systems provide robust capabilities for analyzing large-scale educational data and identifying patterns in performance, engagement, and academic risk. In particular, AI-based approaches have been widely used for prediction, classification, and early identification of at-risk students. However, despite these advancements, most existing systems remain primarily oriented toward outcome estimation, with limited support for how students interpret their academic situations [3], [4].

This limitation is particularly important in the context of international students, who often face additional challenges when navigating unfamiliar academic environments. Differences in academic communication practices, educational systems, and implicit expectations can make it difficult to accurately interpret feedback, assessment criteria, and performance indicators. Prior work has shown that academic stress in such contexts is not only driven by workload or outcomes, but also by difficulties in interpreting academic signals [5]. This highlights a critical need for systems that support students not only in receiving information, but also in meaningfully interpreting that information.

Recent research has explored the role of explainable artificial intelligence (XAI) in improving the transparency of AI systems in education [6]. While these approaches enhance visibility into how models operate, explainability is often treated as a technical property that reveals model behavior [7], [8]. As a result, students may still face challenges in connecting system outputs to their own academic experiences. This indicates that transparency alone is insufficient to support meaningful understanding.

Based on these limitations, a clear research gap emerges: current AI-supported educational systems provide limited support for interpretation and awareness, particularly in contexts where students must actively make sense of complex and unfamiliar academic conditions. Addressing this gap requires moving beyond prediction and transparency to support students in interpreting academic information and engaging in reflection that promotes awareness of their academic conditions.

Our previous work highlighted this research gap through a comprehensive review of explainable AI and academic stress among international university students, identifying the need for student-facing systems that support awareness and interpretation rather than prediction alone [5]. However, that study did not propose a framework architecture or specify how such awareness-oriented support could be realized in practice. The present study addresses this gap by proposing the LAURA framework, which comprises a five-phase conceptual architecture that integrates learning context modeling, academic stress assessment, understanding-oriented explanation, reflection support, and adaptive awareness feedback into a unified interaction cycle.

Building on this foundation, the present study introduces the LAURA conceptual framework, an awareness-oriented approach designed to support students in developing awareness of their academic stress conditions. The framework conceptualizes academic stress as an interpretive process in which students construct meaning through interaction with system feedback. Rather than treating stress estimation as the final system outcome, LAURA is designed to help students understand how different academic factors contribute to their stress experiences and to promote awareness through explanation and reflection.

The main contributions of this study are fourfold. First, it advances an awareness-oriented conceptualization of academic stress in AI-supported educational systems by emphasizing interpretation over prediction. Second, it introduces the LAURA framework as a five-phase conceptual architecture that extends existing learning analytics and educational XAI approaches by integrating learning context modeling, academic stress assessment, understanding-oriented explanation, reflection support, and adaptive awareness feedback within a unified interaction cycle. Third, it repositions explainable AI from a mechanism for revealing model behavior to a form of cognitive support that enables students' interpretation and meaning-making. Finally, it provides awareness-oriented design principles for developing student-facing AI systems, particularly for students navigating unfamiliar academic environments, including international students.

The remainder of this study is organized as follows:

- Section II: Related Work reviews existing studies on academic stress, student awareness, and AI-based approaches in education.
- Section III: Framework Development Methodology presents the conceptual design approach, architectural structure of LAURA, and awareness-oriented design logic.
- Section IV: Conceptual Interaction and Awareness Development describes the interaction process and how awareness is developed through the framework.
- Section V: Discussion discusses the theoretical, design, and international student implications of the framework, presents its limitations, and outlines research implications.
- Section VI: Conclusion summarizes the main contributions of the study and highlights the significance of the proposed framework.

II. Related Work

This section reviews the main research areas related to the development of the LAURA framework. The discussion focuses on four themes: academic stress in higher education, artificial intelligence approaches for analyzing academic stress indicators, learning analytics dashboards and student awareness, and the role of explainable artificial intelligence in educational systems. Examining these areas helps situate the proposed framework within the current literature and highlights the limitations that motivate the development of LAURA.

A. Academic Stress in Higher Education

Academic stress has been widely recognized as an important factor influencing students' learning experiences, well-being, and academic performance. University students frequently encounter multiple academic demands, including coursework, assignments, examinations, and performance expectations. These demands may create pressure that affects both academic engagement and students' perceptions of their learning environment.

Previous research has identified several common contributors to academic stress in higher education. Among the most frequently reported factors are perceived academic workload, deadline pressure, unclear academic expectations, and difficulties in understanding course materials [5], [9], [10]. Studies show that academic demands, assessment pressure, and time constraints represent major sources of stress among students in higher education. Other research also indicates that uncertainty regarding grading criteria and course expectations can increase academic pressure among students.

In addition to workload-related factors, interpretive uncertainty plays an important role in academic stress experiences. Students may experience additional pressure when they struggle to interpret academic signals such as instructor feedback, grading standards, or course expectations [11]. These challenges may become more pronounced in international learning environments where students encounter unfamiliar educational systems or language-related comprehension difficulties [12].

Students may also interpret academic signals differently depending on their prior experiences, confidence levels, and familiarity with the learning environment. Such differences in interpretation may influence how academic demands are perceived and how strongly students experience academic pressure [13].

Academic stress may be particularly significant for international students who study in unfamiliar educational environments [14]. International students often face additional challenges, including language-related comprehension difficulties, unfamiliar academic expectations, and differences in instructional communication styles. These factors may increase uncertainty when interpreting academic signals such as feedback, grading standards, and course requirements. As a result, international students may experience greater academic pressure when they are unsure how to interpret or respond to academic expectations [15].

Although traditional academic stress research provides valuable insights into the factors influencing student experiences, most studies rely on surveys or psychological measurement instruments. As a result, these approaches often offer limited technological support to help students actively interpret and understand their experiences of academic stress during the learning process.

B. Artificial Intelligence Approaches for Analyzing Academic Stress Indicators

Recent advances in artificial intelligence and machine learning have introduced new opportunities to analyze student behavior and indicators of academic stress in educational environments [16]. Researchers have increasingly explored how machine learning models can identify patterns related to academic workload, engagement, and stress-related experiences among students [17].

Several studies have applied machine learning techniques to analyze stress-related indicators collected from university students. These studies demonstrate that machine learning models can identify relationships between contextual academic factors and students' reported stress experiences. By analyzing academic and behavioral data, AI models can reveal patterns associated with students' learning conditions and stress indicators.

Recent literature reviews also highlight the growing interest in applying artificial intelligence techniques to analyze indicators of student well-being and academic stress in higher education. These studies show that AI-based analytical models can support the analysis of complex relationships between academic factors and student experiences [18].

Despite these developments, many artificial intelligence approaches primarily focus on identifying patterns or estimating stress levels within student datasets [19]. In many cases, the models serve primarily as analytical tools for researchers or institutional monitoring rather than as interactive systems that support students' understanding of their academic experiences [16].

Consequently, although machine learning models can reveal relationships between academic factors and stress indicators, students may still struggle to understand how these factors shape their individual experiences. This limitation highlights the importance of designing AI-supported systems that not only analyze academic data but also help students interpret the factors that influence their learning conditions.

C. Learning Analytics Dashboards and Student Awareness

Learning analytics dashboards have become a widely used approach for presenting educational data and supporting student awareness of learning progress. These dashboards typically visualize information such as grades, participation levels, assignment completion rates, and learning activity indicators. By presenting such information, dashboards aim to help students monitor their academic progress and gain insight into their learning performance [20].

A growing body of research has examined the design and effectiveness of learning analytics dashboards. Many dashboards successfully provide visual summaries of student data and help learners observe their academic progress. However, research also indicates that dashboards often provide limited support for helping students interpret the meaning of these indicators [21], [22].

One of the main challenges identified in dashboard research is the gap between data visualization and meaningful interpretation [23]. Although dashboards present useful academic indicators, students may still struggle to understand how different academic factors contribute to their experiences. As a result, observing performance indicators does not always lead to deeper awareness of learning conditions [24].

Recent studies suggest that explanation mechanisms can help address this limitation. When systems provide explanations that clarify how different indicators relate to academic conditions, students are better able to interpret dashboard information and understand the factors influencing their learning experiences [25].

Research also highlights the importance of reflection in supporting student awareness and self-regulated learning. Reflection prompts encourage students to actively interpret academic information rather than simply observing it. When students reflect on system feedback, they are more likely to connect learning indicators with their own behaviors and learning strategies. Studies have shown that systems incorporating reflection mechanisms can improve students' understanding of their learning processes and support more informed academic decision-making [24], [26].

These findings indicate that learning analytics systems can more effectively support student awareness when they combine data visualization with explanatory and reflective support. Because explanation plays a key role in helping users interpret analytical outputs, recent research has increasingly explored integrating explainable artificial intelligence into educational systems.

D. Explainable Artificial Intelligence in Education

Explainable artificial intelligence has received increasing attention as researchers seek to make AI systems more transparent and understandable for users. In educational contexts, explainability is particularly important because students and instructors often need to understand how analytical outputs are generated and how different variables influence those outputs [6].

Recent studies emphasize that explainable AI should support human understanding rather than only providing technical transparency. When explanations are presented clearly and meaningfully, users are more likely to interpret system outputs correctly and incorporate that information into their decision-making [27].

Interpretable modeling approaches play an important role in this context. Interpretable models allow users to understand how individual input variables contribute to the final analytical result [28]. When applied in educational environments, such models can help students see how different academic factors influence the results produced by analytical systems [29].

Despite the increasing interest in explainable AI, many educational applications still rely on complex analytical models that may be difficult for students to interpret. This limitation highlights the need to design AI-supported educational systems that combine transparent modeling with explanations that are meaningful and accessible for learners [30].

E. Positioning LAURA Within Existing Approaches

Existing research on academic stress and learning analytics has introduced a variety of systems that analyze student behavior or present academic indicators. However, these systems are often designed for monitoring or prediction purposes rather than for supporting students' understanding of their academic conditions [31]. As a result, students may receive analytical outputs without sufficient support to interpret how different academic factors contribute to their stress experiences.

To position the proposed framework within this research landscape, Fig. 1 compares the LAURA framework with representative approaches, including learning analytics dashboards, AI-based stress analysis systems, and traditional academic stress models.

The comparison highlights several important gaps in existing approaches. Learning analytics dashboards typically present academic indicators but require students to interpret them independently. AI-based stress analysis systems often focus on predictive modeling, while providing limited support for explanation or reflection.

In contrast, the LAURA framework integrates interpretable modeling, explanation support, and structured reflection within a unified architecture. This design enables students not only to observe academic indicators but also to understand how different academic factors contribute to their academic stress.

By integrating explanation and reflection into an iterative feedback process, LAURA goes beyond prediction-oriented systems by fostering a deeper awareness among students of their academic stress.

F. Research Gap and Motivations

The reviewed literature shows important progress in academic stress research, artificial intelligence applications, learning analytics dashboards, and explainable AI in education. Traditional academic stress studies provide a strong theoretical understanding of stress factors, while AI-based approaches enable the analysis of complex student data. Learning analytics dashboards, on the other hand, support the visualization of academic indicators.

Despite these contributions, these approaches are often developed separately and focus on different objectives. Many AI-based systems emphasize data analysis or prediction, whereas learning analytics dashboards primarily present performance indicators with insufficient support for interpretation. As a result, students may observe academic information but still struggle to understand how different academic conditions contribute to their experiences of stress.

This gap indicates the need for systems that not only present or analyze data, but also support students in interpreting academic signals and reflecting on their learning situations. In particular, integrating interpretable models, explanations of contributing factors, and structured reflection can provide more meaningful support for students' awareness.

To address this need, the proposed LAURA framework integrates interpretable modeling, explanation mechanisms, and reflection prompts within a unified architecture. This design aims to support students in understanding their academic conditions and in developing awareness of the factors influencing their academic stress.

The following section presents the LAURA framework and explains its conceptual structure and development methodology.

III. LAURA Framework Development Methodology

This section presents the development methodology of the LAURA framework and explains how its main components are conceptually organized. The focus is not on technical implementation but on the design rationale and theoretical foundations that guided the framework's development. Accordingly, this work establishes the conceptual architecture and theoretical design rationale of the LAURA framework, providing a foundation for its future implementation and empirical validation.

The design of LAURA is informed by research on academic stress, interpretive challenges in higher education, explainable artificial intelligence (XAI), and reflection in learning analytics. These research areas highlight a common limitation in many existing systems. Although academic indicators are often presented to students, such systems provide limited support for helping students interpret how these indicators relate to their academic situations.

To address this limitation, LAURA is designed as an awareness-oriented explainable architecture. The framework integrates interpretable modeling, explanation of contributing academic factors, and structured reflection prompts that guide students in interpreting their academic conditions. Rather than focusing only on estimation, LAURA aims to support meaningful understanding and academic self-awareness.

A. Conceptual Design Approach

The conceptual design of LAURA follows a theory-informed synthesis process. Rather than starting with technical modeling techniques, the framework development begins with an educational objective: supporting students in interpreting the academic conditions that influence their stress experiences.

First, academic stress was conceptualized as an appraisal process. According to stress appraisal theory, stress arises when individuals evaluate academic demands relative to their perceived coping resources [34]. In higher education environments, perceived workload, deadline pressure, unclear expectations, and performance uncertainty are frequently identified as major contributors to academic stress. Recent studies also indicate that uncertainty regarding grading criteria and academic expectations can increase stress levels among university students [13].

Second, research indicates that students may experience higher stress when academic signals are unclear or difficult to interpret. For example, unclear feedback, unfamiliar evaluation systems, or language-related comprehension difficulties may

Characteristic	Primary Objective	Explanation	Reflection	Model Transparency	User Role	Feedback	Contribution Perspective
LAURA Framework	Academic stress awareness	Central explanatory component	Structured reflection prompts	Interpretable additive modeling	Active interpretation	Iterative awareness feedback	Integrates interpretable analysis, explanation, reflection, and adaptive awareness support
Learning Analytics Dashboards	Learning progress monitoring	Limited or indicator-based	Often implicit	Indicator-based analytics	Passive observation	Progress visualizations	Focus on monitoring academic indicators rather than understanding stress conditions
AI-Based Stress Analysis Systems	Stress detection or prediction	Rare or minimal	Usually absent	Often black-box ML models	Limited involvement	Stress prediction alerts	Emphasis on prediction accuracy rather than awareness or reflection
Traditional Academic Stress Models	Psychological explanation of stress	Core theoretical explanations	External reflection processes	Highly interpretable statistical models	Questionnaire participation	Psychological assessment feedback	Provide theoretical insight but lack interactive technological support

Fig. 1. Comparison of the proposed LAURA framework with representative approaches for academic stress support. Adapted from [20], [23], [18], [16], [32], [33].

increase confusion and uncertainty among students, particularly in international educational environments. In these situations, the issue is not only the academic demand itself, but also the difficulty of correctly interpreting academic signals [35].

Third, recent developments in explainable artificial intelligence emphasize the importance of transparency when AI systems interact directly with users. When the goal of the system is to support human understanding rather than purely optimize predictive performance, interpretable models are generally preferred over complex black-box algorithms. In educational contexts, clear explanations have been shown to improve user trust and understanding of system outputs [6] [36].

Finally, research on learning analytics dashboards demonstrates that presenting data alone is often insufficient for supporting awareness. Students benefit more when systems include structured reflection prompts that encourage interpretation and self-regulated learning. Reflection supports metacognitive thinking and helps students connect system feedback with their own academic behaviors [37].

By integrating insights from these research areas, the LAURA framework was developed as an awareness-oriented system that combines academic context modeling, transparent estimation, explanation, and reflection within a continuous interaction cycle [5].

B. Architectural Structure of LAURA

Fig. 2 illustrates the overall architecture of the LAURA framework. The framework is designed as an awareness-oriented interaction cycle that integrates academic context modeling, interpretable stress estimation, explanation, reflection, and adaptive feedback. Rather than treating academic stress as a static outcome, LAURA conceptualizes awareness as a continuous process in which students interpret academic conditions, receive explanations, reflect on contributing factors, and progressively refine their understanding.

Structurally, the LAURA framework operates as a multi-stage, awareness-oriented cycle comprising five interconnected

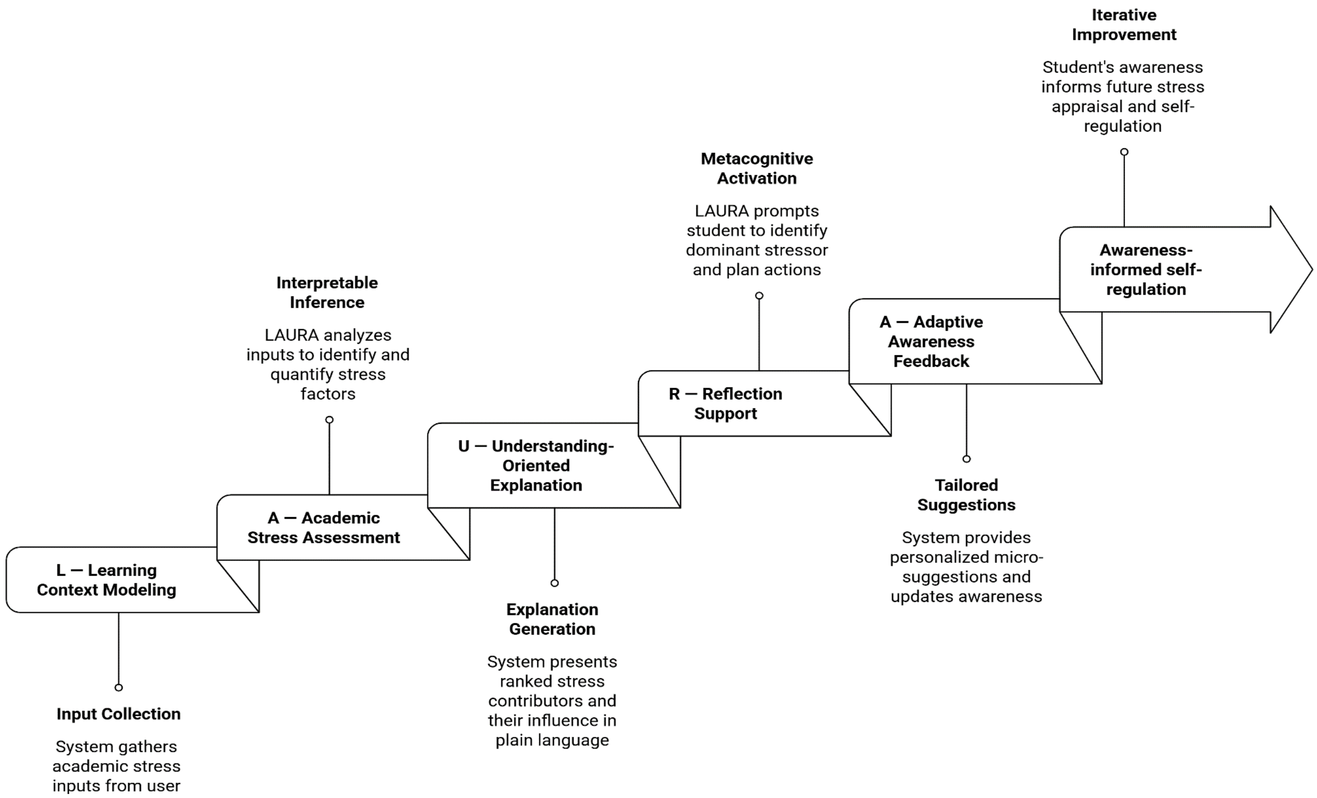

Fig. 2. The LAURA framework: An awareness-oriented explainable interaction cycle.

phases.

1) Phase 1: Learning context modeling: The process begins with Learning Context Modeling, where key academic indicators such as perceived workload, deadline pressure, clarity of academic expectations, and comprehension or interpretation difficulty are collected to represent the student's academic environment. These factors capture how students perceive and evaluate their academic conditions, rather than the objective workload alone.

This phase is designed as a structured input layer that reflects students' appraisal of academic demands. Consistent with research on academic stress, these indicators represent common sources of uncertainty in higher education contexts, particularly for students navigating unfamiliar academic environments [9] [38] [13].

2) Phase 2: Academic stress assessment: The academic indicators derived from the Learning Context Modeling phase serve as inputs for the Academic Stress Assessment phase. Depending on the educational context and the available data sources, these indicators may include course workload, assessment demands, class participation, learning engagement, assignment completion, and student self-reported academic experiences. In this stage, students' academic stress level is estimated using an interpretable approach that makes the contributions of individual academic factors transparent in the overall stress estimation [17].

To support interpretability, this phase adopts an interpretable modeling approach that enables transparent representation of how individual academic factors contribute to the overall stress estimation. Such an approach may be implemented using inherently interpretable techniques, including additive models, consistent with recommendations from interpretable machine learning literature that emphasize transparency in user-facing systems [39]. Importantly, this stage is intended to support the structured interpretation of students' academic conditions rather than to provide clinical prediction.

3) Phase 3: Understanding-oriented explanation: The output of the Academic Stress Assessment phase is translated into structured explanations that are accessible to students. Instead of presenting raw numerical results, the system identifies and highlights the key academic factors that contribute to the estimated stress level and communicates their influence in clear, simple academic language.

This phase is designed to support interpretation rather than only presenting information. Research in human-centered explainable AI emphasizes that explanations should help users make sense of system outputs, not only reveal model behavior [40]. Explanations that align with human reasoning have been shown to improve both understanding and trust in AI systems [6].

Accordingly, the explanation process in LAURA follows three key principles: 1) attribution clarity, by identifying the most influential academic factors; 2) directional influence, by explaining how each factor increases or decreases stress; and 3) contextual meaning, by presenting explanations in relation to real academic situations.

By combining these elements, this phase reduces interpretive ambiguity and supports students in developing a clearer understanding of their academic conditions.

4) Phase 4: Reflection support: The Reflection Support phase encourages active engagement with the system's explanations. While explanations provide important information, they do not automatically lead to awareness. Therefore, this phase introduces structured reflection prompts to guide students in interpreting and internalizing the results [41].

Research on self-regulated learning highlights the importance of metacognitive processes in supporting adaptive academic behavior [42]. In addition, learning analytics studies show that dashboards integrating reflective prompts lead to greater engagement than systems that present only information [24].

Within LAURA, reflection is guided through simple and focused prompts that encourage students to 1) identify the main contributing academic factors, 2) consider how their recent academic experiences relate to these factors, and 3) think about possible small adjustments in their study strategies.

By supporting this reflective process, the system helps transform explanations into meaningful awareness. This phase enables students to move from passive observation to active interpretation of their academic conditions [43].

5) Phase 5: Adaptive awareness feedback: The Adaptive Awareness Feedback phase provides contextual and personalized suggestions based on the identified contributors to academic stress. These suggestions are designed to support awareness-informed academic adjustments rather than prescribe fixed or rigid interventions [44].

This phase closes the framework's awareness loop by linking explanation and reflection to actionable feedback. Through this process, students are encouraged to gradually adjust their academic strategies in response to the identified factors. Such feedback supports self-regulated learning by helping students translate understanding into practice [45].

The framework operates as an iterative process in which increased awareness can influence how students evaluate future academic demands, consistent with appraisal-based stress theory. Over time, this process may support improved self-regulation and reduce interpretive uncertainty.

By integrating modeling, explanation, reflection, and adaptive feedback, LAURA conceptualizes explainable AI as a cognitive support tool that promotes awareness and understanding rather than performance monitoring.

Through these interconnected phases, the framework supports an ongoing awareness process rather than a one-time estimation of academic stress.

Overall, the LAURA framework is grounded in academic stress theory, interpretive uncertainty in higher education, explainable artificial intelligence, and reflection-based learning design. It integrates context modeling, interpretable estimation, explanation, reflection, and adaptive feedback within a unified structure.

C. Awareness-Oriented Design Logic

The LAURA framework is designed primarily to support student awareness rather than to increase algorithmic complexity. While many AI-supported educational systems emphasize performance prediction or risk estimation and often rely on opaque models, LAURA adopts a different design perspective centered on helping students understand their academic conditions.

This perspective is reflected in three guiding design principles. First, transparency over complexity emphasizes the use of interpretable modeling structures that allow students to clearly see how academic factors contribute to outcomes. Second, explanation as communication focuses on translating analytical outputs into meaningful academic language that students can easily understand. Third, reflection as mediation highlights the role of structured reflection in helping students interpret and internalize system feedback. Fig. 3 illustrates how the three core design principles, transparency, explanation, and reflection, interact to support student awareness within the LAURA framework.

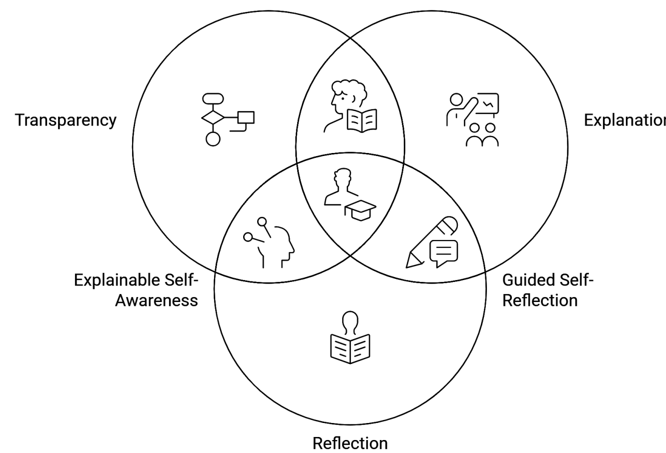

Fig. 3. Design principles supporting student awareness in the LAURA framework.

Together, these principles define LAURA as an awareness-oriented framework that supports interpretation, rather than prediction alone. In this way, explainable AI is positioned as a cognitive support mechanism that helps students better understand and navigate their academic experiences.

IV. Conceptual Interaction and Awareness Development

This section explains how the components of the LAURA framework interact conceptually to support students' awareness of their academic conditions. Rather than focusing on technical implementation, the emphasis is placed on how students engage with the system and how awareness develops through this interaction.

The interaction process begins when academic context indicators, such as perceived workload, deadline pressure, clarity of expectations, and comprehension difficulty, are represented in the system. These indicators provide a structured view of the student's academic environment and serve as the foundation for subsequent interpretation.

Based on these inputs, the system generates an interpretable estimation of academic stress. Instead of presenting this estimate as a final result, it is framed as an explanation that highlights the main academic factors contributing. To ensure accessibility, explanations are conveyed in simple, non-technical academic language, as recommended in human-centered explainable AI research [46], with a focus on clarity and relevance to students' everyday academic experiences. This design helps reduce confusion that may arise from overly technical or abstract system outputs.

Following this, students engage with the reflection component. Through structured prompts, they are encouraged to interpret the explanation, relate it to their recent academic experiences, and identify potential areas for adjustment. To support engagement, the interaction is designed to feel conversational and context-aware, allowing students to connect system feedback with their personal academic situations. This is important, as awareness does not emerge from information alone, consistent with findings in learning analytics research [47] [48], but from active interpretation and engagement.

The system then provides adaptive feedback based on the interpreted results. These suggestions help students make small, manageable adjustments to their academic strategies, reinforcing the connection between understanding and action.

Importantly, this process is not linear but iterative. As students interact with the system over time, their understanding of academic conditions may evolve. This evolving awareness can influence how they interpret future academic demands, creating a continuous process of interpretation, reflection, and adjustment.

This interaction design is particularly important for students in diverse and international educational contexts, where differences in language, academic expectations, and communication styles may increase uncertainty when interpreting academic signals. By emphasizing clarity, explanation, and reflection, the framework supports inclusive understanding across different student backgrounds.

Through this interaction, LAURA supports the development of awareness as an ongoing cognitive activity. Rather than treating students as passive recipients of information, the framework encourages active engagement, interpretation, and gradual refinement of academic understanding.

V. Discussion

A. Theoretical Implications

The LAURA framework contributes to the theoretical understanding of academic stress by reconceptualizing it as an interpretive and awareness-driven process rather than a static or purely measurable outcome. While prior research has largely approached academic stress through psychological measurement or predictive modeling, this framework shifts the focus toward how students make sense of academic conditions. In this view, stress is determined not only by external demands but also by how those demands are interpreted within specific academic contexts. This perspective builds on prior work that emphasized the role of explainable AI in supporting student awareness of academic stress, particularly among international students [5].

This reconceptualization extends appraisal-based theories of stress into the domain of interactive and AI-supported educational systems. Rather than treating appraisal as an internal cognitive process detached from system design, LAURA positions it as a process that can be actively supported through interaction. By embedding interpretation within system feedback, the framework suggests that academic stress can be better understood when students are guided to examine how different academic factors contribute to their experiences.

From a system design perspective, a central theoretical contribution of this work lies in redefining the role of artificial intelligence in educational settings. Existing AI-based approaches in higher education have predominantly focused on prediction, classification, or early detection of risk. In contrast, the LAURA framework reframes AI as a mechanism for supporting meaning-making. In this context, explainability is not treated as a supplementary feature that reveals model behavior, but as a core component that enables students to interpret academic signals in a meaningful and contextually relevant way. This perspective shifts explainable AI from a technical property of models to a cognitive support mechanism within learning environments.

Furthermore, the framework establishes a conceptual link between explainable AI and metacognitive processes. While explanations can make system outputs more transparent, they do not necessarily lead to understanding on their own. LAURA addresses this limitation by integrating structured reflection into the interaction cycle, emphasizing that awareness emerges through active interpretation rather than passive exposure to information. This integration highlights the importance of reflection as a mediating process that transforms explanations into meaningful understanding.

By connecting interpretability, explanation, and reflection within a unified framework, LAURA provides a theoretical bridge between computational modeling and student-centered learning theories. It suggests that effective AI-supported educational systems should not only analyze academic conditions, but also support students in constructing an understanding of those conditions. In doing so, the framework advances a shift from performance-oriented analytics to awareness-oriented design, in which understanding becomes a primary outcome of the system.

B. Design Implications

The LAURA framework provides several implications for the design of student-facing AI systems, particularly in contexts where the primary goal is to support understanding rather than prediction. First, the framework highlights the importance of prioritizing interpretability over algorithmic complexity when systems are intended for direct interaction with students. In such contexts, models should be designed to allow clear identification of how individual academic factors contribute to system outputs, rather than relying on opaque approaches that limit user understanding.

Second, the findings suggest that explanations should be designed as a form of communication rather than technical disclosure. Presenting numerical scores or abstract feature weights alone is insufficient for supporting student understanding. Instead, explanations should translate analytical outputs into clear academic meaning by explicitly linking system results to recognizable academic conditions, such as workload, deadline pressure, or clarity of expectations. This implies that explanation interfaces should prioritize clarity, contextual relevance, and alignment with students' everyday academic experiences.

Third, the integration of structured reflection highlights that awareness does not emerge automatically from exposure to system outputs. Systems should actively guide students in interpreting results with simple, focused reflection prompts. These prompts should encourage students to identify key contributing factors, relate them to recent academic experiences, and consider small, manageable adjustments. This suggests that reflection should be treated as a core design component, rather than an optional feature layered on top of analytics.

Finally, the iterative nature of the LAURA framework suggests that feedback should support gradual, continuous adjustment rather than immediate correction. Instead of prescribing fixed actions, systems should provide context-aware suggestions that help students refine their understanding over time. This approach aligns with how students regulate their learning in practice, where changes are often incremental and influenced by evolving academic conditions.

C. Implications for International Students

The LAURA framework is particularly relevant for international students, where challenges often arise not only from academic demands but also from difficulties in interpreting academic expectations and feedback. In such environments, students must navigate unfamiliar educational systems, grading practices, and communication styles, which can introduce additional layers of uncertainty beyond the academic workload itself. As a result, academic stress is often shaped by interpretive ambiguity rather than objective demands alone.

This context highlights a limitation in many existing learning analytics and AI-based systems. When systems present performance indicators or predictive outputs without sufficient explanatory support, they assume that students can interpret academic signals accurately. However, this assumption does not always hold for international students, who may lack familiarity with implicit academic norms or language-specific cues. In this sense, international student contexts make visible a broader issue: the gap between data presentation and meaningful understanding.

By emphasizing explanation and reflection, the LAURA framework directly addresses this interpretive gap. The framework supports students in making sense of academic signals by linking system outputs to clear and contextually meaningful explanations. In addition, structured reflection encourages students to actively interpret these explanations in relation to their own experiences, reducing uncertainty and supporting more informed academic decision-making.

Importantly, this perspective avoids framing international students in deficit-based or clinical terms. Instead, it treats the challenges they experience as issues of interpretation and understanding within complex academic environments. This allows for the design of supportive systems that empower students to navigate unfamiliar contexts more effectively, while also highlighting the importance of inclusive and accessible explanation design.

D. Limitations

Despite its contributions, the proposed LAURA framework has several limitations. First, LAURA is presented as a conceptual framework that establishes an awareness-oriented architectural and theoretical foundation for explainable AI in higher education. As such, its practical implementation and empirical evaluation were not addressed in the present study. Second, although the framework defines the key architectural components and interaction process, its effectiveness in supporting students' awareness, understanding, and academic decision-making has not yet been examined through prototype development or user studies. Finally, the framework is informed primarily by research on higher education, with particular attention to international students. Future research should therefore examine its applicability across diverse higher education contexts, student populations, and institutional settings.

E. Research Implications

The LAURA framework establishes a foundation for research that shifts the focus of AI-supported educational systems from predictive performance toward awareness and understanding. This shift suggests the need for evaluation approaches that go beyond accuracy-based metrics and instead assess how effectively systems support students' interpretation of academic conditions. In this context, constructs such as awareness, comprehension, and perceived interpretability should be treated as primary evaluation outcomes rather than secondary considerations.

Future studies should evaluate the LAURA framework by developing a functional prototype and conducting user studies in authentic higher education settings. These studies should examine whether the framework supports students in interpreting academic signals, developing awareness of the factors contributing to their academic stress, and engaging in meaningful reflection on their academic experiences. The evaluations should also examine the framework's perceived clarity, usefulness, and trustworthiness, and provide empirical evidence to refine it and assess its practical value in awareness-oriented educational AI systems.

This perspective opens several directions for empirical investigation. One important direction is to examine the extent to which explanation alone is sufficient to support understanding, compared with systems that integrate both explanation and structured reflection. Subsequent research can investigate whether reflection mechanisms significantly enhance students' ability to interpret academic signals and make informed adjustments to their learning strategies.

Another research direction concerns the design of explanation formats and their impact on student engagement and understanding. Variations in language, level of detail, and presentation style may influence how students interpret system outputs, particularly in diverse and international educational contexts. Exploring these variations can provide deeper insight into how explainable systems can be tailored to support different student needs.

In addition, the framework raises questions about the trade-off between model complexity and interpretability in student-facing systems. While complex models may offer higher predictive performance, simpler, more transparent approaches may be more effective at supporting understanding and awareness. Investigating this balance can help clarify when interpretability should be prioritized over predictive accuracy in educational applications.

Overall, the LAURA framework encourages future research to move beyond performance-centered models and toward awareness-oriented system design. By emphasizing understanding as a primary outcome, this perspective supports the development of AI systems that not only analyze academic conditions but also help students meaningfully engage with and interpret their learning experiences.

VI. Conclusion

This study presented the LAURA framework as an awareness-oriented approach to help students understand their academic stress. The framework was developed in response to a key limitation in many existing academic analytics and AI-supported systems, which tend to emphasize prediction and performance monitoring while offering limited support for interpretation and understanding.

By bringing together transparent modeling, explanation, and structured reflection within a single interaction cycle, LAURA repositions the role of explainable AI in educational contexts. Rather than focusing only on estimating outcomes, the framework highlights the importance of helping students make sense of academic signals and connect them to their own experiences. In this way, awareness is treated as something that develops through interpretation, not simply through access to data.

A key contribution of this work is the view of explainable AI as a form of cognitive support within learning environments. Instead of serving only as a tool for analysis, the framework demonstrates how AI can help students identify relevant academic factors, understand their influence, and gradually adjust their approaches to learning. This perspective shifts attention from performance-focused analytics toward systems that support meaningful understanding.

The framework also highlights the challenges students face in interpreting academic expectations, particularly in unfamiliar educational settings. In such contexts, difficulties are not always related to workload alone, but to uncertainty in how academic signals are understood. By focusing on interpretation and reflection, LAURA offers a foundation for designing systems that are more accessible, inclusive, and supportive of diverse student experiences.

Overall, LAURA provides a conceptual foundation for the future development of awareness-oriented educational AI systems. Future studies should focus on developing functional prototypes, conducting user studies in authentic higher education settings, and examining how effectively the framework supports students' awareness, interpretation of academic signals, and reflective engagement. Such investigations will provide empirical evidence to refine the framework and further assess its practical value for awareness-oriented educational AI systems.

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