Explainable AI for Enhancing Awareness of Academic Stress Among International University Students

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***Abstract*—Academic stress is a common challenge in higher education, especially for international university students who must adapt to new academic systems, expectations, and learning environments. In recent years, artificial intelligence has been increasingly used to analyze academic data and estimate student stress. However, most AI-based systems prioritize prediction accuracy over providing valuable support for student understanding. As a result, students may receive stress-related indicators without a clear explanation of how these results relate to their academic tasks or activities. This state-of-the-art review discusses current research on explainable artificial intelligence in the field of academic stress and student awareness. Based on literature published between 2020 and 2025, this review synthesizes work from educational technology, learning analytics, and explainable AI from a Human–Computer Interaction perspective. The analysis focuses on the representation of academic stress, the design of explanatory frameworks, and the extent to which existing systems facilitate students' ability to interpret and reflect on their work. The review finds that awareness is rarely treated as an explicit outcome in existing research. Although explainable models are increasingly used, the explanations they produce are often technical and not student-oriented. International students are an underrepresented group in the literature, despite the apparent differences in their academic preparation, linguistic ability, and expectations. Consequently, these shortcomings limit the effectiveness of artificial intelligence systems as tools for enhancing student awareness. This review highlights the need to shift from prediction-oriented approaches toward awareness-oriented explainable AI systems that prioritize student understanding. By emphasizing human-centered explanation design and inclusive evaluation, future research can better support students in making sense of academic stress within diverse higher education environments.**

***Keywords*—Explainable artificial intelligence; academic stress; student awareness; international university students; learning analytics; Human–Computer Interaction**

I. Introduction

Academic stress is a common experience in higher education, but it is often more challenging for international university students. These students must adapt to new academic systems, assessment styles, teaching practices, and expectations, usually while studying in a second language [1]. As universities increasingly rely on digital platforms and data-driven tools, students are exposed to a range of academic indicators, including grades, progress dashboards, and automated feedback. While these tools are intended to support learning, they can also generate confusion when students do not clearly understand how the information relates to their academic situation [2]. Unmanaged academic stress may further influence academic decision-making, increasing the risk of maladaptive coping behaviors in high-pressure learning contexts [3]. These challenges highlight the importance of supporting students in interpreting academic information to reduce stress and promote informed decision-making.

In recent years, artificial intelligence (AI) has been widely adopted in educational environments to analyze student data and support academic decision-making [4]. AI-based systems are increasingly used to estimate academic stress, anticipate risk, and identify patterns related to engagement and performance [5]. Although such systems often promise early insight and personalized support [6], many present their results as scores, categories, or alerts without sufficient explanation [7]. When explanations are limited or unclear [8], students may struggle to interpret system outputs and relate them to their daily academic activities.

Research in Human–Computer Interaction and learning analytics suggests that awareness is not achieved simply by presenting information. Rather, awareness involves processes of understanding, interpretation, and reflection [9]. Students must be able to make sense of academic signals and understand how factors such as workload, deadlines, or engagement patterns contribute to their experiences [10]. Without adequate support for this sensemaking process, data-driven feedback may remain abstract or even increase uncertainty. This challenge is particularly pronounced for international students, who may not share the same academic background, language proficiency, or implicit assumptions as system designers [11], which further complicates how system outputs are interpreted in practice.

Explainable Artificial Intelligence (XAI) has emerged as an approach to address concerns related to transparency and trust in AI systems. XAI seeks to make model outputs more understandable by clarifying how and why a system produces a particular result. In educational contexts, explainability can transform AI systems from opaque predictors into tools that support student understanding. However, many existing explainable approaches are designed primarily for researchers or developers and rely on technical explanations that are not always meaningful to students [12], [13]. As a result, their effectiveness in student-facing contexts remains limited.

At the same time, there is increasing recognition that student-facing AI systems should be evaluated not only by technical performance, but also by how well they support students' understanding of their academic situation [8], [14]. For international students, explainability must account for language clarity, cultural differences, and unfamiliar academic norms [15], [16]. Explanations that do not consider these factors may fail to foster awareness and reduce uncertainty, thereby limiting their usefulness across diverse educational contexts.

This state-of-the-art review offers a conceptual reframing of explainable artificial intelligence in academic stress research, shifting the focus from prediction-oriented systems to awareness-oriented, student-facing systems that prioritize understanding, interpretation, and reflection, particularly for international university students. The review synthesizes recent literature from educational technology, learning analytics, and explainable AI to examine how existing systems convey stress-related information, how explanatory components are designed, and the extent to which they support student awareness. By identifying current practices, limitations, and research gaps, this work outlines directions for future research that place student understanding at the center of explainable AI design.

This study is structured as follows:

- Section II: Presents the review methodology, including the literature search strategy, inclusion and exclusion criteria, and the analysis approach.
- Section III: Academic stress among international university students, focusing on previous studies and key stress-related factors in higher education contexts. Student awareness and reflection in educational technologies and learning analytics systems, with a focus on the challenges faced by international university students. Artificial intelligence–based approaches to academic stress, examining the methods used to analyze and estimate stress in higher education. Explainable Artificial Intelligence for student-facing systems, introducing key concepts, explanation types, and design considerations. Explainable Artificial Intelligence and student awareness of academic stress, synthesizing the literature to highlight how explainability can support awareness.
- Section IV: Presents a detailed discussion on the study insights by highlighting practical implications for student-facing AI systems.
- Section V: Conclusion summarizes the main insights of the review and outlines limitations and directions for future research.

II. Review Methodology

This manuscript employs a state-of-the-art approach to review the recent literature on explainable artificial intelligence, academic stress, as well as student awareness in higher education. The purpose of this review is not to conduct a meta-analysis and quantify effect sizes, but to synthesize current trends in research, methodological designs, and conceptual gaps across interconnected disciplines.

A. Literature Search Strategy

The literature review encompassed peer-reviewed journal articles and conference proceedings published between 2020 and 2025. Such a temporal scope was chosen to reflect recent developments within explainable artificial intelligence, learning analytics, and educational technologies that are facing students. Major academic databases were searched, including Google Scholar, Scopus, Web of Science, and the scientific journals and books in the databases of the Institute of Electrical and Electronics Engineering (IEEE), the Association for Computing Machinery (ACM), and Springer.

Search queries combined terms related to academic stress and student awareness, as well as artificial intelligence and explainability. Examples of the search keywords are academic stress, international students, learning analytics, explainable AI, interpretable machine learning, student dashboards, and student awareness. These keywords were used in various combinations in order to ensure broad coverage across disciplines.

B. Inclusion and Exclusion Criteria

Studies were selected, if they satisfied the following criteria:

- Revolved around education at the higher education level,
- Looked at academic stress, learning pressure, or other related experiences in school,
- Included AI, machine learning, learning analytics, or data-driven systems, and
- Discussed system outputs, explanations, or student-facing feedback.

Studies were excluded, if they were solely clinical diagnosis studies, stressed that they were non-academic, or focused on populations outside higher education. Papers that were purely technical in nature with no relevance to student interaction or interpretation were also excluded.

C. Study Selection and Analysis

After the initial search was carried out, titles and abstracts were evaluated for relevance. The full texts of the selected papers were then read in detail. During this process, the studies were grouped into four main areas: academic stress among foreign students, student awareness and reflection tools, AI-based stress analysis, and explainable AI (XAI).

Rather than extracting numerical results, the objective of the analysis was to find recurring themes, design patterns, and evaluation practices and limitations reported in the literature. Particular attention was paid to the presentation of information to students by systems, as well as whether explanations are designed to support understanding and awareness.

D. Scope and Methodological Considerations

This review focuses more on conceptual synthesis rather than completeness. While the search strategy was designed to include major and influential studies, the possibility exists that some relevant work may have been excluded. Additionally, the review is limited to peer-reviewed English-language publications, which may limit the coverage of regional research or non-English language research.

Despite these limitations, the methodology provides a structured and transparent foundation for understanding the current directions of research and where explainable AI can be effectively utilized to support. Fig. 1 presents an overview of the study workflow, illustrating the main stages of the review process and analysis approach.

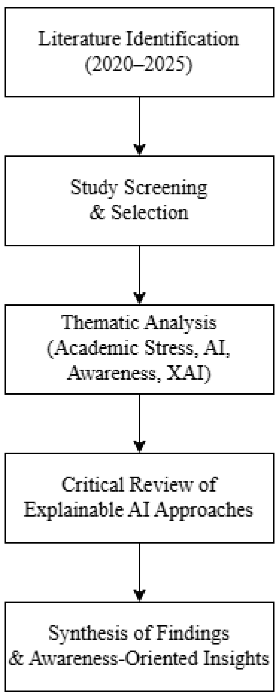

Fig. 1. Overview of the study workflow and analysis process.

III. Related Works

A. Academic Stress among International University Students

Academic stress is a common experience in higher education, but it is often more intense and complex for international university students [1]. Unlike domestic students, international students must adapt not only to academic workload but also to new educational systems, teaching styles, assessment methods, and communication norms [17]. These adjustments require continuous effort and can increase uncertainty during everyday academic tasks [18]. Over time, this sustained pressure may accumulate, affecting students' confidence, motivation, and sense of academic control [19].

Many studies showed that international students face additional academic challenges related to understanding expectations, interpreting feedback, and managing deadlines in a second language [20]. Language proficiency influences how students read course materials, participate in discussions, and interpret assessment criteria [21]. Even students with strong academic backgrounds may struggle when academic instructions or feedback are unclear. As a result, students often invest more time and effort in their studies while still feeling uncertain about their performance, which can intensify academic stress.

Recent research highlights that academic stress among international students does not arise from a single source. Instead, it develops through the interaction between academic demands, institutional systems, and students' ability to correctly interpret academic information [1]. Learning management systems, automated grading, and online dashboards are now widely used; however, they often present information in ways that assume familiarity with local academic culture. For international students, this assumption does not always hold [22]. When academic information is misunderstood, stress may persist even in situations where academic performance is objectively adequate.

Several studies indicate that many academic stress systems focus primarily on measuring or predicting stress levels rather than helping students understand the academic conditions that contribute to stress. For example, AI-based approaches often estimate stress using survey responses or behavioral data collected from digital systems [23]. However, these systems typically offer limited explanation of how workload patterns, assessment timing, or engagement behaviors contribute to stress experiences. As a result, students may receive numerical scores or categorical labels without sufficient context, which can limit their ability to reflect and increase uncertainty [24].

A further challenge is that academic performance indicators are often presented without adequate explanation. A low score, delayed feedback, or system warning may be interpreted as a serious academic failure, even when it reflects a temporary or situational issue [25]. Without contextual clarification, students may overestimate the seriousness of academic signals and experience unnecessary pressure [26]. This heightened stress can impact emotional well-being and decrease students' willingness to seek help or express concerns [27].

Importantly, prior research suggests that sustained academic stress can shape students' academic behavior, particularly when stress is driven by high-performance demands and perceived lack of control. When students experience ongoing pressure related to grades, time constraints, and fear of failure, stress can reduce their ability to engage in deliberate and reflective decision-making. Under such conditions, students may shift their focus from long-term learning goals toward short-term strategies aimed at avoiding negative academic outcomes. In some cases, this shift is associated with an increased risk of academic misconduct, such as plagiarism or inappropriate collaboration, particularly in high-stakes or time-constrained situations. Evidence from multiple educational contexts suggests that academic pressure, anxiety, and perceived consequences are among the most consistent situational factors associated with dishonest behavior. From this perspective, academic dishonesty is better understood as a stress-related risk behavior that emerges under specific conditions of pressure and uncertainty, rather than as a stable individual trait or personal moral failure [28], [29].

Overall, existing research suggests that academic stress among international students is shaped by multiple interacting academic, linguistic, and systemic factors. When stress is not well understood or contextualized, it can negatively affect learning, engagement, and academic decision-making. These findings highlight the need for approaches that not only monitor stress levels but also support students in understanding the causes and consequences of academic stress within their academic environment.

B. Student Awareness and Self-Reflection in Educational Technologies

In educational technology research, student awareness is often described as an important step that helps learners understand their academic situation [30]. Awareness does not mean only that information is available. It means that students can recognize important academic signals, understand their meaning, and relate them to their own study habits. In university contexts, this includes understanding workload, deadlines, feedback, engagement, and progress across different courses [31].

Many students receive a large amount of academic information every day. However, having access to information does not always mean that students understand it well. This is especially true when the information is presented in abstract or numerical forms. As a result, students may view the data but still feel uncertain about its implications for their learning [32].

1) Awareness beyond showing information: Many educational systems present information such as grades, progress bars, activity levels, or performance summaries. These elements are often designed to support awareness. However, previous research indicates that simply presenting information is often insufficient. Students may look at charts or numbers, but still struggle to understand how these indicators relate to their academic situation.

Research in Human–Computer Interaction explains that awareness is an active process. Students need time and support to interpret academic signals and understand how different factors are connected. When systems fail to provide this support, dashboards and analytics tools can be confusing or even stressful [33]. Some students stop using these tools because they do not see a clear value in them [34].

Several review studies report that students usually check dashboards only when they feel worried or uncertain. When the information does not change or is difficult to understand, students may lose interest over time [35], [36]. This suggests that awareness requires explanation and context, not just visual displays.

2) Student-facing learning analytics dashboards: Learning analytics dashboards are one of the most common tools used to support student awareness. These dashboards usually show indicators related to engagement, progress, or predicted outcomes. While many students claim that dashboards are useful, research reveals mixed results regarding their effectiveness in fostering real understanding and long-term use .

Students often report that they do not clearly understand why certain indicators are high or low. They may also be unsure which academic activities influenced the results or what actions they should take next. In many systems, explanations are either missing or written in technical language that is difficult for students new to academic analytics to understand [37], [38].

For international students, these problems can be even stronger. Dashboards are often designed based on local academic norms, which may not be familiar to international students. Recent studies suggest that dashboards are more effective when they clearly explain indicators, display changes over time, and connect results to specific academic activities. However, these features are still not widely used in practice [39], [40].

3) Reflection and self-monitoring tools: Some educational technologies focus on supporting student reflection and self-monitoring. These tools encourage students to reflect on their academic activities and identify patterns in their behavior. Reflection tools often include summaries, weekly reports, or simple prompts that ask students to consider what worked well and what did not.

Research indicates that reflection is more likely to occur when feedback is both timely and personalized. When systems only show raw data, students may feel overwhelmed or unsure how to use the information. On the other hand, tools that guide reflection through concise explanations or simple descriptions can facilitate a deeper understanding [41], [42].

4) Awareness challenges for international students: International students may encounter additional challenges when utilizing awareness and reflection tools. Academic systems, grading styles, and feedback practices can differ significantly from what students have experienced before. Because of this, international students may interpret academic indicators in ways that were not intended by the system designers [43].

Recent studies show that unclear or ambiguous feedback can increase confusion for international students. When explanations are missing, students may misinterpret academic signals and feel unnecessary pressure. Language difficulty and unfamiliar academic terms can also reduce engagement with dashboards and analytics tools [44].

In addition to language and feedback interpretation, international students often face challenges related to academic norms and expectations. Practices such as class participation, independent study, and self-directed learning may be emphasized differently across educational systems [45]. When awareness tools present indicators related to engagement or participation, international students may not always understand how these indicators align with instructors' expectations. This can create uncertainty about whether they are performing adequately or falling behind [46].

Another challenge is related to comparison and benchmarking features commonly used in dashboards. Some systems show how a student's activity or performance compares to class averages or peer groups. While such comparisons are intended to support awareness, international students may interpret them negatively, especially if they are unfamiliar with local grading distributions or participation norms. Without explanation, comparison-based indicators may increase pressure rather than support understanding.

Time-related indicators can also be difficult to interpret. Academic systems often track time spent on learning platforms, assignment submission times, or activity frequency. For international students, these indicators may not fully reflect their actual effort, especially when learning in a second language requires additional time for reading and comprehension. When systems do not explain how time-related data is interpreted, students may feel that their effort is not accurately represented [47].

Furthermore, international students may have limited opportunities to clarify system feedback through informal communication. Domestic students may ask peers or instructors for clarification more easily, while international students may hesitate due to language concerns or cultural norms. In such cases, awareness tools become even more important as a source of guidance. When these tools lack a clear explanation, students are left without reliable support for understanding their academic situation [34].

Overall, the literature suggests that student awareness is not automatically created by providing data. Awareness is an active process that requires interpretation and reflection. Although dashboards and analytics tools are widely used, they often provide limited support for understanding. Reflection works better when systems offer explanation and context. International students may face additional challenges because of language and academic culture differences. These insights help explain why more transparent and explainable approaches are needed, which will be discussed in the next sections.

C. Artificial Intelligence in Academic Stress Research

In recent years, Artificial Intelligence (AI) has been increasingly utilized in educational research to gain a deeper understanding of students' academic experiences. One important area where AI has gained attention is the study of academic stress. Researchers use AI models to analyze large datasets and identify patterns that are difficult to capture using traditional statistical methods. These approaches aim to provide insights into how different academic and contextual factors relate to students' stress levels [23].

Most AI-based studies in this area focus on detecting, predicting, or classifying academic stress. The goal is often to identify students who may be experiencing high stress or to estimate stress levels based on observable data. While these approaches can provide useful information at a system level, they often do not focus on how students themselves understand or utilize the results [48].

1) Data sources used in AI-based stress studies: AI models for academic stress commonly rely on different types of data. Survey-based data are one of the most widely used sources of information. Students are asked to report their stress levels, academic workload, study habits, or learning experiences. These self-reported measures are then used as inputs for machine learning models [48].

In addition to surveys, some studies use behavioral data collected from learning management systems. This may include information such as login frequency, time spent on course materials, assignment submissions, and interaction with online resources. Other studies combine academic data with contextual or demographic variables, such as year of study, major, or learning environment [49].

Recent research has also explored the use of multimodal data, where survey responses are combined with behavioral or contextual indicators. These approaches aim to capture a more comprehensive picture of academic stress by considering multiple sources, simultaneously [50].

2) Machine learning techniques and model performance: A wide range of machine learning techniques has been applied in academic stress research. Commonly used models include logistic regression, decision trees, support vector machines, random forests, and gradient boosting methods. Some studies also explore neural networks, especially when working with larger or more complex datasets [23], [51].

Many papers report strong model performance in terms of accuracy, precision, recall, or F1-score [48]. These results are often presented as evidence that AI can successfully model academic stress. While performance metrics are important, they primarily reflect how well a model fits the data, rather than its utility for students or educators in real-world contexts [52].

As a result, AI-based stress models are often evaluated from a technical perspective. Less attention is given to how the model outputs are presented to students or how students might interpret the results in relation to their academic activities [53].

3) Focus on prediction rather than student experience: A common characteristic of AI-based academic stress research is its emphasis on prediction outcomes. Many studies aim to answer questions such as whether a student is experiencing high or low stress, or which factors are most strongly associated with stress levels. These questions are important, but they often place students in a passive role [54].

In many systems, students receive a label, score, or category that summarizes their level of stress. However, the reasoning behind this output is not always clear. Without explanation, students may not understand how their academic behavior, workload, or engagement contributed to the result. This can limit the usefulness of AI systems for supporting awareness or reflection [55].

Recent studies using interpretable models show that it is possible to identify key contributing factors, such as workload, learning goals, or study environment [56]. However, these explanations are often reported for researchers or practitioners rather than designed for direct student interaction [57].

Overall, the literature indicates that AI has become a significant tool for investigating academic stress. Researchers use different data sources and machine learning techniques to predict stress levels and identify contributing factors. However, most existing work focuses on technical performance and prediction accuracy. The role of AI in supporting students' understanding of their academic situation remains limited. These observations motivate further exploration of explainable and student-facing AI approaches, which are discussed in the next section.

D. Explainable Artificial Intelligence (XAI): Concepts and Approaches

As Artificial Intelligence systems become more common in education, concerns about transparency and understanding have also increased [12]. Many AI models can produce accurate predictions, but their internal decision processes are often difficult to understand. This has led to growing interest in XAI [58]. XAI aims to make AI systems more transparent by helping users understand how and why a model produces a specific output [59].

In educational contexts, explainability is crucial because AI systems are increasingly influencing decisions related to learning, performance, and support. When students receive predictions or indicators without explanation, they may feel confused or uncertain about how to interpret them. XAI offers an opportunity to shift AI systems from being opaque tools to systems that can support understanding and awareness [60].

1) What is explainable AI ?: Explainable AI refers to methods and techniques that allow users to understand the reasoning behind AI model outputs [59]. Instead of providing only a final prediction or score, an explainable system offers additional information that clarifies which factors influenced the result and how these factors interacted with each other [61].

Explainability can take different forms. Some explanations describe the overall behavior of a model, while others focus on explaining individual predictions [62]. In educational systems, explanation is often needed at the individual level, where students want to understand why a particular result applies to them [63].

Importantly, explainability is not only a technical concept. It also involves communication and design. An explanation that is mathematically correct may still be difficult for students to understand if it is presented in complex or technical language [12], [64].

2) Common explainable AI techniques used in education: Several XAI techniques are commonly used in educational and student-related research. Feature importance methods show which input variables contribute most to a model's predictions. These methods help identify factors such as workload, engagement, or study patterns that influence outcomes [65].

Other approaches include rule-based explanations, where model decisions are expressed as simple rules, and example-based explanations, which show similar past cases to help users understand predictions [66]. Some studies also employ visualization techniques to present explanations in graphical form [67].

Among these methods, post-hoc explanation techniques such as SHAP are widely used because they can be applied to many types of machine learning models. These techniques are popular in research because they provide detailed insights into model behavior. However, they are often designed for researchers or analysts, rather than for direct use by students [68], [59]. Table I below shows common explainable AI (XAI) techniques used in education.

TABLE I. COMMON EXPLAINABLE AI (XAI) TECHNIQUES USED IN EDUCATION

XAI Technique	Educational Use	Example
SHAP (SHapley Additive exPlanations)	Feature attribution indicating the importance of each variable for making predictions (e.g., risk, grades, dropout).	Student success prediction, identification of at-risk learners, understanding key drivers to performance, stability analysis of models,
LIME (Local Interpretable Model-agnostic Explanations)	Local surrogate models to explain black box model single predictions	Explaining individual grade predictions, supporting decisions of teachers about particular students.
Partial Dependence Plots (PDPs) / Global Feature Importance	Global perspective of the relationship between features and results, ranking the highest impact factors.	Course failure risk, dropout prediction, and identifying important behavioral and academic indicators
Transparent / Interpretable Models (e.g., decision trees, rule-based models, simple linear models)	Using inherently interpretable models rather than post hoc explanations.	Many AI in Education (AIED) systems (dashboards, adaptive tutors) are designed to make it more directly understandable to teachers and students.
Open Learner Models (OLMs)	Visual/structural representations of a learner's knowledge/skills, which make system inferences explicit.	Student-facing dashboards, self-regulated learning support, and intelligent tutoring systems.
XAI for Trees / Tree-based Explanation Methods	Global and local explanations tailored to ensembles of decision trees.	Explaining learning analytics models based on tree ensembles (e.g., dropout and performance models).
Clustering-based Explanations (unsupervised XAI)	Explaining clusters or profiles (e.g., learner groups) to educators through visual and text	Teacher dashboards that display student knowledge profiles and similarities.
Multimodal / Generative-enhanced XAI	Combining traditional XAI (i.e., SHAP, LIME) with generative models to obtain personalized, multimodal explanations.	Transparent adaptive learning systems tailor explanations to different user types (e.g., students, teachers, admins).
Prescriptive Analytics with XAI	Translating explanations into suggested action and/or feedback to learners and instructors	Systems that help not only identify at-risk students, but that produce evidence-based, human-readable advice

Adapted from [12], [69], [70], [71], [72], [73], [74].

3) Explainability from a human-centered perspective: From a Human–Computer Interaction perspective, explainability should be considered as part of the interaction between the user and the system [64]. An explanation is useful only if it helps the user understand the system output and relate it to their own experience [75]. This means that explanations should be clear, concise, and relevant to the user's context [76].

Research indicates that overly complex explanations can erode trust and lead to increased confusion. When explanations include too many variables or technical terms, users may overlook or misinterpret their meaning [77]. On the other hand, explanations that are too simple may fail to provide meaningful insight [78].

For students, especially international students, explanations should be written in clear, accessible language and connected to familiar academic concepts and activities. Explanations that refer directly to assignments, deadlines, or study behaviors are more likely to support understanding than abstract statistical descriptions [79], [80].

4) Explainable AI in student-facing systems: In recent years, several studies have explored the use of explainable AI in student-facing systems. These systems aim to provide students with insights into predictions related to performance, engagement, or stress. Some studies show that explanations can help students better understand system outputs and reflect on their academic behavior [8], [81].

However, many explainable systems still prioritize technical transparency over student understanding. Explanations are often presented as feature rankings or numerical values, which may be difficult for students to interpret. In some cases, explanations are available only to instructors or researchers, rather than directly to students [82], [13].

This highlights the importance of designing explainable AI systems that are not only accurate and transparent but also usable and meaningful for students. Explainability should support awareness and reflection, rather than simply revealing model internals [16], [83].

In summary, explainable AI provides methods to make AI systems more transparent and understandable. In educational contexts, explainability has the potential to support student awareness by clarifying how predictions are generated. However, explainability is not only a technical challenge, but also a design and communication challenge. To be effective for students, explanations must be human-centered, easy to understand, and connected to academic experiences. These considerations are particularly important when designing systems for diverse student populations, including those from international backgrounds.

E. Explainable AI for Enhancing Awareness of Academic Stress

Explainable AI presents a significant opportunity to transcend traditional academic stress systems that primarily focus on detection or prediction [84]. Instead of treating stress as a hidden state that needs to be identified by the system, explainable AI allows students to see how academic activities, workload, and engagement patterns are connected to their stress experiences. In this way, explainable AI can support awareness rather than merely monitoring.

In student-facing systems, awareness is created when students understand why the system produces a certain output and how this output relates to their daily academic life. Explainable AI can support this process by making model reasoning more visible and meaningful. When explanations are clear and relevant, students can reflect on their academic behavior and gain a better understanding of the sources of pressure [85], [86].

1) From prediction to awareness: Most existing AI-based academic stress systems are designed to answer predictive questions, such as whether a student is experiencing high or low stress. While these predictions may be useful at an institutional level, they often provide limited value to students if the reasoning behind them is unclear. A stress score or category alone does not explain what caused the stress or how it developed over time [87].

Explainable AI shifts the focus from outcomes to the processes behind them. By showing which academic factors contributed to a prediction, explainable systems allow students to connect system feedback to concrete experiences, such as heavy coursework, approaching deadlines, or reduced engagement. This connection supports awareness by helping students recognize patterns rather than react to isolated indicators [88].

2) Supporting reflection through explanation: Reflection plays a key role in awareness. When students can reflect on their academic activities and understand how these activities relate to stress, they are more likely to develop meaningful insights [89]. Explainable AI can support reflection by presenting explanations that highlight relevant factors and changes over time, allowing for a deeper understanding of the underlying processes.

For example, explanations that show how workload increased during certain weeks or how engagement decreased before stressful periods can help students reflect on their academic routines [90]. Studies suggest that explanations are more effective when they are presented in a narrative or descriptive form rather than as technical graphs or numerical values [91].

Explainable AI can also help reduce uncertainty. When students understand why a system output appears, they may feel more confident in interpreting it and less likely to assume the worst [92]. This is particularly important for international students, who may already experience uncertainty when interpreting academic feedback [59].

3) Designing explainable systems for students: For explainable AI to effectively support awareness, explanations must be designed with students in mind. Many current explainable systems rely on feature importance rankings or complex visualizations. While these methods are useful for researchers, they may be difficult for students to understand or apply.

Student-centered explainable systems should use simple language and relate explanations directly to academic activities. Instead of stating that a variable has a high contribution, explanations could describe how specific behaviors or workload patterns influenced the system output. This approach helps students connect explanations to their own experiences [12], [81].

Another important design consideration is timing. Explanations should be provided at moments when students are most likely to reflect, such as after completing an assignment or during weekly reviews. When explanations are delivered at appropriate times, they are more likely to support awareness rather than add to cognitive load [93], [94].

4) Explainable AI and international student contexts: International students form a highly diverse group, not only in terms of language ability, but also in academic training, assessment experience, and expectations about feedback. Students arrive from educational systems that differ in grading standards, teaching styles, and communication practices. As a result, the same academic signal or system output may be interpreted in very different ways [95]. Explainable AI systems that aim to support awareness must therefore consider this diversity rather than assume a shared academic background [96].

One challenge for international students is that many AI-generated explanations are implicitly designed around local academic norms and expectations. For example, explanations may reference participation levels, submission timing, or comparisons with peers without clarifying why these indicators are relevant. For international students who are still learning how the academic system operates, such explanations may increase uncertainty instead of reducing it [97]. Without contextual framing, students may misinterpret system feedback as a sign of poor performance or failure [98].

Language also plays an important role in how explanations are understood. Even when international students have sufficient proficiency to complete coursework, technical or abstract explanations can be difficult to interpret. Terms such as "engagement score", "risk level", or "feature contribution" may not be meaningful without additional clarification [99]. Explainable AI systems that utilize simple language and concrete references to academic activities, such as assignments, exams, or study routines, may be more accessible to international students [100].

Another important factor is the emotional interpretation of explanations. International students may already experience uncertainty or self-doubt when navigating a new academic environment [101]. When explanations are unclear or overly complex, students may focus on negative interpretations rather than reflective understanding [102]. In contrast, explanations that align with students' daily academic experiences can help them make sense of feedback in a calmer and more constructive way [103].

Recent studies suggest that explainable systems can support trust when explanations align with students' lived experiences and expectations. When students recognize their own academic behavior in the explanation, they are more likely to accept the system output and reflect on it. However, when explanations conflict with students' perceptions or appear disconnected from their actual experience, trust can decrease, and students may ignore or reject the system feedback [8], [104].

Finally, international students may have fewer opportunities to seek informal clarification from peers or instructors [105]. This makes explainable systems particularly important as a source of guidance. If explanations are not clear or accessible, students may be left without support for understanding their academic situation. This highlights the importance of carefully designing and evaluating explainable AI systems that account for linguistic, cultural, and academic diversity when supporting student awareness [95].

IV. Discussion

This review synthesizes research from the domains of educational technology, learning analytics, and explainable artificial intelligence to enhance our understanding of how AI-based systems can promote students' awareness of academic stress. Across these bodies of literature, a common theme is evident: whilst universities increasingly rely on appropriately data-driven and AI-supported systems, students often face problems arising from the implications of this information for their personal academic situation. The presence of data, indicators, or predictions does not necessarily lead to understanding; students must actively make sense of system outputs.

An important insight from the reviewed studies is that academic stress experienced by international students is primarily constructed through the ongoing academic systems in institutions, rather than being due to discrete individual characteristics. Peak workloads, assessment scheduling, modalities of feedback, and the use of digital learning platforms collectively shape students' experience and understanding of academic pressure. When these components are communicated through dashboards or AI-generated indicators without sufficient textual explanations to aid understanding, students often struggle to align system feedback with their normal institutionalized educational routines. These dynamics help explain why some student-facing systems are considered unhelpful or stressful, even when they are highly technically precise.

Empirical studies indicate that many AI-based approaches to academic stress primarily focus on predictive performance measures rather than understanding students' experiences and contexts. Model efficacy is typically measured by metrics such as accuracy and precision, thereby revealing the system's technical competence. Nonetheless, such metrics only imperfectly address the question of learners' apprehension of the outputs or their perceived pertinence. While occasionally interpretable modelling techniques are used, the explanations associated with them are often disseminated in researcher-centric formats, such as feature importance rankings or fancy visuals. As a result, these elucidations may not address the concrete, pragmatic questions students have about the causal underpinnings of a prediction or its relevance to their academic work.

The gap between technical explainability and student understanding highlights a growing concern in the current research environment. Explainability is often conceived as an inherent feature of the model rather than a part of an interactive process between the system and the learner. As a result, systems may be transparent at the theoretical level but opaque in practice. From a human-centered perspective, explainability should support students in developing a coherent understanding of the context in their academic world, rather than merely exposing the model's inner workings.

International students face additional challenges in this situation. Differences in scholarly culture, linguistic usage, and assessment conventions can significantly impact the interpretation of feedback, including that generated by automated systems. Packages of data are provided on a multitude of student-oriented platforms, with the implicit assumption that students will learn the common academic norms, including the criteria for adequate participation and acceptable progress. When such presumptions do not hold, international learners may misinterpret academic indicators or harbor undue apprehensions. Nevertheless, the existing literature provides little analysis of how explainable artificial intelligence systems work for international learners or of how their explanatory mechanisms can be adapted to their heterogeneous academic antecedents.

One additional limitation that pervades the literature concerns evaluation methodologies. A preponderance of studies deploy systems in short-term trials or focus on short-term usage measures rather than on long-term changes in learner comprehension. Consciousness-raising and sensemaking unfold incrementally over time through interactions and reflective practice. In the absence of longitudinal or direct assessments of understanding, it is also unclear how explainable systems can be regarded as truly able to foster awareness or simply augment information content.

Collectively, based on the evidence presented, XAI has considerable capability to augment student awareness of academic stress; however, at the same time, there is also a degree to which this potential has not been fully realized. Progress requires an overt desire for awareness and an explicit goal, rather than an implicit byproduct of data availability. Achieving this transition requires greater attention to how explanatory content is formulated, communicated, and evaluated from the learner's perspective.

Specifically for international students, XAI implementations should focus less on introducing additional complexity and more on reducing uncertainty. The use of unequivocal terminology, the connection to tangible academic tasks, and the recognition of the 'heterogeneous experiences of the learners' can help contextualize the output of the system. Through nurturing understanding and reflection practices, XAI may transition from being an instrument of surveillance to a substantive working mechanism for students facing academic stress.

A. Practical Implications

The findings of this review point to several practical considerations for the design and use of student-facing artificial intelligence systems in higher education.

For designers of student-facing AI systems, the results suggest that awareness should be prioritized over prediction. Explanations need to be straightforward to understand, especially for students unfamiliar with technical terms. It is also important to connect explanations to everyday academic activities, such as assignments, deadlines, and study habits. Instead of showing stress scores or risk levels alone, systems should help students understand why certain academic situations may contribute to stress and how they can make sense of this information.

For developers of learning analytics dashboards, the review highlights the need to move beyond static indicators or simple rankings. Dashboards can be more helpful when they provide context, show how patterns change over time, and explain what the information means in practice. In particular, dashboards should avoid assuming familiarity with local academic norms for international students. Clear explanations of expectations can reduce confusion and help prevent unnecessary stress.

For universities that support international students, the findings suggest that AI-based student analytics tools should not focus only on identifying risk or early warning signs. Instead, these systems can be used to support understanding and encourage students to engage with available support resources. Integrating explainable dashboards into advising sessions, orientation programs, or academic support services may help international students better understand their academic situation and feel more confident navigating unfamiliar educational environments.

V. Conclusion

This study aimed to review and synthesize recent research on the use of explainable artificial intelligence to enhance students' awareness of academic stress, with a particular focus on international university students. The review examined literature from educational technology, learning analytics, and explainable AI to understand how current systems support or fail to support students' understanding of academic stressors.

The results showed that while AI-based systems are increasingly used to analyze and estimate academic stress, most existing approaches focus on prediction and technical performance rather than on student awareness. Even when explainable models are applied, explanations are often designed for researchers or system developers, not for students. As a result, many systems provide information without adequately supporting interpretation, reflection, or sensemaking, especially for students who are unfamiliar with local academic norms.

These findings highlight the importance of treating awareness as a central outcome in the design and evaluation of student-facing AI systems. Rather than assuming that access to data or predictions leads to understanding, explainable AI should be viewed as a communication and interaction process that helps students connect system feedback to their everyday academic activities. This perspective contributes to expanding our understanding of how explainable AI can play a meaningful role in educational settings, particularly within the context of Human–Computer Interaction and learning analytics.

On a practical level, these results suggest the possibility of designing explainable AI systems that help students better understand academic stress and respond to it constructively. Systems that use simple language, reference concrete academic activities, and consider diverse academic backgrounds may better support reflection and awareness, especially for international students navigating unfamiliar educational environments.

However, it is worth noting that this study is limited by its reliance on existing literature and the scope of the reviewed studies. Many of the reviewed works are short-term, focus on technical evaluation, and provide limited insight into how student awareness develops over time. In addition, relatively few studies explicitly address international student contexts or evaluate explanations from the students' perspective.

Therefore, future research is recommended to focus on awareness-oriented explainable AI designs, with a stronger emphasis on student-centered evaluation and longitudinal studies. Further work should explore how different explanation styles support understanding across diverse student populations and how explainable systems can be integrated into real academic practices over time, reinforcing a shift from prediction-focused models toward awareness-oriented, student-facing explainable AI systems.

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