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Cultivating Innovation Readiness in Biology Education: The Mediating Roles of Plant Attitudes and Scientific Argumentation in Deep Learning and Cognitive Flexibility

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ABSTRACT: Innovation readiness has become an essential competency in biology education, enabling students to engage in evidence-based reasoning, problem-solving, and responsible scientific innovation. This study examined the relationships among cognitive flexibility, deep learning, plant attitudes, scientific argumentation, and innovation readiness among undergraduate Biology and Biology Education students. A cross-sectional survey was conducted with 538 students at Universitas Negeri Makassar, Indonesia, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Two structural models were compared to evaluate the contribution of plant attitudes to the predictive performance of the framework. The findings demonstrated that the inclusion of plant attitudes substantially improved the explanatory power of the model. Cognitive flexibility significantly predicted both plant attitudes and scientific argumentation, influencing innovation readiness primarily through indirect pathways. Deep learning emerged as the strongest predictor of innovation readiness through both direct and mediated effects. Plant attitudes significantly enhanced scientific argumentation and directly contributed to innovation readiness, while scientific argumentation further strengthened students' readiness for innovation-oriented activities. Multi-group analysis revealed generally stable structural relationships across academic programs, although the effect of plant attitudes on innovation readiness differed significantly between Biology and Biology Education students. The study highlights the importance of integrating affective engagement with plants, deep learning strategies, and scientific argumentation practices to foster innovation readiness in biology education.

Keywords: Innovation readiness, Scientific argumentation, Plant attitudes, Cognitive flexibility, Deep learning.

I. INTRODUCTION

In the twenty first century, the quality of science in higher education is increasingly judged not only by students' command of disciplinary concepts, but also by their capacity to engage in higher order thinking, develop meaningful scientific literacy, and respond to global challenges through innovation [1-3]. Within biology education, these expectations have become particularly pressing [4]. Accelerating biodiversity loss, environmental degradation, and intensifying demands for sound biological understanding call for graduates who can interpret complex biological information, appraise evidence responsibly, and contribute to science-based solutions that are ethically accountable [5]. In this context, innovation readiness among biology students should not be reduced to technological preparedness. Rather, innovation readiness is more appropriately conceptualized as a dispositional-cognitive readiness to evaluate, select, and implement innovations rationally, reflectively, and responsibly in accordance with ecological and social needs [6]. This conception is particularly relevant in higher education because students are increasingly expected not only to understand scientific advances, but also to judge their credibility, appropriateness, and consequences in complex real-world contexts.

Innovation readiness does not emerge independently of learning processes. Research in science education and educational psychology suggests that students' readiness to engage with innovation is shaped by how they manage complexity, connect knowledge across contexts, and use evidence in forming judgments [7]. Biology is intrinsically complex, characterized by hierarchical organization, nonlinear interactions, and multidimensional phenomena [8]. As a result, students are frequently required to reconsider interpretations when new information becomes available. This makes cognitive adaptability and meaningful learning particularly important in biology, because students must move across levels of organisation, reconcile competing explanations, and interpret evidence in uncertain contexts [9]. Within this educational reality, upstream cognitive and learning processes are likely to play a foundational role in preparing students to engage with innovation in ways that are analytically rigorous rather than merely reactive.

At the same time, innovation-related learning in biology is not only a matter of cognition. It is also influenced by whether learners perceive the object of inquiry as meaningful, relevant, and worthy of sustained attention. This issue becomes especially important in plant-related learning. A distinctive challenge in biology education that has received international attention is the low level of learner attention and engagement with plants, commonly discussed as plant blindness or, more recently, plant awareness disparity [10, 11]. This phenomenon is not merely a lack of factual knowledge. It also reflects patterns of low salience, limited interest, and reduced perceived relevance of plants compared with other organisms [12]. International evidence indicates that this problem appears across multiple educational contexts, suggesting a broad challenge in how learners assign value to plants within science learning [13-15]. This issue is especially salient in biology education because plants are central to biodiversity, climate resilience, ecosystem stability, food systems, and sustainability transitions, yet they are often not treated by learners as equally compelling objects of scientific attention.

Such conditions matter because what students perceive as important influences what they attend to, what they investigate seriously, and how far they are willing to engage with evidence [16]. In this study, Plant Attitudes refer to students' affective cognitive evaluations of the importance of plants, interest in learning about plants, and concern for the role of plants in life and sustainability. Rather than treating Plant Attitudes as a peripheral affective outcome, this study considers them as a potentially important domain-specific mechanism for connecting general learning processes to biology-specific innovation outcomes. This issue is especially relevant because plants are central to sustainability, biodiversity, food systems, and ecological resilience, yet they are often marginalized in learners' value frameworks [13, 17]. Accordingly, Plant Attitudes are treated as a possible domain-specific attitudinal anchor through which broad learning capacities may become more meaningfully oriented toward biologically relevant innovation judgments.

A further issue concerns how students transform learning into evidence-based judgment. Scientific argumentation is essential because students are expected not only to understand concepts, but also to evaluate claims, examine evidence, consider alternatives, and justify conclusions responsibly [18-20]. Accordingly, innovation readiness in biology is unlikely to arise from cognitive or learning processes alone; it is more plausibly strengthened when those processes are translated into disciplined epistemic practice. From this perspective, an integrated pathway linking learning processes, Plant Attitudes, scientific argumentation, and innovation readiness provides a meaningful basis for explaining how students become prepared to judge and engage with innovation responsibly. Scientific argumentation can be viewed as the epistemic mechanism through which cognitive and attitudinal resources are converted into evidence-based judgments about innovation.

Although prior research has examined relationships among cognitive flexibility, deep learning, and argumentation across educational contexts, existing models of innovation-related outcomes have tended to emphasize general cognitive or learning variables more strongly than domain-specific value orientations. As a result, such models may remain theoretically under-specified when explaining how upstream learning processes become context-sensitive readiness for innovation in biology. Thus, the key gap addressed in this study is not simply that Plant Attitudes have been under-studied, but that innovation readiness models have rarely tested whether a domain-specific attitudinal anchor contributes additional explanatory and predictive value beyond general cognitive and learning variables. In other words, the unresolved theoretical issue is whether innovation readiness in biology can be sufficiently explained by general cognitive-learning pathways alone, or whether it requires an additional domain-sensitive mechanism that anchors those pathways to a valued object of inquiry.

To address this gap, the present study tests and compares two alternative structural models using PLS SEM. Model I position Plant Attitudes as a key domain specific mediator in the pathway toward scientific argumentation and innovation readiness, whereas Model II evaluates an alternative explanation that excludes Plant Attitudes. This design allows the study to function as a predictive structural comparison, assessing whether the inclusion of a domain-specific attitudinal anchor improves the model's explanatory power and predictive performance [21]. In addition, the study examines whether the structural relationships differ between students in Biology programs and students in Biology Education programs, given that program orientation may shape how domain attitudes and epistemic practices translate into innovation readiness. This question is particularly relevant in Indonesia, a biodiversity-rich context in which plant-related knowledge, sustainability challenges, and biology education intersect strongly, yet where students' evaluative orientation toward plants may develop differently across disciplinary and teacher-education pathways.

On the basis of these aims, the study is guided by four research questions. First, how do cognitive flexibility and deep learning contribute to scientific argumentation and innovation readiness among biology students. Second, do Plant Attitudes function as a domain specific mediator that strengthens the relationship between learning processes and innovation readiness. Third, does the inclusion of Plant Attitudes improve the explanatory power and predictive capability of the model compared with a model that excludes Plant Attitudes. Fourth, do the structural relationships differ between Biology students and Biology Education students. Theoretically, this study advances a domain sensitive account of innovation readiness by demonstrating how affective cognitive orientations toward disciplinary objects can bind epistemic practices to innovation outcomes. Practically, the findings are expected to inform instructional design that intentionally cultivates deep learning, strengthens value-oriented orientations toward plants, and develops scientific argumentation as a pathway toward responsible innovation in biology education. More broadly, the study is also aligned with sustainability-oriented higher education, which increasingly expects students to connect disciplinary understanding with ecological responsibility, systems thinking, and socially accountable decision-making.

1. THEORETICAL FRAMEWORK: CORE CONSTRUCTS AND CONCEPTUAL LENS

This study is grounded in an integrated theoretical framework drawing on Cognitive Flexibility Theory, Student Approaches to Learning Theory, Expectancy-Value Theory, epistemic cognition, and Responsible Innovation. Within this framework, cognitive flexibility is understood as an adaptive cognitive capacity that enables learners to revise interpretations, shift perspectives, and respond to science complexity and changing evidence [9, 22]. Deep learning, derived from Student Approaches to Learning Theory, refers to a meaningful learning orientation characterized by conceptual understanding, integration of ideas, reflection, and transfer beyond rote reproduction [23-25]. In biology, these two constructs are closely connected because adaptive cognition supports students in dealing with complex life systems, while deep learning transforms that cognitive capacity into coherent and transferable understanding across cellular, organismal, ecological, and socio-scientific contexts. Taken together, these perspectives position cognitive flexibility as an upstream adaptive resource and deep learning as the process through which that resource is translated into sustained meaning-making.

Within Expectancy-Value Theory, Plant Attitudes are conceptualized as a domain-specific value orientation reflecting the perceived importance, relevance, and worth of plants as objects of scientific learning and sustainability concern. This construct is especially important in light of plant awareness disparity, which suggests that plants are often undervalued in learners' attention and interest [10, 11]. Accordingly, Plant Attitudes are theorized not simply as a by-product of biology learning, but as a value-based domain anchor that directs students' engagement toward plant-related content as meaningful, important, and worthy of effort [12]. Scientific argumentation, grounded in epistemic cognition, is treated as an epistemic practice through which students evaluate evidence, justify claims, and construct reasoned positions [26]. From this perspective, scientific argumentation is more than a communication skill; it is the mechanism by which learners transform conceptual understanding and value-based engagement into disciplined judgment under conditions of uncertainty. Finally, from the perspective of Responsible Innovation, innovation readiness is defined as a dispositional-cognitive readiness to evaluate, adopt, and implement innovations through evidence-based, reflective, and context-sensitive judgement [6, 27], rather than as actual innovative behaviour. This framing is especially compatible with higher education because students are often required to judge emerging ideas, methods, and technologies before they are in positions to enact innovation behaviour directly.

This framework suggests that cognitive flexibility provides adaptive capacity [28], deep learning supports meaning-making [29], Plant Attitudes anchor engagement to a valued biological domain, and scientific argumentation converts these resources into evidence-based judgement that supports innovation readiness [30]. The integration of these theoretical perspectives is therefore not additive but sequentially coherent: Cognitive Flexibility Theory explains how students adaptively process complexity [31, 32]; Student Approaches to Learning Theory explains how such adaptive capacity is enacted through meaningful learning [33]; Expectancy-Value Theory explains how that learning becomes anchored to a valued domain object [34]; epistemic cognition explains how value-laden engagement is translated into disciplined argumentation [35]; and Responsible Innovation explains why the resulting outcome is best understood as reflective, evidence-based readiness for innovation [36]. This integrated lens provides the conceptual justification for modelling Plant Attitudes and scientific argumentation not as peripheral variables, but as theoretically necessary linking mechanisms between upstream learning processes and downstream innovation readiness.

2. HYPOTHESES DEVELOPMENT

Students with stronger cognitive flexibility are more capable of shifting perspectives, reconstructing understanding, and adapting reasoning when encountering biological complexity [32]. Such adaptive processing may increase openness toward plant-related issues by reducing rigid and superficial modes of engagement, thereby supporting more positive Plant Attitudes [37, 38]. Cognitive flexibility is also important for scientific argumentation because argumentation requires learners to consider alternative explanations, weigh evidence, and revise conclusions in light of stronger justification [7, 20]. In biology, where phenomena are often complex and context dependent, students with higher cognitive flexibility are therefore more likely to construct well-reasoned arguments rather than rely on fixed interpretations. Because plants are often overlooked as objects of scientific relevance, adaptive cognition may be particularly important for helping students reframe plant-related content as conceptually and practically significant rather than peripheral.

- H1. Cognitive Flexibility positively predicts Plant Attitudes.
- H2. Cognitive Flexibility positively predicts Scientific Argumentation.

Cognitive flexibility enables students to reconsider alternatives, adjust their reasoning, and respond adaptively to novelty, uncertainty, and complexity [27, 39]. These capacities are particularly important in science, where innovation often involves complex evidence, changing conditions, and context-sensitive judgment [22, 40, 41]. Students with higher cognitive flexibility are therefore more likely to evaluate new ideas reflectively, weigh their relevance and feasibility, and engage with innovation in a more responsive and informed manner [35]. Although this influence may also operate indirectly through downstream processes, cognitive flexibility is expected to make a direct contribution to students' readiness for innovation by strengthening their capacity to deal with innovation-related uncertainty.

- H3. Cognitive Flexibility positively predicts Innovation Readiness.

Deep learning encourages learners to pursue conceptual understanding, connect knowledge across contexts, and relate disciplinary content to real-world issues [24, 42]. In biology, such meaningful engagement may increase students' appreciation of plants as important to sustainability, biodiversity, and human well-being, thereby strengthening Plant Attitudes [43]. Deep learning is also likely to promote higher-quality scientific argumentation because students who learn for understanding are better able to construct coherent explanations, evaluate justificatory grounds, and use evidence reflectively [44]. This is particularly relevant in sustainability-oriented biology learning, where students are expected to connect scientific knowledge with ecological consequence, societal relevance, and responsible judgement.

- H4. Deep Learning positively predicts Plant Attitudes.
- H5. Deep Learning positively predicts Scientific Argumentation.

Students who engage in deep learning are more likely to develop coherent explanatory frameworks and transfer knowledge to novel problems [24, 45]. Because innovation readiness involves evaluating and responding to new ideas in context-sensitive ways, deep learning should directly support such readiness by strengthening meaning-based judgement and problem-oriented understanding [46, 47]. Students who seek understanding rather than reproduction are therefore more likely to judge innovation not only in terms of novelty, but also in terms of coherence, usefulness, and contextual appropriateness.

- H6. Deep Learning positively predicts Innovation Readiness.

When students perceive plants as meaningful and worthy of sustained attention, they are more likely to invest effort in examining evidence, testing claims, and forming justified conclusions in plant-related contexts [30, 48]. Plant Attitudes should therefore strengthen scientific argumentation by increasing motivation and domain-relevant engagement [43]. In addition, students who hold stronger value-based orientations toward plants may be more prepared to engage with scientific innovation responsibly, especially when such innovation concerns sustainability, biodiversity, or ecological systems [49, 50]. In this sense, Plant Attitudes are expected to operate as a domain-specific attitudinal anchor that helps convert broad learning dispositions into context-sensitive epistemic and innovation-related outcomes.

- H7. Plant Attitudes positively predict Scientific Argumentation.
- H8. Plant Attitudes positively predict Innovation Readiness.

Scientific argumentation supports disciplined evidence evaluation, critical appraisal of alternatives, and reasoned justification [51]. These capacities are essential for innovation readiness because students must judge not only whether an innovation is novel, but whether it is credible, feasible, and contextually appropriate [52-54]. Students with stronger argumentation are therefore expected to show greater readiness to evaluate and engage with innovation. This relationship is central to the present model because it locates innovation readiness within an epistemic, rather than purely attitudinal or technological, logic of judgement.

- H9. Scientific Argumentation positively predicts Innovation Readiness.

Beyond the direct paths hypothesized above, the integrated framework also implies a serial mediation process. Cognitive flexibility provides adaptive capacity; deep learning supports meaningful integration; Plant Attitudes anchor learning to a valued biological object; and scientific argumentation converts these resources into evidence-based judgement. Thus, innovation readiness is expected to emerge most strongly when these processes operate in sequence. Although the primary hypotheses concern direct structural paths, the model also tests whether Plant Attitudes and Scientific Argumentation mediate the effects of Cognitive Flexibility and Deep Learning on Innovation Readiness. This sequential logic is theoretically important because the mediators are not treated as interchangeable. Plant Attitudes are expected to provide value-based domain engagement, whereas scientific argumentation provides epistemic conversion of that engagement into reasoned judgement. For this reason, the model examines not only isolated indirect effects but also the possibility of a serial pathway in which domain-specific valuing and epistemic practice jointly transmit the influence of upstream learning processes to downstream innovation readiness.

II. MATERIAL AND METHOD

1. STUDY DESIGN AND RESEARCH APPROACH

This study employed a theory driven quantitative approach within an explanatory research framework, using a cross-sectional survey design [55]. The study aimed to test and compare two alternative structural models that explain cognitive pathways to students' scientific argumentation and innovation readiness through the roles of deep learning and plant attitudes [56]. Model I incorporated Plant Attitudes as a pivotal construct that mediates the effects of Cognitive Flexibility and Deep Learning on Scientific Argumentation and Innovation Readiness. Model II tested the same structural framework while excluding Plant Attitudes, thereby estimating the effects of Cognitive Flexibility and Deep Learning on Scientific Argumentation and Innovation Readiness directly. Data were analyzed using Partial Least Squares Structural Equation Modelling, given its suitability for predictive model testing with simultaneous relationships, mediation assessment, and comparative evaluation of model performance [21]. PLS-SEM was selected because the present study was designed as a predictive structural comparison study that prioritized explained variance, predictive relevance, and the comparison of alternative theoretically plausible models. In addition, the study involved multiple simultaneous direct and indirect relationships, including serial mediation and multi-group comparison, for which PLS-SEM is well suited when the analytical objective is theory extension and prediction-oriented model assessment rather than strict overall model fit confirmation alone [57].

Two structural models were estimated [56, 58]. Model I, which included Plant Attitudes, specified direct paths from Cognitive Flexibility and Deep Learning to Plant Attitudes, Scientific Argumentation, and Innovation Readiness, as well as paths from Plant Attitudes to Scientific Argumentation and Innovation Readiness. In addition, Scientific Argumentation was specified as a direct predictor of Innovation Readiness. Model II, which excluded Plant Attitudes, removed this construct from the model such that Cognitive Flexibility and Deep Learning were specified as direct predictors of Scientific Argumentation and Innovation Readiness, while Scientific Argumentation remained a predictor of Innovation Readiness. Both models employed identical measurement instruments for the retained constructs, and the only structural difference was the inclusion versus exclusion of Plant Attitudes. Accordingly, the model comparison represents an empirical test of the incremental explanatory value contributed by Plant Attitudes. The hypothesised path diagrams are presented in Figure 1.

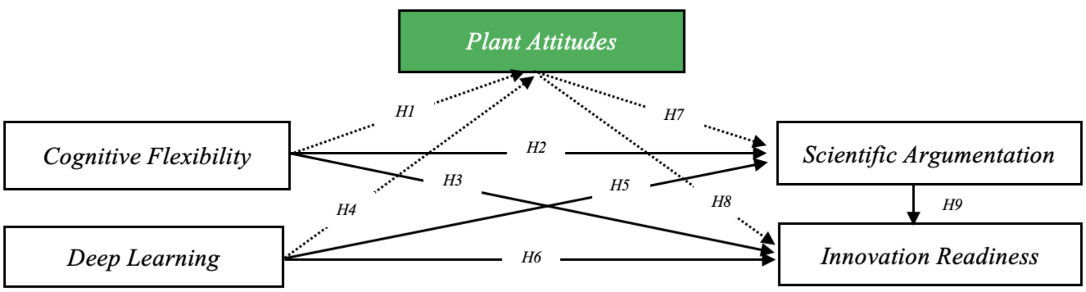

FIGURE 1. Hypothesized research pathways.

2. POPULATION, SAMPLE, AND SAMPLING TECHNIQUE

The study population comprised all active students enrolled in the Biology and Biology Education programmes at Universitas Negeri Makassar, Indonesia. Participants were selected using purposive sampling based on the following eligibility criteria: active enrolment status, completion of at least two semesters of study, and willingness to provide informed consent. Sample size was determined via power analysis using a significance level of 0.05, minimum statistical power of 0.80, and an assumed medium effect size of f squared equals 0.15 [21]. To enhance the stability of path estimates and the reliability of cross model comparisons, the study targeted 538 respondents, consisting of 232 Biology students and 306 Biology Education students.

Purposive sampling was used because the study sought theory-relevant respondents who had sufficient exposure to university biology learning contexts to provide informed responses on cognitive flexibility, deep learning, plant attitudes, scientific argumentation, and innovation readiness. Accordingly, the findings are interpreted primarily as evidence for structural relationships within an eligible student population rather than as population estimates requiring probability-based inference. This sampling strategy limits strict statistical generalizability, it does not in itself invalidate the estimation of relationships among latent constructs in a theory-testing SEM framework, provided that respondents meet the substantive inclusion criteria and that measurement quality is demonstrated empirically. In addition, the sample adequately represented the two programme contexts central to the study design, namely Biology and Biology Education, thereby supporting the intended cross-programme comparison.

3. *INSTRUMENTS AND VALIDATION*

The research instrument was developed through a comprehensive literature review and the adaptation of relevant items to fit the student context. Cognitive Flexibility assessed students' capacity to revise understanding and adjust thinking strategies when encountering complex or contradictory information [22]. Deep Learning captured a tendency toward meaningful learning through deep conceptual understanding, connections among concepts, reflection, and application to real world contexts [25]. Plant Attitudes assessed students' affective cognitive evaluations of plants, including appreciation, care, and valuing the importance of plants for life and sustainability [59]. Scientific Argumentation assessed the ability to construct, evaluate, and revise evidence-based arguments in a logically coherent and ethically responsible manner [60]. Innovation Readiness assessed readiness to adopt and implement innovations in learning and professional practice, including openness to new technologies or approaches and the capacity to adapt to change [61]. All constructs were measured using a seven-point Likert scale ranging from 1 strongly disagree to 7 strongly agree.

All constructs in this study were specified as reflective constructs [62]. This specification was adopted because the indicators were conceptualized as observable manifestations of their respective latent variables, such that variation in the underlying construct was expected to be reflected in corresponding variation across the indicators. In addition, the indicators within each construct were designed to capture closely related aspects of a shared conceptual domain rather than distinct components that would jointly form the construct, which supports reflective rather than formative specification [63]. Content validity was established through expert review by specialists in biology education, psychology, and research methodology to ensure alignment between indicators, construct definitions, and the respondent context. The instrument then underwent a limited pilot test to assess clarity of wording, readability, and potential comprehension bias. Empirical validation was conducted by evaluating reliability and construct validity within the PLS SEM measurement model framework. Measurement model evaluation procedures were applied consistently across both structural models to ensure comparability of results.

4. *DATA COLLECTION AND ANALYTICAL PROCEDURES*

Data were collected via an online questionnaire distributed to students. Respondents received information regarding the study purpose, data anonymity, response confidentiality, and participation rights through an informed consent form. All responses were collected anonymously and screened to ensure data quality prior to analysis. Because the online survey system required respondents to complete all items before submission, missing data accounted for 0.00% of all response cells. Consequently, no missing-data treatment, such as imputation or case deletion, was required. The study adhered to ethical principles for social research, including voluntary participation, anonymity, and data confidentiality. Participants provided informed consent prior to completing the questionnaire. Data were used solely for academic purposes and stored securely. Responses that exhibited straight-lining patterns, duplicate submissions, or implausibly short completion times were removed during data screening. The final analytic sample consisted of 538 valid cases.

To minimize common method bias, both procedural and statistical remedies were implemented [64]. Procedurally, anonymity was ensured and instructions emphasized that there were no right or wrong answers. Statistically, common method bias was evaluated using full collinearity assessment, applying a variance inflation factor threshold below 3.3 as an indicator that method bias did not dominate the data [65].

Data were analyzed using PLS SEM to test and compare Model I, which included Plant Attitudes, and Model II, which excluded Plant Attitudes. Measurement model evaluation was conducted on the complete sample to establish aggregated reliability and validity prior to structural analysis and multi group comparisons, because this stage aimed to verify indicator and latent construct quality overall rather than to compare measurement properties across groups. For reflective constructs, measurement quality was assessed using established threshold criteria, namely outer loadings of at least 0.70, Cronbach's alpha of at least 0.70, composite reliability of at least 0.70, and average variance extracted (AVE) of at least 0.50 [21]. Discriminant validity was evaluated using both the heterotrait-monotrait ratio (HTMT), with values below 0.90 indicating adequate construct distinctiveness [63, 66, 67]. Structural model evaluation was performed by estimating path coefficients and their significance using bootstrapping with 5000 resamples at an alpha level of 0.05. Model explanatory power was assessed using R squared, and effect sizes were evaluated using f squared, with thresholds of 0.02 small, 0.15 medium, and 0.35 large [63].

Because the study was explicitly predictive in orientation, model assessment extended beyond path significance and explained variance. Predictive performance was evaluated using PLSpredict, which assesses out-of-sample prediction by comparing the prediction errors generated by the PLS-SEM model with those of a linear benchmark model at the indicator level [21]. This procedure was used to examine whether the model including Plant Attitudes provided superior predictive performance relative to the reduced model without Plant Attitudes.

In Model I, mediation analysis examined the role of Plant Attitudes, including serial mediation via Scientific Argumentation to Innovation Readiness, using bootstrapped indirect effects. Statistical significance was inferred when confidence intervals did not cross zero. Model performance was compared between Model I and Model II primarily by examining differences in R squared and f squared for Scientific Argumentation and Innovation Readiness, enabling a quantitative interpretation of the incremental empirical value of including Plant Attitudes. Model comparison further included comparison of key structural coefficients across Model I and Model II in order to determine whether the inclusion of Plant Attitudes altered the magnitude and pattern of the hypothesized relationships. To test whether the strengths of structural relationships differed between Biology students and Biology Education students, a PLS SEM based Multi Group Analysis was conducted [68]. Differences significant at an alpha level of 0.05 were interpreted as evidence that the influence between constructs was stronger in one programme group than in the other.

III. DATA ANALYSIS

All reflective constructs, namely Cognitive Flexibility, Deep Learning, Plant Attitudes, Scientific Argumentation, and Innovation Readiness, demonstrated very strong reliability and convergent validity. This confirms that the instrument represents the underlying latent constructs consistently, stably, and with high accuracy. All retained indicators exhibited outer loadings above the 0.70 threshold, indicating substantial indicator contributions to explaining construct variance and adequate conceptual representation.

Cronbach's alpha and composite reliability estimates, including rho A and rho C, for all constructs were well above the recommended minimum values, indicating excellent internal consistency and a low risk of measurement error. Average Variance Extracted values for all constructs exceeded 0.50, further supporting convergent validity because each construct accounted for more than half of the variance in its indicators.

One indicator within the Deep Learning construct, DL7, was removed from the measurement model because it did not meet the specified statistical adequacy criteria. This removal was implemented to improve the overall reliability and validity of the construct. The refined measurement model therefore provides a robust empirical foundation with no evidence of substantive measurement bias for subsequent testing of the structural relationships among constructs in explaining biology students' innovation readiness.

Table 1. Presents the measurement model evaluation.

Variables/Constructs	Outer Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Cognitive Flexibility.	0.811 0.838 0.821 0.833 0.865 0.806 0.861	0.927	0.928	0.941	0.695
Deep Learning	0.868 0.897 0.897 0.902 0.841 0.872	0.942	0.942	0.954	0.774
Plant Attitudes	0.861 0.877 0.898 0.858 0.851 0.883 0.823	0.944	0.944	0.954	0.748
Scientific Argumentation	0.893 0.855 0.887 0.844 0.845 0.886 0.833	0.943	0.945	0.954	0.746
Innovation Readiness	0.871 0.880 0.874 0.813 0.896 0.900	0.945	0.946	0.955	0.753

0.837

Discriminant validity assessed using the HTMT criterion indicated acceptable construct separation across the full sample and both programme subgroups. All HTMT values were below the threshold of 0.90, supporting discriminant validity for Cognitive Flexibility, Deep Learning, Plant Attitudes, Scientific Argumentation, and Innovation Readiness. In the full sample, the highest HTMT value was observed between Cognitive Flexibility and Scientific Argumentation (0.893), but it remained below the recommended cut-off. A similar pattern was observed in the biology subgroup, where the highest value was 0.875, and in the Biology Education subgroup, where the highest value was 0.883. Overall, these results indicate that discriminant validity was supported across the complete sample, Biology students, and Biology Education students.

Table 2. HTMT Ratios for assessing discriminant validity across student groups.

Variables/Constructs	CF	DL	PA	SA	IR
Complete					
Cognitive Flexibility (CF)	–				
Deep Learning (DL)	0.819	–			
Plant Attitudes (PA)	0.757	0.760	–		
Scientific Argumentation (SA)	0.893	0.842	0.805	–	
Innovation Readiness (IR)	0.802	0.810	0.769	0.807	–
Biology					
Cognitive Flexibility (CF)	–				
Deep Learning (DL)	0.844	–			
Plant Attitudes (PA)	0.830	0.827	–		
Scientific Argumentation (SA)	0.803	0.875	0.853	–	
Innovation Readiness (IR)	0.801	0.812	0.869	0.834	–
Biology Education					
Cognitive Flexibility (CF)	–				
Deep Learning (DL)	0.876	–			
Plant Attitudes (PA)	0.654	0.672	–		
Scientific Argumentation (SA)	0.883	0.797	0.747	–	
Innovation Readiness (IR)	0.788	0.788	0.646	0.764	–

The cross-loading analysis indicated that all indicators consistently loaded more strongly on their intended constructs than on any other constructs. This pattern suggests that each indicator represents its target latent construct with specificity and does not exhibit substantial conceptual overlap with other constructs in the model. Although several indicators displayed moderate cross loadings on theoretically related constructs, such as between Cognitive Flexibility and Deep Learning or between Scientific Argumentation and Innovation Readiness, the primary loadings remained clearly dominant on the original constructs. Therefore, indicator level discriminant validity criteria were satisfied.

Table 3. Indicator cross-loadings for complete sample.

Indicators	**CF**	**DL**	**PA**	**SA**	**IR**
			Complete		
CF1	0.811	0.690	0.585	0.694	0.597
CF2	0.838	0.697	0.579	0.705	0.625
CF3	0.821	0.710	0.550	0.659	0.630
CF4	0.833	0.747	0.586	0.705	0.608

CF5	0.865	0.748	0.639	0.739	0.651
CF6	0.806	0.674	0.591	0.676	0.563
CF7	0.861	0.748	0.606	0.702	0.706
DL1	0.729	0.868	0.630	0.656	0.647
DL2	0.763	0.897	0.632	0.701	0.647
DL3	0.780	0.897	0.620	0.736	0.679
DL4	0.775	0.902	0.666	0.733	0.685
DL5	0.716	0.841	0.603	0.682	0.661
DL6	0.772	0.872	0.630	0.690	0.716
SA1	0.739	0.692	0.692	0.893	0.725
SA2	0.702	0.668	0.638	0.855	0.597
SA3	0.721	0.733	0.675	0.887	0.676
SA4	0.678	0.591	0.603	0.844	0.576
SA5	0.724	0.657	0.625	0.845	0.662
SA6	0.739	0.732	0.672	0.886	0.669
SA7	0.745	0.727	0.683	0.833	0.701
IR1	0.646	0.697	0.616	0.661	0.871
IR2	0.685	0.685	0.618	0.688	0.880
IR3	0.651	0.670	0.626	0.658	0.874
IR4	0.609	0.598	0.588	0.618	0.813
IR5	0.650	0.651	0.667	0.627	0.896
IR6	0.646	0.668	0.660	0.677	0.900
IR7	0.672	0.670	0.638	0.712	0.837

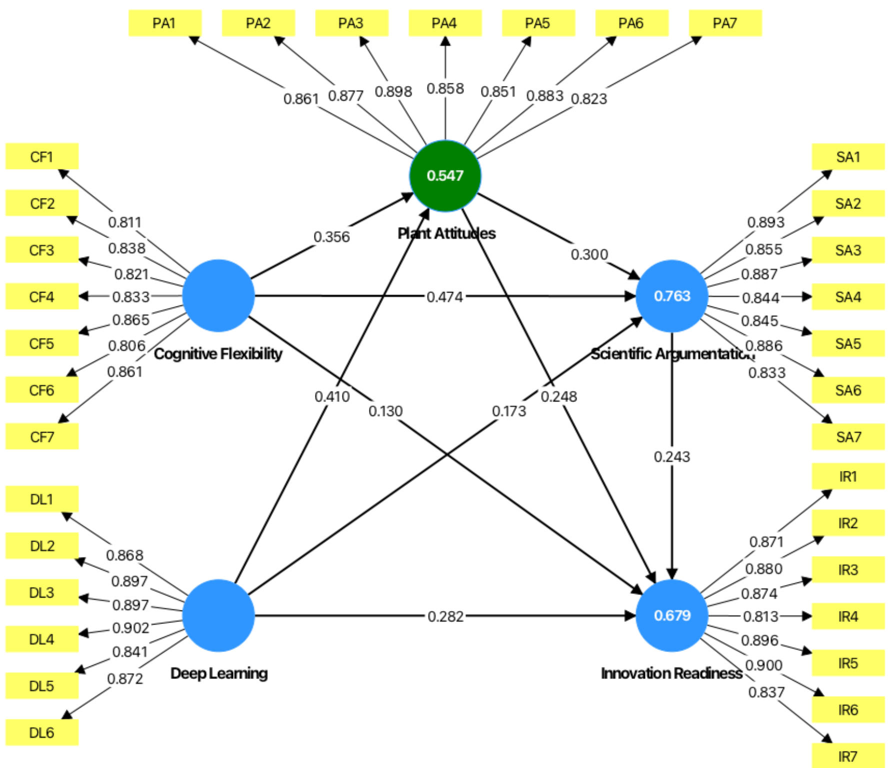

FIGURE 2. PLS-SEM Structural model with plant attitudes as a domain-specific mediator.

Model I showed stronger explanatory power than Model II for the endogenous constructs. In Model I, the predictors accounted for 76.3% of the variance in Scientific Argumentation and 67.9% of the variance in Innovation Readiness, indicating substantial explanatory capacity. When Plant Attitudes were excluded in Model II, the R^2 values declined to 0.722 for Scientific Argumentation and 0.656 for Innovation Readiness. This reduction indicates that Plant Attitudes contribute meaningful additional explanatory value beyond general cognitive and learning variables, strengthening the model's account of how scientific argumentation and innovation readiness are formed in biology students.

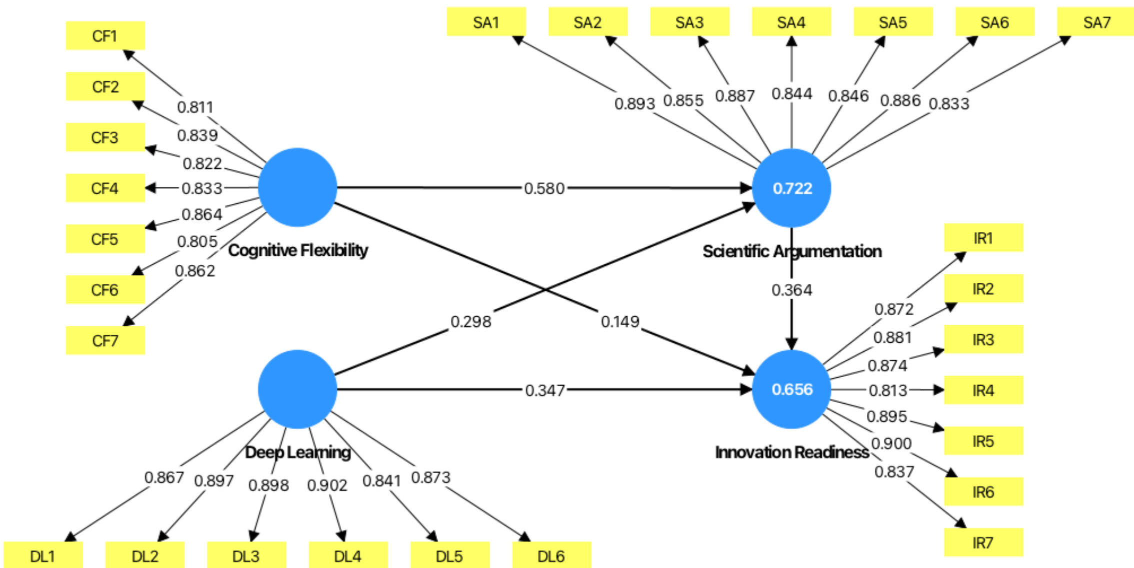

FIGURE 3. PLS-SEM Structural model without plant attitudes.

Table 4 presents the VIF values, direct effects with 95% confidence intervals, total effects, and effect sizes for all hypothesized paths in Model I. The VIF values ranged from 1.205 to 3.054, indicating no collinearity concerns. Most direct effects were positive and significant, except for the direct path from Cognitive Flexibility to Innovation Readiness. The total effects were all positive, and the effect sizes were mostly medium, with large effects observed for Cognitive Flexibility on Scientific Argumentation and Deep Learning on Innovation Readiness.

Table 4. Structural path coefficients and effect sizes.

Path and Hypothesis	**VIF**	**Direct Effect β [95% CI]**	**Total Effect β**	**f^2 (Effect Size)**
Cognitive Flexibility to Plant Attitudes (H1)	1.826	0.356 [0.238, 0.484]***	0.356	Medium
Cognitive Flexibility to Scientific Argumentation (H2)	2.106	0.474 [0.371, 0.584]***	0.581	Large
Cognitive Flexibility to Innovation Readiness (H3)	3.054	0.130 [−0.009, 0.282]	0.360	Medium
Deep Learning to Plant Attitudes (H4)	1.826	0.410 [0.280, 0.528]***	0.410	Medium
Deep Learning to Scientific Argumentation (H5)	2.197	0.173 [0.073, 0.270]**	0.297	Medium
Deep Learning to Innovation Readiness (H6)	2.324	0.282 [0.135, 0.420]***	0.455	Large
Plant Attitudes to Scientific Argumentation (H7)	1.205	0.300 [0.185, 0.411]***	0.300	Medium
Plant Attitudes to Innovation Readiness (H8)	1.585	0.248 [0.158, 0.348]***	0.321	Medium
Scientific Argumentation to Innovation Readiness (H9)	2.215	0.243 [0.090, 0.380]**	0.243	Medium

*p < .05, ** p < .01, *** p < .001.

Table 5 presents the indirect and total effects for the mediation analysis in Model I. All indirect effects were positive and significant, indicating the presence of meaningful mediated relationships. The largest indirect effect was observed for Cognitive Flexibility on Innovation Readiness (β = 0.230), followed by Deep Learning on Innovation Readiness (β = 0.174). The total effects were also positive across all reported paths, with the highest total effect found for Cognitive Flexibility on Scientific Argumentation (β = 0.581).

Table 5. Indirect and total effects for the mediation analysis.

Path	Indirect Effect β [95% CI]	Total Effect β
Cognitive Flexibility to Scientific Argumentation	0.107 [0.059, 0.165]***	0.581
Cognitive Flexibility to Innovation Readiness	0.230 [0.140, 0.324]***	0.360
Deep Learning to Scientific Argumentation	0.123 [0.066, 0.191]***	0.297
Deep Learning to Innovation Readiness	0.174 [0.106, 0.254]***	0.455
Plant Attitudes to Innovation Readiness	0.073 [0.025, 0.125]**	0.321

*p < .05, ** p < .01, *** p < .001.

Based on the PLSpredict results, both models demonstrated predictive relevance, as all Q^2predict values were positive. However, Model I proved superior to Model II for the shared endogenous constructs, namely Innovation Readiness and Scientific Argumentation, because it showed higher Q^2predict values as well as lower RMSE and MAE values. In addition, Plant Attitudes in Model I also demonstrated good predictive relevance. Overall, these findings confirm that the inclusion of Plant Attitudes improved the predictive performance of the model, indicating that Model I was stronger than Model II both theoretically and predictively.

Table 6. PLSpredict results and predictive performance comparison for model i and model ii.

Model	Endogenous Construct	Q^2predict	RMSE	MAE
Model I	Innovation Readiness	0.734	0.426	0.342
Model I	Plant Attitudes	0.742	0.582	0.413
Model I	Scientific Argumentation	0.716	0.436	0.421
Model II	Innovation Readiness	0.615	0.525	0.442
Model II	Scientific Argumentation	0.606	0.536	0.481

Model fit evaluation indicated that both Model I and Model II satisfied acceptable fit criteria within the PLS-SEM framework. Both models showed SRMR values of 0.047, which were below the recommended threshold and therefore indicated adequate model fit. However, Model I demonstrated lower d_ULS, d_G, and chi-square values than Model II, suggesting smaller discrepancies between the empirical and model-implied matrices. Model I also produced a slightly higher NFI value, indicating a better fit relative to the baseline model. Overall, these results suggest that although both models were acceptable, Model I provided the better overall fit.

Table 7. Model fit indices for the estimated structural models (model i and model ii).

Model Fit Index	Model I – Saturated	Model I – Estimated	Model II – Saturated	Model II – Estimated
SRMR	0.047	0.047	0.047	0.047
d_ULS	0.826	0.826	1.302	1.302
d_G	0.659	0.659	0.967	0.967
Chi-square	2053.992	2053.992	3066.239	3066.239
NFI	0.866	0.866	0.846	0.846

The multi group analysis further indicated that most structural paths were stable across Biology and Biology Education students. However, the path from Plant Attitudes to Innovation Readiness differed significantly between groups. This suggests that the role of attitudes toward plants in shaping innovation readiness is more salient in one programme group than in the other, highlighting programme specific contextual nuance in the mechanisms underpinning innovation readiness.

Table 8. Multi-Group analysis (MGA) for biology and biology education students.

Path	MGA Difference (Biology – Biology Education)	MGA p-value (2-tailed)
Cognitive Flexibility to Plant Attitudes	0.160	0.235
Cognitive Flexibility to Scientific Argumentation	−0.074	0.532
Cognitive Flexibility to Innovation Readiness	−0.203	0.153
Deep Learning to Plant Attitudes	−0.003	0.984
Deep Learning to Scientific Argumentation	0.035	0.736
Deep Learning to Innovation Readiness	−0.142	0.377
Plant Attitudes to Scientific Argumentation	0.021	0.842
Plant Attitudes to Innovation Readiness	0.368	0.000
Scientific Argumentation to Innovation Readiness	0.019	0.878

IV. DISCUSSION

The roles of cognitive flexibility and deep learning in shaping scientific argumentation and innovation readiness. The findings indicate that cognitive flexibility operates as an upstream cognitive capacity that primarily strengthens scientific argumentation rather than directly promoting innovation readiness. Students with higher flexibility are better able to shift representations, scrutinize alternative explanations, weigh evidence, and revise justifications when confronted with biological complexity and contradiction, thereby enhancing the quality of their argumentation [39]. In addition, the significant influence of cognitive flexibility on Plant Attitudes suggests that flexibility also facilitates openness and domain specific engagement with the object of inquiry, which in turn supports scientific argumentation. Because the direct path to innovation readiness was not significant while indirect effects were meaningful, the contribution of cognitive flexibility is best interpreted as mediated. Flexibility becomes consequential for innovation readiness once it is translated through domain specific attitudes and argumentative practice as evaluative mechanisms [69]. This pattern is consistent with the theoretical position advanced in this study, namely that general adaptive cognition alone is insufficient to explain innovation readiness unless it is channeled through domain-sensitive and epistemic processes. In this sense, the findings directly address the theoretical gap identified in the introduction by showing that innovation readiness is not adequately captured by general cognitive pathways alone.

By contrast, deep learning emerged as a more proximal and consistently influential determinant of both scientific argumentation and innovation readiness, operating through direct and mediated pathways. A deep learning orientation promotes conceptual integration, coherence checking of explanations, and critical reflection on justificatory grounds, which collectively support more stable evidence-based argumentation [42]. Deep learning also strengthens Plant Attitudes, which subsequently increases argumentative engagement and readiness to use knowledge to judge the feasibility of novel ideas [17]. Within this framework, scientific argumentation functions as a conversion node that transforms meaningful understanding into rational innovation related decision making through explicit appraisal of benefit risk tradeoffs and evidentiary sufficiency. Overall, cognitive flexibility supplies adaptive capacity, deep learning provides meaning making and evaluative mechanisms, and both converge through scientific argumentation to shape innovation readiness. The stronger and more consistent role of deep learning also suggests that meaningful learning is not only academically beneficial, but functionally important for preparing students to evaluate innovation in context-sensitive ways [70]. This interpretation is especially relevant to sustainability-oriented higher education, where students are expected to connect disciplinary understanding with ecological responsibility, systems thinking, and socially accountable judgement rather than merely reproduce knowledge.

1. THE URGENCY OF PLANT ATTITUDES AS A DOMAIN SPECIFIC MEDIATOR

Plant Attitudes played a crucial role as a domain specific mediator because it both improved the explanatory and predictive performance of the model and captured a psychological mechanism that cannot be fully represented by general cognitive constructs. With Plant Attitudes included, the model gained an affective and contextual component that anchors thinking capacities and learning strategies to the biological object of inquiry. Consequently, variance in Scientific Argumentation and Innovation Readiness was explained more strongly than in the model without this mediator. The reduction in R squared when Plant Attitudes was excluded indicates a loss of important predictive information and suggests potential missing variable bias when attitudinal dimensions are ignored. Theoretically, Plant Attitudes functions as an anchor of relevance and value that directs knowledge use [10]. Positive attitudes toward plants increase meaningful engagement, strengthen curiosity, and promote more serious evidence appraisal, thereby increasing the likelihood that cognitive flexibility and deep learning are enacted as epistemic practice in the form of scientific argumentation [71]. These findings reinforce the argument that Plant Attitudes should not be treated as a peripheral affective outcome, but as a theoretically meaningful domain anchor that links learning processes to innovation-related judgement in biology.

Plant Attitudes also clarifies why innovation readiness does not necessarily arise directly from cognitive flexibility or deep learning. Innovation readiness requires motivation to apply knowledge in value laden decisions, including benefit risk appraisal, perceived utility, and commitment to act [72]. Domain specific attitudes provide motivational energy and an evaluative orientation that makes students willing to bear the cognitive costs of argumentation and to take positions regarding innovation [73]. The significant paths from Plant Attitudes to Scientific Argumentation and to Innovation Readiness indicate that attitudes are not merely an affective background factor but a conversion mechanism that prevents knowledge and skills from becoming inert, particularly in plant related issues that are vulnerable to low attention and perceived irrelevance. The observed cross group variation in the Plant Attitudes to Innovation Readiness path further underscores its contextual nature. Including this mediator therefore makes the model more realistic, more sensitive to programme ecology, and more useful for informing biology learning interventions that explicitly target innovation readiness. From a curriculum perspective, this implies that plant-related content should not be presented only as factual subject matter, but as a meaningful domain through which students can develop evaluative commitment, evidence-based judgement, and responsible orientation toward biological innovation.

2. DIFFERENCES IN STRUCTURAL RELATIONSHIP PATTERNS BETWEEN BIOLOGY AND BIOLOGY EDUCATION STUDENTS

Group differences were most evident in the Plant Attitudes to Innovation Readiness path, which differed significantly, whereas most other structural paths were relatively stable across Biology and Biology Education students. The stability of the effects of cognitive flexibility and deep learning on scientific argumentation, as well as the contribution of scientific argumentation to innovation readiness, indicates a shared core mechanism [74]. Adaptive capacity and meaningful learning strengthen evidence-based evaluation, and that evaluation supports readiness for innovation [75]. However, the difference in the Plant Attitudes to Innovation Readiness path indicates that domain specific affective factors do not operate with equal intensity across programme contexts. In one group, attitudes toward plants are more decisive in determining whether knowledge and argumentation culminate in readiness to adopt or evaluate innovations

[12]. In the other group, innovation readiness is more strongly supported by cognitive and argumentative mechanisms that are less dependent on domain specific attitudes.

Substantively, this pattern can be interpreted in light of differences in programme ecology. Biology students are typically more tightly coupled to scientific practice and disciplinary objects of inquiry. Plant Attitudes may serve as an anchor of relevance and value that stimulates engagement, exploration, and willingness to make innovation-oriented decisions on biological issues [11]. In contrast, for Biology Education students, innovation is often construed within a pedagogical horizon, such as learning design, assessment, and classroom implementation. Innovation readiness may therefore be channeled through deep learning and scientific argumentation as tools for professional justification without requiring strong affect toward a particular domain object. The implication is that interventions to strengthen innovation readiness should be differentiated [46]. For groups that are more sensitive to Plant Attitudes, interventions should emphasise authentic experiences that cultivate domain attachment. For groups that are less dependent on Plant Attitudes, interventions should prioritise meaningful learning and evidence-based argumentation training within professional decision-making contexts. In practical terms, such interventions could include scientific-focused inquiry projects, analysis of local biodiversity and conservation cases, argumentation-based assignments on plant sustainability issues, and innovation proposal tasks that require students to justify biological or educational innovations using evidence [74, 75]. For Biology Education students specifically, these activities could be extended into lesson design, classroom simulation, or assessment development tasks so that innovation readiness is linked not only to disciplinary knowledge but also to pedagogical decision making.

3. ALTERNATIVE EXPLANATIONS AND BOUNDARY CONDITIONS

Although the structural results support the proposed model, alternative explanations should be acknowledged. Because the study used a cross-sectional design, the hypothesized directions are theory-based but cannot be interpreted as definitive causal proof. Students who already feel more ready to engage with innovation may also report stronger scientific argumentation or more positive Plant Attitudes, and reciprocal relationships among deep learning, Plant Attitudes, and scientific argumentation cannot be ruled out. Thus, the reported paths should be interpreted as theoretically supported associations rather than final causal sequences. Future longitudinal or experimental studies are needed to test these pathways more directly.

The findings should also be interpreted within their contextual boundary conditions. This study was conducted in Indonesia, specifically among Biology and Biology Education students at Universitas Negeri Makassar, in a context where biodiversity, plant-related knowledge, and sustainability challenges are highly salient. In such settings, plants may carry stronger scientific, social, and ecological relevance than in other educational contexts. Accordingly, the model may be especially informative for higher education settings in biodiversity-rich regions, while generalization to other disciplinary or national contexts should be made with caution.

4. PRACTICAL IMPLICATIONS FOR CURRICULUM AND INSTRUCTION

The practical implications of these findings extend beyond general calls to improve learning. First, the strong role of deep learning suggests that biology instruction should emphasize conceptual integration, explanation, and transfer rather than memorization alone. This can be supported through inquiry-based learning, plant-focused case analysis, and tasks linking plant biology with ecological, agricultural, or conservation issues. Second, because Plant Attitudes functioned as a domain-specific mediator, curriculum design should intentionally strengthen students' sense of relevance toward plants through field observation, local biodiversity analysis, sustainability projects, and discussions that position plants as central to environmental and human futures. Third, the significant role of scientific argumentation indicates the importance of embedding evidence-based reasoning tasks, such as structured debates, claim-evidence-reasoning assignments, and innovation appraisal activities.

Taken together, these implications support a curriculum approach in which plant-focused inquiry, value-based engagement, and scientific argumentation are integrated to strengthen innovation readiness. For

Biology students, this may be especially relevant in biodiversity, conservation, biotechnology, or sustainable agriculture contexts. For Biology Education students, the same logic can be translated into pedagogical innovation tasks, such as designing plant-based inquiry lessons or assessment activities that require science-based justification.

V. CONCLUSION

The present study examined biology students' innovation readiness by comparing two alternative PLS-SEM structural models, one including Plant Attitudes as a domain-specific mediator and one excluding it. Overall, the findings indicate that innovation readiness is best understood as a dispositional-cognitive outcome shaped by adaptive cognition, meaningful learning, and epistemic practice. The measurement model showed adequate reliability and validity across the full sample and both programme groups, supporting interpretation of the structural results. Compared with Model II, Model I demonstrated stronger explanatory and predictive performance, indicating that Plant Attitudes contribute meaningful incremental value beyond general cognitive and learning variables in explaining scientific argumentation and innovation readiness.

At the structural level, Cognitive Flexibility functioned mainly as an upstream capacity that supported Scientific Argumentation and Plant Attitudes, with its contribution to Innovation Readiness occurring primarily through indirect pathways. Deep Learning emerged as a more proximal and consistently influential predictor of both Scientific Argumentation and Innovation Readiness, operating through both direct and mediated effects. Plant Attitudes played a strategic role by strengthening scientific argumentation and directly supporting innovation readiness, suggesting that readiness for innovation in biology depends not only on cognitive and argumentative processes, but also on a domain-relevant evaluative orientation toward plants. Multi-group analysis further showed that most structural relationships were stable across Biology and Biology Education students, although the Plant Attitudes-Innovation Readiness path differed significantly, indicating programme-specific nuance. These findings support instructional approaches that integrate deep learning, plant-focused relevance, and evidence-based argumentation to strengthen innovation readiness in biology-related higher education contexts.

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Author Contributions

Conceptualization, I., A.B.J., and A.M.; methodology, A.M.; validation, A.C.P. and A.B.J.; formal analysis, I., A.M. and A.B.J.; investigation, I., A.B.J. and A.C.P.; data curation, I. and A.B.J.; writing-original draft preparation, I., A.B.J., and A.M.; writing-review and editing, A.B.J., M.P., and A.; visualization, A.M. and A.C.P.; resources, M.P. and A.; supervision, A.M., M.P., and A. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors can provide the data supporting the research findings and conclusions upon request.

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