Students' perceptions of curriculum alignment, assessment and personalised learning in AI-supported diploma radiography education

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ABSTRACT

While artificial intelligence (AI) has the potential to facilitate personalised learning in radiography education, positive perceptions do not necessarily mean that a curriculum is complete, assessments are valid or clinical competence is achieved. The study evaluated students' perception of the coverage of the curriculum, conceptual understanding, accuracy of assessment, alignment with learning needs, targeted support and perceived improvement in knowledge and skills in AI-supported Diploma in Radiography and Imaging education using the framework of Constructive Alignment Theory and the competency-based medical education framework. This was a descriptive cross-sectional survey of 150 students sampled by stratified random sampling from five Kenya Medical Training College campuses with 149 records having valid item responses. Data were gathered through a computer-based, structured questionnaire of 18 five-point Likert items in three six-item domains, one of which is the six-item AI-tailored modules and assessment domain. Frequencies, percentages, means and sample standard deviations (disagree = 1, neutral = 2, agree = 3) and Spearman's correlations were calculated. Agreement was highest for perceived improvement in knowledge and skills (73.2%, M = 2.63, SD = 0.661), and lowest for curriculum coverage (51.7%, M = 2.28, SD = 0.823); agreement for assessment accuracy, alignment with learning needs and targeted support was 65.8%, 67.1% and 68.5%, respectively. Correlations varied from .133 to .552. The conclusion is that targeted support was more consistently valued by students than comprehensive curriculum coverage, but the results are perception based and do not demonstrate effectiveness or competence. Programmes are recommended to map modules and assessments to programme outcomes, to connect personalised support to educator assessed outcomes, to have supervised practice and reassessment, and to have prospective evaluations with objective measures.

Keywords: Artificial Intelligence, Curriculum Alignment, Formative Assessment, Personalised Learning, Radiography Education

I. INTRODUCTION

Artificial intelligence (AI) generates two related education challenges in medical imaging: equipping students with the understanding of AI in the clinical context, and leveraging AI to facilitate education, assessment and personalisation. These priorities overlap and can't be substituted. Not every module that provides information on AI concepts is adaptive and not every platform that recommends content is comprehensive in covering the curriculum. It is therefore important that integration is effective in terms of the learning, the identification of needs and the assessment of the subsequent performance.

International evidence suggests that further development is important and there are key limitations. A postgraduate AI module for radiographers was evaluated by Van de Venter et al. (2023) and the following were identified as clinically relevant content, flexible delivery, differing learner backgrounds, and alignment between teaching and assessment. Loi et al. (2025) mapped out the education of AI in medical imaging, covering the basic knowledge, techniques, information utilization, and practical application. Hui et al. (2025) explored how AI could be used in radiology education, such as creating personalised learning plans and evaluating learning outcomes. These studies combined, provide ideas and guidance in curriculum design, but do not prove the effectiveness of any one assessment-driven intervention for Kenyan diploma radiography students.

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The contextual concerns are brought by African professional perspectives. Antwi et al. (2021) identified some expected benefits of AI and issues of professional skills, costs, maintenance and data protection. In Kenya, Mwaniki et al. (2023) found that there were differences in the general exposure to AI information, familiarity with the technical concepts, and routine clinical use between radiologists and radiology residents. As this preprint is about a different professional group, it does not directly address the learning needs of radiography students but offers contextual justification for local investigation of learning.

In the current study, curriculum alignment is defined as the perceived connections between the content of the modules and the overall diploma programme. Assessment accuracy is not a property of the algorithm that is measured, but rather a judgment made by students as to whether assessments are accurate in pointing out their weaknesses. Personalised support is about how relevant the content assigned to a difficulty is perceived. These differences define the contribution and limit the scope of each questionnaire item and avoid general statements about the 'effectiveness of AI' obscuring the different educational questions.

These questions are presented in a sequence in the proposed educational model but are not shown to be sequential in the data. The curriculum outcomes outline the abilities that are to be developed, assessment identifies potential areas of gaps, the instruction addresses the gaps, and reassessment looks at the subsequent performance. A perception survey will be able to determine areas of learner endorsement or challenge of that pathway. It cannot verify that the sequence assessment-to-instruction was uniform and had the desired effect.

1.1 Statement of the Problem

The challenge of education goes beyond making digital content available. The intended curriculum outcomes, learning activities, assessment tasks and individual remediation should be a logical sequence (van de Venter et al., 2023; Loi et al., 2025). Selected modules might be useful for students, but might not provide comprehensive coverage, and automated feedback might be appreciated by students, but not necessarily be effective in identifying competence gaps (Hui et al., 2025). Perceptions of learners are hence important indicators of implementation and cannot be interpreted as a measure of assessment validity or demonstrated competence. The practical gap is that there is not enough differentiated evidence of what learners find useful and what needs to be looked at, regarding AI-supported instruction. One satisfaction rating can mask issues of content not covered, relevance of assessment, or lack of focused teaching. The present assessment thus considers these aspects individually and relates them to the feedback from the learners and the development priorities. It is intended to provide information on refinement, not to imply that acceptance of the information means it is not effective, nor that self-reported improvement means that the individual is clinically competent.

1.2 Research Objective

To assess students' perceptions of curriculum alignment, assessment and personalised learning in AI-supported Diploma Radiography Education.

II. LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 Constructive Alignment Theory

Constructive alignment is the link between the intended learning outcomes, teaching and learning activities and assessment tasks (Biggs, 2007). In the field of radiography education, modules should focus on the programme outcomes which can be identified, offer activities that build the outcomes, and assess the same knowledge or application. The assessment should not only be based on terminology, as this would not demonstrate the ability to critically appraise clinical outputs supported by AI. The alignment should also be cross-module and cross-year – the individual learning units should help to cover the programme in a coherent way (Biggs & Tang, 2007).

In the proposed refinement process, if evidence of a learning gap occurs, then there should be an explicit instructional response and a clearly defined opportunity for demonstration of progress. The type of response will vary with the result – explanation and worked examples might be needed if the problem is conceptual, but if the problem is practical, supervised activity might be needed. This use of competency-based education is not a statement that all competency domains were measured with the questionnaire, or that the progression decision was automated (Frank et al., 2010).

2.2 Empirical Review

Van de Venter et al. (2023) assessed a post-graduate AI module with qualitative participatory action research. Learners appreciated flexible access, clinically relevant assignments and scaffolded content, and there were challenges with time constraints and misaligned instructional preparation and assessment expectations. The study allows for differentiation based on previous knowledge and professional interests, however, no differentiation between an adaptive

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and a non-adaptive learning pathway has been made and no validation of the automated identification of learning needs was performed. It also has a postgraduate professional context which is not conducive to direct transfer to diploma education. It thus provides design principles and not evidence of the effectiveness of a specific algorithm for enhancing competence.

Loi et al. (2025) offer a more general overview of the content and methods for curriculum delivery. They found objectives across the spectrum of foundational knowledge of AI, technical skills, use of information and application. Majority of the residents are radiology, thus direct transfer to radiography diploma learners would not be possible due to the differences in their learning and clinical skills. Reception to the programme is also positive, and there is no transfer or retained competence to clinical practice.

It is important to note that the radiology and radiography populations are different and therefore the interpretation of the curriculum review is different. Shared imaging environments do not mean that the learning outcomes, practical responsibilities or starting knowledge are the same. Therefore, the topics of candidates for AI should be chosen with respect to the already existing diploma curriculum and not transferred 1:1 from the resident education. The importance of the review is to guide towards a structured selection process, and the local curriculum team will need to make decisions about the scope, sequence and level that is appropriate for their learners (Loi et al., 2025).

Hui et al. (2025) offer a more direct link to personalisation with AI in education through their review of educational applications. Personalised content and automated evaluation provide potential ways to connect assessment and instruction, but a variety of applications should not be considered a single validated intervention. They focus on AI augmenting existing pedagogical methods and on more long-term assessment, which helps maintain teacher control and assessment of performance outside of the tasks performed with AI.

Regarding the current goal, Hui et al. (2025) make the most valuable contribution by allowing the linking of assessment data to future teaching. But automated evaluation, generation of personalised resources and support during a task are different functions. One function study does not provide evidence of the educational value of all three. It is therefore important to report the AI functions and the role of the educator to explain what students assessed and what a subsequent effectiveness study should test.

Antwi et al. (2021) and Mwaniki et al. (2023) do not provide information on the effectiveness of the intervention but rather the context. The former categorizes African issues related to the workforce for educational content and feasibility while the latter offer preliminary Kenyan evidence related to professional knowledge and use. Both are a substitute for an institution-specific assessment of student needs. The current survey thus offers a learner voice and the separation of educational acceptance, curriculum alignment and demonstrated learning.

It is important to be guided by regional evidence when developing questions and not by local findings. It is important to consider professional concerns, training opportunities and data security as explained by Antwi et al. (2021) and exposure and reported familiarity as explained by Mwaniki et al. (2023). Neither specifies the need for specific modules for the KMTC students. Starting knowledge and intended outcomes should be determined at the local level and differentiated pathways should be set prior to evaluation and then evaluated to determine if the differentiated pathway was appropriate.

The conclusions related to development implications are more consistent across the evidence compared to effectiveness conclusions. Useful considerations are clinically relevant content, flexible pathways, prior learning and involvement of the educator. Independent performance is another evidential question which needs to be sustained. The current manuscript thus employs the literature to interpret issues about curriculum and assessment, and views results of the local survey as feedback to the implementation of the curriculum, not as confirmation of the causal model.

III. METHODOLOGY

3.1 Research Design

This study was a descriptive cross-sectional survey on student's perception of AI supported learning in Diploma in Radiography and Imaging programme of Kenya Medical Training College (KMTC). Four reasons justified the use of a descriptive cross-sectional survey. The study aimed to describe students' perceptions of curriculum alignment, assessment and personalised learning at one point in time, and a cross-sectional design measures exposures and outcomes at the same time without following the participants over time, which is suitable for describing the distribution of perceptions (Setia, 2016). Second, the research problem was not whether AI leads to competence gains, but what learners find useful in AI-supported instruction, as no intervention and comparison groups, baseline or follow-up measures existed, an experimental, quasi-experimental or longitudinal design could not have been used. Third, a survey was conducted to collect standardised data from many students across five campuses and three academic years using a structured Likert questionnaire which is relatively fast and inexpensive (Setia, 2016) and supports the descriptive statistics (frequencies, percentages, means and standard deviations) and Spearman's correlations used to meet the objective. Fourth, the results offer baseline evidence to inform curriculum improvement and the development of

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subsequent prospective evaluations, and the limitations of the design to allow causal inferences (Setia, 2016) are recognized.

The campuses involved were: Eldoret, Kisumu, Mombasa, Nairobi and Nakuru. The student survey was explained as being part of an overall evaluation. This manuscript does not include a complete mixed-methods analysis but rather presents its quantitative student component. No baseline or follow up measures were reported or a conventional-teaching comparison group was defined.

Student questionnaire record was used as the unit of analysis. The main results were six self-reported judgements of the modules but not measured examination performance or clinical outcomes. Sample composition was described by the demographic variables and the co-variation in perceptions was described by the item correlations. This specification is designed to ensure that the design is in line with the evaluation part of the development objective and not as a comparison experiment or as a finished validation of the adaptive system.

3.2 Study Area

The study was carried out in the Diploma in Radiography and Imaging programme in Kenya Medical Training College (KMTC) in five campuses namely; Eldoret, Kisumu, Mombasa, Nairobi and Nakuru. The study population consisted of all students in all three academic years who were actively enrolled and participating in the AI enhanced modules at these campuses.

3.3 Participants and Sampling

Thirty (30) students from each of the five participating campuses were included in the sample for a total of 150 Diploma in Radiography and Imaging students. The number of students allocated for each academic year was 48 in Year 1, 53 in Year 2 and 49 in Year 3. The study documentation outlines stratified random sampling, based on the criteria of being actively enrolled and participating in the AI-enhanced modules, across campuses and academic years. The participating sites were fairly represented with equal campus allocation. Does not represent all KMTC campuses and all radiography learners in Kenya.

3.4 Instrument

A structured questionnaire consisted of 18 five-point Likert items across three six-item domains: adaptive personalised learning; AI tailored modules and assessment; and perceived knowledge, technical skills and clinical readiness. This manuscript contains the AI customized modules and assessment domain. It has six items related to curriculum coverage, conceptual understanding, perceived identification of weaknesses, alignment with actual learning needs, support for specific challenges and perceived improvement in knowledge and skills.

The responses varied from strongly disagree to strongly agree. Strongly disagree and disagree were grouped together and so were agree and strongly agreed to create three categories: disagree, neutral and agree. These collapsed categories were coded as 1, 2 and 3, and the means and standard deviations reported here are for these categories.

Each item was interpreted individually since each item is related to a different aspect of the educational experience. Coverage and conceptual understanding are issues related to the content of the curriculum; identification of weaknesses and alignment with needs are issues related to the relevance of the assessment; targeted support and perceived improvement are issues related to the experience of the learner with the subsequent instruction. These groupings are for the purpose of organisation of interpretation only. They are not new subscales that have been validated and no new domain scores or thresholds were developed for this analysis.

3.5 Reliability and Validity

Content-validity procedures were reported, but did not include numerical content-validity indices, domain-specific internal consistency coefficients, results from pilot-testing, or factor-analytic evidence. Thus, the six-item domain has not been psychometrically validated in this report. Items were not considered as a validated competence scale but were interpreted individually. The perceived accuracy of assessment is not an independent validation of the AI assessment process but is still a learner judgement.

3.6 Data Collection

The questionnaire was computer based. There were 150 records in the dataset, one of which did not have any Likert responses, but did have demographic information. For demographic descriptions 150 records were used, and 149 valid responses were used for each item-level analysis. There was no information on the number of students eligible for recruitment, so a recruitment response rate was not calculated. No information was available on the collection window or length of exposure of the module.

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3.7 Data Analysis

Participant characteristics and distributions of responses were summarised by frequencies and percentages. Means and standard deviations of the sample were reported for the collapsed categories (1 = disagree, 2 = neutral, 3 = agree). These values are for the three-category distribution and should not be viewed as scores on the original 5-point scale. The reported means and standard deviations were compared with the frequencies of the categories and were in line with this coding.

Spearman rank correlations provided an overview of relationships between the six perception items. There were 149 observations reported per pair of the reported matrix. Coefficients are descriptively interpreted due to lack of documentation of the original response coding and inferential output for verification. There are no significance markers and correlation magnitude are not considered as evidence of a causal mechanism or a change in performance. The analysis makes a difference between the relationships between learner judgements and the relationships between separately assessed competencies.

The main findings are those for the six separate items and the correlations reported for these items. The rules for aggregation and classification of a composite classification were not specified, so it is not interpreted. No comparison of demographic subgroups is provided: a categorical cross-tabulation was provided that did not have gender totals that matched the totals in the participant summary. The data from different denominators were not combined. A comparison with conventional teaching was not done as there were no defined intervention and comparison groups.

3.8 Ethical Considerations

Institutional and ethical approvals, informed consent, voluntary participation, anonymisation and secure data storage is documented in the study. No information was provided about the review committee and approval identifiers in the report available. This article does not show any information about each participant. Results are not patient level clinical outcomes but are related to the students' learning experiences.

IV. FINDINGS & DISCUSSION

4.1 Response Rates

Of the 150 students, 115 (76.7%) were female and 35 (23.3%) were male. Academic years were also depicted but allocations were not the same. 30 students were from each campus (20.0% each; Table 1). These distributions represent the sampled students and are not representative of the nation.

Table 1

Participant Characteristics

Characteristic	Category	n	%
Gender	Female	115	76.7
Gender	Male	35	23.3
Academic year	Year 1	48	32.0
Academic year	Year 2	53	35.3
Academic year	Year 3	49	32.7
Campus	Eldoret	30	20.0
Campus	Kisumu	30	20.0
Campus	Mombasa	30	20.0
Campus	Nairobi	30	20.0
Campus	Nakuru	30	20.0

N = 150. There were 149 students who had item level responses.

4.1.1 Curriculum, Assessment and Personalised Support

Agreement with the coverage of all key areas of the curriculum was 51.7% (77 of 149 students), 23.5% disagreed and 24.8% were neutral. The item with the lowest mean and highest dispersion of the six items was this item (M = 2.28, SD = 0.823). In contrast, 67.8% agreed that the content gave a comprehensive knowledge of the concepts of radiography and imaging (M = 2.55, SD = 0.711; Table 2). Sixty-five percent (65.8%) of the students agreed that assessments targeted their weaknesses (M = 2.53, SD = 0.712) and 67.1% (100) agreed that assessments matched their actual learning needs (M = 2.57, SD = 0.670). The mean score for agreement on support for specific learning challenges was 2.56 (SD = 0.711) and 68.5% of the responses agreed. The highest means (M = 2.63, SD = 0.661) and highest agreement (73.2% (109 students)) was for the perceived improvement in knowledge and skills. These ratings are not independent measures of performance gains, but rather are students' perceptions.

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The distribution also shows the number of people who don't agree with each statement. 48.3% were neutral or disagreed on coverage of the curriculum. The percentages for conceptual understanding, identification of weaknesses, alignment with needs, targeted support and perceived improvement were 32.2%, 34.2%, 32.9%, 31.5% and 26.8%, respectively. The categories do not indicate homogenous dissatisfaction: neutrality and disagreement are reported positions. That distinction is maintained in their separation in Table 2 and it helps to identify questions for follow-up.

Table 2

Students' assessments of AI personalized modules and assessments

Item	Disagree, n (%)	Neutral, n (%)	Agree, n (%)	*M*	*SD*
Coverage of key curriculum areas	35 (23.5)	37 (24.8)	77 (51.7)	2.28	0.823
Thorough conceptual understanding	19 (12.8)	29 (19.5)	101 (67.8)	2.55	0.711
Identification of learning weaknesses	19 (12.8)	32 (21.5)	98 (65.8)	2.53	0.712
Alignment with actual learning needs	15 (10.1)	34 (22.8)	100 (67.1)	2.57	0.670
Support for specific learning challenges	19 (12.8)	28 (18.8)	102 (68.5)	2.56	0.711
Perceived improvement in knowledge and skills	15 (10.1)	25 (16.8)	109 (73.2)	2.63	0.661

n = 149 per item. M = Mean and SD = Sample standard deviation.

4.1.2 Associations

Correlations reported were positive and varied between .133 and .552 (Table 3). The strongest correlation was between curriculum coverage and conceptual understanding ($\rho = 0.552$); conceptual understanding and perceived improvement ($\rho = 0.548$) were the next strongest. There was a significant association between targeted support and perceived improvement ($\rho = 0.515$) and perceived identification of weaknesses ($\rho = 0.494$). There was the lowest correlation between curriculum coverage and targeted support ($\rho = 0.133$). These associations don't necessarily provide a causal chain from assessment to remediation to competence.

Table 3

Spearman Correlations among Perception Items

Variable	1	2	3	4	5	6
1. Curriculum coverage	1.000					
2. Conceptual understanding	0.552	1.000				
3. Identification of weaknesses	0.384	0.420	1.000			
4. Alignment with learning needs	0.215	0.304	0.458	1.000		
5. Targeted support	0.133	0.328	0.494	0.388	1.000	
6. Perceived improvement	0.405	0.548	0.448	0.242	0.515	1.000

4.2 Discussion

The results show, in general, positive attitudes towards AI-assisted assessment and personalised learning support and less support for extensive coverage of the curriculum. The mean score for perceived improvement was the highest and lowest for curriculum coverage. The relevance of this contrast, from an education perspective, is that it distinguishes between usefulness of the learning activities selected and the extent to which they are integrated in the diploma curriculum. It does not find a statistically significant difference between the means of the items, nor does it indicate the specific content areas that may be lacking.

Constructive alignment offers a foundation to understand the coverage finding (Biggs, 2007). A module can be used to solve an immediate problem of students but not be well linked with other programme outcomes. It is therefore imperative that curriculum mapping be done to determine which outcomes are taught, practised, assessed and reassessed from year to year. The survey indicates that coverage is worthy of further exploration, but an examination of the content of the modules and an educator review is needed to ascertain the nature and extent of any gaps. The results align with the design concerns identified by van de Venter et al. (2023) such as the importance of learner backgrounds and the alignment of the preparation and assessment. But their postgraduate population is not the same as the one analysed here. Similarly, the curriculum areas identified by Loi et al. (2025) offer potential areas for adaptation instead of a local curriculum that is already in place. Selection and sequencing should consider the current level of achievement in radiography and the level of training of the learners.

When it comes to assessment, agreement on the accuracy and relevance of the assessment is a sign of acceptance of the assessment functions, but not proof that the AI system is correct in diagnosing the competency gaps. Rapid feedback or easy explanations can be important to students even when assessment content is limited to a portion of the curriculum. The AI-generated profiles must be compared with the educators' judgements and suitable performance

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measures to verify. The assessment blueprint should clearly state the relationship between the curriculum outcomes, item content, task demands and remediation decisions.

One of the validation questions is: Is the difficulty for the same learner the same as the system and the educator? Where there is disagreement, the task, the scoring rule and/or the interpretation should be reviewed rather than an automatic preference given to either judgement. The second question is the activity suggested solving the problem identified? These distinguish between diagnostic and instructional relevance. Both need to be assessed to allow for high-stakes decisions to be made based on favourable survey responses for progression or readiness. Competency-based medical education focuses on the demonstrated performance and reassessment (Frank et al., 2010). Some conceptual gaps can be filled with more digital content, but practical and/or clinical skills need to be addressed in an appropriate manner. Therefore, supervised practice, image critique, simulation or clinical assessment may be required in conjunction with digital learning. These are suggested modifications, not activities known to have been accomplished by this survey.

The 73.2% agreement on improvement is good feedback from the learners, but there is no independent pre–post-performance comparison in the questionnaire. The study is thus unable to conclude the extent to which knowledge and/or skills changed, if any, or if it transferred to clinical practice. A prospective evaluation should differentiate between assisted performance of a task, performance after assistance is withdrawn and longer-term retention. Hui et al. (2025) advocate for further research on the use of AI in education and stress that it should be used alongside human teachers and that its impact needs to be assessed over the long term. This is especially relevant in cases where an intervention is both about AI and uses AI to provide instruction. The quality of content, adaptability and educational outcomes should be assessed separately, to avoid positive perceptions of one aspect being used as proxy for the other.

The contextual feasibility and data protection highlighted by Antwi et al. (2021) in the context of Africa's workforce is further underscored by the factors identified. Mwaniki et al. (2023) also note in their Kenyan preprint that the exposure to AI and their use should not be confused with understanding or regular use. The conditions on the participating campuses are not established by either source but must be assessed locally. Faculty support, access to learners and procedures for handling data should be written and not assumed from the platform being available. Assessment content should be reviewed by educators and educators should be able to overrule inappropriate recommendations, as well as interpreting learner profiles. Documented revision process can help to explain responsibility for content of modules and decisions made that impact the learner. The current findings suggest there is a need to explore these processes more, but do not suggest that a specific governance structure has been adopted or shown to work well.

4.3 Implications for Practice

The results suggest that there are three priorities for programme review. Firstly, there is a need for a map that shows the relationship between each module and assessment and the diploma outcomes and academic years, given the lower endorsement of curriculum completeness. This would enable us to differentiate between support of immediate difficulties and programme coverage. Second, if there is a perceived lack of accuracy in the assessment, then the blueprint and rules for assigning targeted content should be examined. Even if learners' feedback is favourable, educator supervision is still needed as it does not validate the learning needs diagnosis.

Third, personalised digital learning should be connected to supervised practical or clinical performance and re-assessment if the learning goal is related to a practical or clinical outcome. These implications are not evidence that a specific implementation model has already enhanced competence but rather are used to further refine. A development response should be practical and follow a documented sequence and not simply more digital content. The pathway below is a representation of learner feedback and conceptual framework, and the proposed design actions. Is not delivered as an existing and proven intervention. It outlines links between programme outcomes, needs identified and instructional decisions and subsequent performance and gives an explicit development agenda for future evaluation.

4.3.1 Proposed Module-Refinement Pathway

Write down the goal, school year, content area, learning activity and assessment task for each existing module. Record outcomes that are not achieved, repeated and no progression or evaluated at a level other than the level taught. The output should be a map that shows the difference between a competency that is not taught in the programme and a competency that is taught in another part of the programme. This approach reflects the principle of constructive alignment, which emphasises the relationship between intended learning outcomes, teaching and learning activities, and assessment tasks (Biggs, 1996). This distinction is important as it does not imply that students are not being taught the same content in the wider curriculum.

The inventory should include a description of the purpose of each module. Depending on the unit, there might be some basic AI concepts taught, or some units might utilize AI to make adaptations to the teaching of radiography. These functions would not be recorded separately as this would lead to an AI-content unit being evaluated as evidence for adaptive delivery. The inventory could be used to identify outcomes that need to be addressed with a common core

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and outcomes that allow for additional differentiated support (du Plooy et al., 2024). This is an organisational tool not an account of materials independently verified in this study.

Then, discuss assessment decisions. The purpose, outcome link, scoring rules and interpretation must be documented for each task (Biggs, 1996). The refinement team should provide criteria for giving extra explanation, practice or educator review. The process should identify the person(s) who review the discrepancy and how the decision is documented if there is a discrepancy between the AI recommendation and the observed student performance. These proposed controls shift the focus from algorithmic correctness to questions that can be explored and analyzed for perceived relevance. Learners should be shown the information, and this should be reviewed in assessment. Feedback should relate to the outcome, describe the difficulty observed and what action is recommended. If it is not clear, the learner should be referred to educator assessment and not be given an unqualified judgement. It would be useful to have a record of any changes or overrides to the recommendations to help with scrutiny of the process. This sort of documentation would be visible and could be used to examine if the system is always in support of the desired educational decisions. Human oversight and the pedagogical validation of AI-supported educational tools are consistent with UNESCO's guidance on the responsible use of generative AI in education (Miao & Holmes, 2023).

Then relate recommendations with learning activities. A pathway should include a justification for the choice of resource for the identified difficulty and what the learner should do with the resource. If the content assignment, task difficulty and pacing are separate adaptive functions, these should be reported separately. This will make it easier to differentiate between the contribution of relevant content and convenience or speed of feedback in future evaluations. Personalisation should not just be a tag on a digital resource and should be a recorded decision for instruction (du Plooy et al., 2024).

A pathway should include information on the timing of when learners can ask for help, how understanding will be tested and what will occur if the initial activity is not successful. If the same material is repeated, this doesn't necessarily mean that it is more personalised. Review should consider the need for the learner to have another explanation, a different activity or supervised practice. The proposed decision points would help to clarify the pathway and link to a record of the learning that has been delivered.

Lastly, explain reassessment/revision. A learner must be given the chance to demonstrate the outcome(s) of competency without assistance through a task appropriate to competency. The original need, assigned activity, educator input and subsequent evidence should be kept on the module record. A review of that record can help to identify recommendations that seem to be helpful, recommendations that need to be adjusted and outcomes that have not been sufficiently assessed. The current survey will help to investigate this pathway but will not provide performance evidence to verify the success of this pathway. Engagement with the pathway is described by access, completion, time spent and feedback. Independent assessment task correct performance: answers to a different question. Both types of information are not a substitute for one another. Reporting both would help to identify if an apparently ineffective pathway was poorly accessed, poorly matched to need or inadequate to develop the capability. The current survey provides perceptions but doesn't solve these alternatives.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

The overall attitude of students towards AI-based assessment and personalised content was positive, whereas the attitude towards complete curriculum coverage was not as positive. The results indicate areas of focus for curriculum integration and targeted supports and are not intended to show causal effectiveness or objective competence. The programme outcomes, reviewed assessment, individualised instruction, supervised practice and reassessment should be linked in a defensible refinement process. Perceived benefits should be followed up with prospective evaluation to determine if they are reflected in independently demonstrated and retained performance. This study does not suggest that curriculum should be reviewed in a general manner, but rather focused on specific areas which should be reviewed in relation to student learning.

5.2 Recommendations

Match modules to programme outcomes and support students with personalised support based on educator assessed outcomes. Link remediation to supervised practice and reassessment, record development decisions and enhance faculty oversight and data protection. Prior to making claims of effectiveness or scalability, evaluate outcomes in a prospective manner with objective measures, baseline and follow-up assessments, and an appropriate comparison group.

Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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