Constructing a Scale for Students' Attitudes Toward AI-Enhanced Project-Based Learning

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Abstract:

The study aimed to develop a Guttman scale and test its validity to measure students' attitudes toward AI-enhanced project-based learning in higher education. The scale went through a systematic process involving 300 university students (176 female, 124 male) from the Arts and Humanities, Applied Sciences and Engineering disciplines. The process began with an expert review (n=10) and content validation using (CVR) index. It initially resulted in a 7-item scale. The first phase of analysis showed strong psychometric properties, exceeding recommended thresholds, with Reproducibility (0.96) and Scalability (0.95) coefficients. However, exploratory factor analysis revealed structural complexities which required refinement. The final 5-item scale showed enhanced psychometric properties, with improved Reproducibility (0.98) and Scalability (0.97) coefficients. The scale demonstrated a clear unifactorial structure which accounted for 60.785% of the variance. Although the developed scale provides a psychometrically robust tool for measuring students' attitudes toward AI-enhanced project-based learning, further validation across different populations is recommended for broader generalizability.

Keywords: *Artificial Intelligence, Project-Based Learning, Guttman Scale, Students' Attitudes.*

Introduction

Learning is affected by various interconnected factors such as cognitive abilities, learning environments, teaching methods and psychological concepts which contribute to shaping students' educational experiences. Attitude is also considered one of these factors. It is defined as relatively persistent tendencies that affect thoughts, feelings and behaviors toward particular objects or situations (Getie, 2020). Attitudes are instrumental in creating human behavior to, and experiences in, education. In addition, they tend to significantly impact students' learning readiness, interaction and academic achievement, especially in innovative teaching environments which make use of novel teaching approaches and technologies.

Over the past few years, the educational landscape has substantially changed due to the emergence of project-based learning (PBL). By employing student-centered teaching methods, teachers can engage students in learning through collaborative projects that simulate real-world challenges and allow them to work with authentic materials (Khalaf & Alshammari, 2023).

Furthermore, the development of artificial intelligence (AI) and its integration into pedagogy has significantly improved the effectiveness of PBL through computer programs designed to stimulate human intelligence for learning, reasoning and problem-solving (Simangunsong et al., 2024). These programs help develop innovative research, analysis and content-creating capabilities that can change the traditional learning paradigm.

The effectiveness of both BPL and AI tools in improving students' motivation and development of critical thinking skills has been consistently reported in research (Azamatova et al., 2023; Sumarni & Kadarwati, 2020). Despite integrating BPL and AI tools, it remains essential to understand students' attitudes toward this integration through using validated measurement tools to ensure the success of this integration for education (ALHarthy & Alsoudi, 2023). This level of understanding is important in higher education settings where measuring students' attitudes and behavior toward AI technologies using validated

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tools can provide insights which would enhance teaching methods and educational practices (Alzahrani, 2023).

Researchers have developed various methods to effectively measure students' attitudes, such as Likert, Thurstone and semantic differential scales which have been used in different contexts. The Guttman scale which provides a hierarchical, cumulative way to measure attitudes is one of these scales (Guttman & Suchman, 1947). This scale is known for its unidimensionality, deterministic nature and ordinal arrangement of data (Dimitrov, 2023), and it requires specific statistical criteria such as a reproducibility coefficient of at least 0.90 and scalability between 0.60 and 0.65 (Mokkan & Lewis, 1982). Therefore, learning about various measurement methodologies can help create a solid framework for developing robust instruments that measure students' predispositions and readiness to engage with AI-enhanced project-based learning (Alsoudi & ALHarthy, 2024). This will eventually inform pedagogical decision-making and enhance educational outcomes in this ever evolving digital era.

Literature review

Contemporary research has investigated the positive impact of project-based learning (PBL) and artificial intelligence on students' academic achievement, motivation and skill development (Zhang & Ma, 2023). Moreover, studies conducted in various geographical contexts have arrived at promising findings. Simangunsong et al. (2024), for example, reported significant enhancements in students' creativity (increasing from 45.45% to 86.26%) and learning achievement (rising from 59.09% to 90.90%) when PBL combined with AI tools were applied. Azamatova et al. (2023) arrived at similar findings among university students who showed significantly higher

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levels of achievement and motivation when they used AI-enhanced PBL compared to traditional methods. Furthermore, some other research has found discrepancies in students' perspectives on, and usage patterns in, AI integration, despite generally positive attitudes toward it. Ho (2024) found out that IT students who were interested in AI tools, such as ChatGPT, still appreciated traditional classroom instruction, while Stewart et al. (2023) observed that medical students showed a lack of confidence in, and understanding of, AI's fundamental principles (33.3%) and limitations (46.2%) although they were greatly interested in AI (82.6%). Fosner's (2024) research further supports these results by revealing that 89% of the sample of university students who were surveyed remained skeptical about certain benefits of AI such as improved language ability (5%) or improved grades (10%). Students' usage patterns vary depending on their academic level and field of study. In fact, students tend to use AI for tasks such as translation, grammar checking and paraphrasing, primarily outside of the classroom (Wang, 2024). Notably, a significant gap exists between student interest and formal AI education. Stewart et al. (2023) stated that 87.5% of medical students who demonstrated strong interest in AI in education did not receive formal AI education. This indicates a need for a structured AI education in academic curricula.

Several studies from the reviewed scholarly works highlighted the practical implementation and effectiveness of combining PBL and AI tools in educational settings (Zhang & Ma, 2023; Simangunsong et al., 2024; Azamatova et al., 2023). Nevertheless, a significant gap still exists in understanding students' attitudes towards integrating AI tools in higher education contexts. Those studies primarily focused on investigating the practical impacts of both PBL and AI on students' achievement and motivation, while mainly examining

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the effective implementation of each separately or together rather than exploring students’ perspectives on the integration of AI tools in higher education. Moreover, there is a growing need for standardized measurement tools that explore students’ attitudes toward AI-enhanced project-based learning. This need is supported by a noticeable fluctuation in the results of the reviewed studies on students’ attitudes and usage patterns within various contexts and the reported lack of formal AI training in educational settings. This necessitates developing a comprehensive, valid tool to measure these attitudes. This gap is of particular significance at the university level due to the availability of an ideal environment for implementing both PBL and AI tools at this educational stage in addition to students’ advanced cognitive abilities, research skills and project managment. To understand students’ attitudes at this stage, an informed, effective integration of AI tools in the project-based learning environment can be considered, with the growing tendencies for AI literacy and project management skills in higher education and future workforce requirements. Therefore, this study aims to construct and validate a scale using the Guttman scaling method to measure students’ attitudes toward AI-enhanced project-based learning at the university level and ensure a cumulative and unidimensional measurement approach that provides a reliable assessment tool for future studies in similar educational contexts.

Methodology

Purpose of the Study

This study aimed to develop a scale for measuring students' attitudes toward AI-enhanced project-based learning using the Guttman scaling method.

Participants

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The participants in the study were 300 final-year students (176 female, 124 male) from A'Sharqiyah University in Oman. They represented the Arts and Humanities (166), Applied Sciences (79) and Engineering (55) disciplines. Data was collected electronically via Google Forms after obtaining university approval and participants' informed consent.

Instrument Development

1. Initial Item Construction

The scale development process began with the construction of an initial pool of 10 items which were derived from a comprehensive literature review on AI integration in project-based learning environments (Alzahrani, 2023; Azamatova et al., 2023; Getie, 2020) and the use of AI tools to generate its items. The items were specifically designed to measure a single dimension which was students' attitudes toward AI-enhanced project-based learning (PBL).

To understand the Guttman scaling method used in this study, let us consider a simple example of measuring attitudes toward watching football matches. In a Guttman scale for football enthusiasm, items would be hierarchically ordered from lowest to highest intensity as follows:

1. "I watch football highlights on TV." (lowest intensity)
2. "I watch full matches at home."
3. "I attend live matches in person."(highest intensity)

In this example, someone who agrees with a higher-intensity item (e.g., traveling to matches) would theoretically agree to all lower-intensity items. This cumulative pattern is fundamental to Guttman scaling.

Following the same Guttman scaling principles, the scale's items were carefully crafted to reflect increasing intensity levels which would progress from essential awareness and acceptance of AI in PBL to more advanced implementation. In

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line with Guttman scaling requirements, each item was structured to elicit a dichotomous (yes/no) response format which allowed for a precise determination of item endorsement patterns.

2. Item Review and Refinement

The initial item pool underwent a rigorous review process by a panel of 10 experts who represented diverse, relevant specializations in the field of the study. The expert panel consisted of four specialists in Measurement and Evaluation, three in Education, and three in Psychology. This would ensure comprehensive evaluation from multiple perspectives. The expert review process focused on three main aspects which were content validity, item clarity and the progression of intensity levels.

3. Content Validity

Content validity was systematically assessed using the Content Validity Ratio (CVR) and Content Validity Index (CVI). Following the guidelines of the ten experts, items with CVR values above 0.60 were retained on the following scale version. The analysis yielded a Scale-CVI/Ave of 0.71 which indicated the instrument's overall solid content validity (see Table 1).

Table 1. The CVR rate of the items

Item	**Essential Ratings***	**CVR**	**Included in Final**
1	9/10	0.80	Yes
2	9/10	0.80	Yes
3	8/10	0.60	Yes
4	8/10	0.60	Yes
5	9/10	0.80	Yes
6	7/10	0.40	No

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7	9/10	0.80	Yes
8	7/10	0.40	No
9	8/10	0.60	Yes
10	7/10	0.40	No

**Number of experts rate the items as essential out of 10 total experts*

As a result of the CVR analysis, the developed scale comprised seven items.

5. Pilot Testing

Following the expert review process, a pilot test was administered to 30 students from the target population to assess the clarity of the scale's items and the required response time. The selected items were arranged randomly to avoid a pattern of response. Students' feedback and response time indicated a clear understanding of the items.

Data Analysis

Before conducting the analysis, data were screened for missing values and outliers to ensure data quality and completeness. The analytical framework employed a Guttman methodology to ensure robust scale validation (Guttman, 1944; Mokkan & Lewis, 1982). The Guttman scale analysis aimed to confirm the scale's cumulative structure by examining multiple indicators. This process included calculating the Reproducibility Coefficient (Rep.), where a minimum acceptable value of 0.90 was required to ensure pattern consistency (Guttman, 1944), using the formula:

$$\text{Rep.} = 1 - \sum e/(n \times N) \qquad (1)$$

where $\sum e$ is the total number of errors, n is the number of items and N is the number of respondents (Guttman, 1944).

The Scalability Coefficient (SC) which targeted a minimum permissible range between 0.60-0.65 to verify the scale's

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hierarchical structure (Mokkan & Lewis, 1982) was calculated using the formula:

SC = (Rep. - MinRep)/(1 - MinRep) (2)

where MinRep is the minimum reproducibility coefficient which is calculated as:

MinRep = p(1-p) (3)

where p represents the proportion of responses in the modal category (Guttman, 1944).

Response patterns were thoroughly examined to validate the cumulative structure, while the unidimensionality assumption and item hierarchy were evaluated to ensure proper scale functioning (Guttman & Suchman, 1947). The analysis focused on several key aspects, including verifying unidimensionality through Exploratory Factor Analysis (EFA) and Principal Component Analysis (Gorsuch, 2014). Items were included in the final scale only if they satisfied all the specified statistical criteria.

Results

Phase One: Initial Scale Analysis

The initial analysis which was conducted after the expert panel review examined a 7-item scale administered to 300 participants using Guttman's scaling methodology. Phase One consisted of two stages which focused on the psychometric properties and cumulative structure of the scale's second version that comprised seven items.

Scale Reliability and Reproducibility

The scale's reproducibility was assessed using the formula:

Rep. = 1 - ∑e/(n × N). The analysis yielded a Reproducibility Coefficient of 0.96 which exceeded Guttman's recommended threshold of 0.90.

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Scalability Analysis

The scale's hierarchical structure was validated using the Scalability Coefficient (SC):

SC = (Rep. - MinRep)/(1 - MinRep)

With an average Minimum Reproducibility (MinRep) of 0.107, the analysis produced a Scalability Coefficient of 0.95 which substantially exceeded the minimum threshold of 0.60.

Exploratory Factor Analysis Results

The suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity (see Table 2). The KMO value of .831 surpassed the recommended threshold of .60 (Kaiser, 1974; Pallant, 2020) and indicated good sampling adequacy. Bartlett's test of sphericity was significant ($\chi^2(21)$ = 1012.404, $p < .001$) and confirmed that the correlation matrix was suitable for factor analysis (Pallant, 2020)

Table 2. KMO and Bartlett's Test Results for Initial Scale (7 items)

Test		Value
Kaiser-Meyer-Olkin (KMO)		.831
Bartlett's Test of Sphericity	Approx. Chi-Square	1012.404
	df	21
	Sig.	.000

Principal Component Analysis (PCA) identified two components with eigenvalues greater than 1.0, accounting for 53.361% and 18.225% of the variance, respectively (see Table 3). The first factor accounted for more than 20% of the variance, which meets Reckase's (1979) criterion for unidimensionality. The two-factor solution accounted for 71.586% of the cumulative variance.

Table 3. Total Variance Explained for Initial Scale (7 items)

Component	Initial Eigenvalues	Extraction Sums of

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					Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.735	53.361	53.361	3.735	53.361	53.361
2	1.276	18.225	71.586	1.276	18.225	71.586

The examination of the communalities revealed strong extraction values that ranged from .600 (item 5) to .876 (item 2). This indicated that the two-component solution captured a substantial portion of the variance in each item (Hattie, 1985). All items exhibited communalities above the acceptable threshold of .40, which satisfies the standard communality criteria (Green et al., 1977; Hansford & Hattie, 1982).

Extraction Method: Principal Component Analysis.

The component matrix revealed a complex loading pattern (see Table 4). The first component showed strong positive loadings for all items, ranging from .539 (item 6) to .834 (item 2), which satisfies Reckase's (1979) criterion for significant loadings (>0.30) on the first factor. However, the second component displayed a mixed pattern:

- Items 1, 2, and 3 loaded negatively (-.441, -.424, and -.450 respectively)
- Items 4, 5, 6, and 7 loaded positively (.233, .356, .598, and .402, respectively). This loading pattern, especially the split in item loadings on the second component and the evidence of cross-loading above .40, suggests potential structural complexity (Gorsuch, 2014) that warrants further investigation in Phase Two of the analysis

Table 4. Component Matrix for Initial Scale (7 items)

Item	Component 1	Component 2
Item 1	.764	-.441

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Item 2	.834	-.424
Item 3	.767	-.450
Item 4	.760	.233
Item 5	.688	.356
Item 6	.539	.598
Item 7	.725	.402

Phase Two: Analysis of the Refined Scale

Based on the EFA results from Phase One, items 4 and 6 were removed from the scale's second version due to their problematic loading patterns, and this resulted in a refined 5-item scale. This revised scale underwent Guttman scale analysis to verify its cumulative properties.

The Scale's Reliability and Reproducibility

The reproducibility coefficient was calculated using the formula:

Rep. = $1 - \sum e/(n \times N)$

The analysis yielded an improved Reproducibility coefficient of 0.98 which exceeded the minimum threshold of 0.90 and the Phase One coefficient (0.96).

Scalability Analysis

The Scalability Coefficient (SC) was computed as follows:

SC = (Rep. - MinRep)/(1 - MinRep)

where the average minimum Reproducibility (MinRep) was 0.085, and the resulting Scalability Coefficient was 0.97. This represents a significant improvement over the Phase One Scalability Coefficient (0.95) and far exceeds the minimum threshold of 0.60.

Exploratory Factor Analysis of Refined Scale

After removing items 4 and 6, the refined 5-item scale underwent exploratory factor analysis. The Kaiser-Meyer-Olkin

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measure confirmed acceptable sampling adequacy (KMO = .772; Kaiser, 1974), falling within the 'middling' range of adequacy (Altunisik et al., 2012) and exceeding the recommended threshold of .60 (Pallant, 2020). Bartlett’s test of sphericity revealed sufficiently strong correlations between items ($\chi^2(10)$ = 728.462, $p < .001$. The results of these tests are presented in Table 5.

Table 5. KMO and Bartlett's Test Results for Refined Scale (5 items)

Test		Value
Kaiser-Meyer-Olkin (KMO)		.772
Bartlett's Test of Sphericity	Approx. Chi-Square	728.462
	df	10
	Sig.	.000

Principal Component Analysis revealed a clear unifactorial structure, where one component had an eigenvalue greater than 1.0 (3.039) and accounted for 60.785% of the total variance. This far exceeds Reckase’s (1979) criterion which states that the first factor should explain at least 20% of the total variance (see Table 6). It provides a more parsimonious solution compared to the two-factor structure in Phase One.

Table 6. Total Variance Explained for Refined Scale (5 items)

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.039	60.785	60.785	3.039	60.785	60.785

Examination of communalities indicated good item retention and ranged from .808 (item 2) to .401 (item 5). Thus, all items maintained communality values above the acceptable threshold of .40 (Green et al., 1977; Hattie, 1985).

Extraction Method: Principal Component Analysis.

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The refined scale exhibited enhanced psychometric properties compared to Phase One. In specific terms, it showed a clearer factor structure (single factor instead of two factors), robust factor loadings (all exceeding .60), satisfactory communalities and a notable variance explanation of 60.785%. The final structure of the scale is presented in Table 7.

Table 7. The final scale

NO	Item
1	I recognize the possibility of using AI tools in course projects.
2	I want to use AI tools in my projects.
3	I feel comfortable using AI tools in basic project tasks.
4	I regularly use AI tools to help generate project ideas.
5	I use AI tools to enhance creativity and innovation in the project.

Discussion

The present study used the Guttman scaling method to develop and validate a scale for measuring students' attitudes toward AI-enhanced project-based learning. The findings revealed a successful development of a psychometrically sound 5-item scale through systematic refinement.

The initial analysis showed solid psychometric properties of the 7-item scale, with Reproducibility (Rep = 0.96) and Scalability (SC = 0.95) coefficients exceeding Guttman's (1944) recommended thresholds. However, the exploratory factor analysis revealed structural complexities which required refinement. While a two-factor solution accounted for 71.59% of the variance, mixed loading patterns emerged and suggested potential measurement issues (Reckase, 1979).

Statistical evidence justified the removal of items 4 and 6, while item 6 showed particularly problematic cross-loadings (.539 and .598 on components 1 and 2, respectively) (Gorsuch, 2014). This refinement led to notable improvements in Phase Two which were reflected in increased Reproducibility (0.98)

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and Scalability (0.97) coefficients and highlighted a stronger and more coherent hierarchical structure.

The refined 5-item scale exhibited superior measurement properties which featured a streamlined unifactorial structure that accounted for 60.79% of the variance. (Reckase, 1979). Although this represents a modest reduction in total variance compared to the initial two-factor solution, the improved conceptual clarity and measurement efficiency justify the trade-off. Besides, the refined scale's robustness is supported by strong factor loadings (.633 to .899) and adequate communalities (above .40) (Green et al., 1977; Hattie, 1985).

These results align with Guttman's (1944) theoretical framework which emphasize cumulative structure and unidimensionality in attitude measurement. The progression from a complex two-factor to a streamlined single-factor solution indicates that the refined scale more effectively captures students' attitudes toward AI-enhanced project-based learning while preserving psychometric solid properties.

Conclusion

This study has constructed and validated a 5-item Guttman scale for measuring students' attitudes toward AI-enhanced project-based learning through a systematic approach. The analysis of the initial 7-item scale uncovered strong but complex psychometric properties and highlighted the need for careful refinement. After the removal of two items with problematic loading patterns, the final scale demonstrated improved psychometric properties, including higher Reproducibility (0.98) and Scalability (0.97) coefficients. This scale which was supported by solid factor loadings and adequate commonalities had a clear unifactorial structure which accounted for 60.785% of the variance. These results indicate a

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psychometrically robust instrument for measuring students' attitudes toward AI-enhanced project-based learning in higher education environments.

Recommendations

This study has developed a validated 5-item Guttman scale for measuring students' attitudes toward AI-enhanced project-based learning. The scale demonstrated robust psychometric properties with a Reproducibility coefficient of 0.98 and Scalability coefficient of 0.97. Based on these results, some recommendations for educational institutions and researchers can be proposed.

Educational institutions can adopt this scale as a preliminary assessment tool to evaluate students' or teachers' readiness and attitudes before introducing AI-enhanced project-based learning. This initial assessment can offer insights into students' readiness levels and help identify potential challenges to AI adoption. Based on the scale's results, institutions can customize their AI integration approaches to meet the needs of different student groups. To be effective, institutions should conduct periodic assessments of students' performance throughout their academic journey to track any attitudinal changes and adjust their implementation strategies accordingly. These ongoing assessments can inform decisions about the pace and extent of AI tool integration in project-based activities to ensure a more responsive and student-centered approach.

From a research perspective, future studies can be conducted to verify the scale's validity across different populations and contexts. To further verify the scale's structure and strengthen its theoretical foundation, confirmatory factor analysis can be conducted. In addition, researchers could also explore how the scale relates to other AI learning measures to establish its concurrent validity. This would help provide a

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deeper understanding of how student attitudes align with different aspects of AI-enhanced learning.

Through implementing the above-mentioned recommendations, institutions can develop more effective, evidence-based approaches to integrating AI in project-based learning environments, and researchers can continue to refine and validate the scale's application to different educational contexts.

Limitations

This study has some limitations that should be acknowledged. The sample size of 300 participants selected from just one university is one limitation that prevents the generalizability of the findings. Additionally, the study's single-context setting is another limitation as it did not allow for cultural and linguistic variations that are likely to affect the findings in different ways. A third limitation lies in the choice of a Gutman’s scale as the tool for measuring students’ attitudes toward AI-enhanced project-based learning. As is the case with all scales, there are strengths and weaknesses in the scale developed in this study.

Ethical considerations

This study which aimed at constructing a scale to measure students' attitudes toward AI-enhanced project-based learning followed ethical guidelines for the involvement of human participants. The research was approved by A’Sharqiyah University. All 300 participants provided written informed consent before participating in the study. They were fully informed about the voluntary nature of their participation, their right to withdraw at any time without any consequences and the confidentiality of their responses. All collected data were anonymized and securely stored in compliance with relevant data protection regulations.

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