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AI Use Motives as a Predictor of AI Utilization Among Radiologic Technology Instructors

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Abstract

As Artificial Intelligence (AI) becomes more integrated into education, understanding the motivational factors behind its adoption is crucial. This study explored the relationship between AI use motives—specifically expectancy-value constructs—and AI utilization among 132 radiologic technology instructors in the Region XI using a descriptive predictive design. Descriptive statistics indicated high levels of motivation across all constructs: Expectancy ($\bar{x}$ = 4.10), Attainment ($\bar{x}$ = 4.10), Utility ($\bar{x}$ = 4.15), Intrinsic/Interest Value ($\bar{x}$ = 4.14), and Cost ($\bar{x}$ = 4.09). AI Utilization also showed a high mean ($\bar{x}$ = 3.71), suggesting frequent use with some variation among respondents. Correlation results revealed moderate positive relationships between AI utilization and expectancy ($r_s = 0.401$; $p = 0.000$), attainment ($r_s = 0.442$; $p = 0.000$), and intrinsic/interest value ($r_s = 0.568$; $p = 0.000$), while cost showed a strong positive correlation ($r_s = 0.635$; $p = 0.000$). However, utility value ($r_s = 0.064$; $p = 0.465$) was not significantly related to utilization. Regression analysis identified cost and intrinsic/interest value as significant predictors of AI use, while expectancy had a negative but non-significant effect. The model explained 58.53% of the variance in AI utilization ($R^2 = 0.5853$), indicating a moderately strong fit. These findings suggest that while educators generally value AI and are motivated to use it, practical and personal interest factors, rather than perceived usefulness alone, are more predictive of actual AI integration. The study highlights the need to address implementation barriers and provide targeted training to support effective AI adoption in radiologic technology education. Future research should validate constructs, broaden the sample, and examine long-term trends in AI utilization.

Keywords: *Artificial Intelligence, Radiologic Technology, Descriptive-Predictive, Region XI*

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Introduction

As Artificial Intelligence (AI) becomes more commonly employed in education, it is important to understand what drives educators to continue using it (Kang et al., 2024). One key issue is the gap between what motivates instructors and the support they receive from their institutions. According to Vinichenko et al. (2020), while AI can boost efficiency and innovation in universities, challenges like increased workloads, rigid task structures, and a lack of alignment between instructors' needs and institutional efforts often get in the way. Similarly, Ehsan et al. (2021) found that people's backgrounds with AI influence how they perceive and use it, leading to misunderstandings and uneven adoption. These issues make it crucial to explore how factors like expectancy value (Yurt & Kasarci, 2024, Wang et al., 2023) influence the way Radiologic Technology instructors utilize AI, especially given the unique demands of their field.

Globally, Chan and Zhou (2023) found that individuals' intentions to use AI, like generative tools, are driven by the perceived value of these technologies, with minimal concern for costs. Similarly, Sankaran et al. (2023) noted that motivations are largely shaped by the expected benefits in enhancing academic outcomes. However, challenges such as cognitive load and ethical concerns can hinder adoption. Lim et al. (2023) and Ooi et al. (2023) further explored how generative AI can be both transformative and paradoxical in education, emphasizing the importance of understanding how perceived benefits and challenges influence AI adoption. These insights highlight the need to examine expectancy-value factors in the context of Radiologic Technology instructors.

In the Philippine context, Gustilo et al. (2024) highlighted that while educators see the value of AI tools in achieving teaching goals, challenges like limited access, lack of knowledge, and ethical concerns limit adoption. Agbong-Coates (2024) demonstrated that tools like ChatGPT significantly enhance personalized learning but noted issues such as accessibility and disparities. Similarly, Diloy et al. (2023) found that students value AI writing tools for improved performance, though concerns about responsible use persist. Estrellado and Miranda (2023) emphasized the need for better infrastructure and faculty training to address ethical and digital divide issues. These insights stress the role of expectancy-value factors in understanding how Radiologic Technology instructors adopt AI in their specialized field.

Given the rapidly evolving landscape in healthcare education, research on AI use motives and AI utilization is critically time-sensitive in Davao region. Despite increasing research on AI use in healthcare education, a clear understanding of how expectancy-value factors influence the motives of Radiologic Technology instructors remains limited. Existing studies often focus on broader educational settings (Vinichenko et al., 2020, Sankaran et al., 2023, Lim et al., 2023, Ooi et al., 2023, Gustilo et al., 2024, Agbong-Coates, 2024, & Estrellado and Miranda, 2023), or student perspectives (Diloy et al., 2023), overlooking the unique challenges and needs faced by instructors in specialized fields. This highlights the importance of exploring the unique link between motivation and external barriers within Radiologic Technology education—a field where advanced tools are not just beneficial but essential to teaching and practice.

Methods

The study employed a descriptive-predictive research design to investigate the levels of AI use motives and AI utilization among Radiologic Technology instructors. The descriptive aspect aimed to systematically observe and describe instructors' motivations and behaviors without manipulating any variables, while the predictive component sought to determine the extent to which AI use motives could forecast AI utilization. This combination of approaches provided a comprehensive framework for understanding the integration of AI in radiologic education.

The research was conducted in Region XI, located in the southeastern part of Mindanao, Philippines. Specifically, the study focused on Davao City, Tagum City, and Digos City—urban centers that host higher education institutions offering programs in health sciences and allied fields. The study's participants consisted of 132 Radiologic Technology instructors who were selected by Convenience Sampling. The participants were full-time and part-time instructors of higher education institutions located in Region XI.

To measure AI use motives, the study utilized the Questionnaire of AI Use

Motives (QAIUM) developed by Yurt and Kasarci (2024). This instrument assessed key motivational dimensions such as Expectancy and Task Value using a 5-point Likert scale, and demonstrated strong psychometric properties, with Cronbach's alpha ranging from 0.865 to 0.935 and confirmatory factor analysis results indicating good model fit (CFI = 0.962, TLI = 0.952, RMSEA = 0.070). AI utilization was assessed through a self-constructed questionnaire designed to measure the frequency and extent of AI integration in instructional practices. This instrument was validated by experts with a Content Validity Index (CVI) of 1.0 and showed high internal consistency with a Cronbach's alpha of 0.878. Responses were also collected using a 5-point Likert scale ranging from "Always" to "Never."

The study employed descriptive statistics such as the mean and standard deviation to summarize the central tendencies of the variables. The relationship between AI use motives and AI utilization was examined using Spearman's Rank-Order Correlation Coefficient (Spearman's Rho), while kernel regression was used to further explore the predictive relationship between the variables. Additionally, the Kolmogorov-Smirnov test was conducted to assess the normality of the data distribution.

Results and Discussion

Table 1. Level of AI Use Motives among Radiologic Technology Instructors

		Mean	SD	Interpretation
Expectancy		4.1	0.625	High
Task Value				
	Attainment	4.10	0.457	High
	Utility	4.15	0.641	High
	Intrinsic/Interest Value	4.14	0.628	High
	Cost	4.09	0.657	High

Legend: 1.00-1.49 Very Low; 1.50-2.49 Low; 2.50-3.49 Moderate; 3.50-4.49 High; 4.50-5.00 Very High; n= 13

Table 1 reflects the level of AI use motives and AI utilization among Radiologic Technology instructors. Both indicators show that Radiologic Technology instructors frequently use AI in their instructional practices. This observation aligns with findings from recent studies. For instance, a study analyzing Radiologic Technology students' perceptions of AI applications in radiology found that a significant majority (63.9%) were aware of AI and its applications, suggesting a growing integration of AI in Radiologic Education (Alsharif et al., 2023). Similarly, research evaluating an AI education module for radiographers demonstrated that tailored AI education can enhance the integration of AI into clinical practice, highlighting the importance of AI training in Radiologic curricula (Ryan et al., 2023). Furthermore, a study on the integration of AI in radiology education emphasized that AI has the potential to promote radiology education and improve training for residents, reflecting the increasing adoption of AI technologies in educational settings (Zhang et al., 2025).

Table 2. Level of Utilization among Radiologic Technology Instructors

	Mean	SD	Interpretation
AI Utilization	3.71	0.831	High

Legend: 1.00-1.49 Very Low; 1.50-2.49 Low; 2.50-3.49 Moderate; 3.50-4.49 High; 4.50-5.00 Very High; n= 132

Table 2 shows the level of AI utilization among Radiologic Technology instructors, with a mean score of 3.71 and a standard deviation of 0.831, indicating a high level of AI utilization.

This finding aligns with studies highlighting the increasing integration of AI in medical imaging education. For instance, a survey by the American Society of Radiologic Technologists (ASRT) found that while 84.5% of educators recognized the importance of teaching AI, only 23.7% incorporated it into their curricula, primarily due to a lack of AI knowledge among educators (Stogiannos et al., 2024). Similarly, research in Saudi Arabia, Sudan, and Yemen revealed that 58.1% of radiologic technologists and 61.9% of radiologists were knowledgeable about AI in medical imaging, suggesting room for improvement in AI education (Alsultan et al., 2023).

Table 3. Relationship between AI Use Motives and AI Utilization

AI Use Motives	r_s	P-Value	Decision
Expectancy	$.401^{**}$	.000	Reject null
Task Value:			
Attainment	$.442^{**}$	.000	Reject null
Utility Value	.064	.465	Accept null
Interest/Intrinsic Value	$.568^{**}$	.000	Reject null
Cost	$.635^{**}$	.000	Reject null

***. Correlation is significant at the 0.01 level (2-tailed).; rs = Spearman's rho*

Table 3 reflects the relationship between AI use motives and AI utilization among Radiologic Technology instructors. The expectancy indicator exhibits a moderate positive correlation with AI utilization (r_s=0.401), suggesting that instructors who anticipate successful outcomes from AI integration are more likely to utilize these technologies. This finding aligns with the expectancy-value theory, which posits that individuals' motivation to engage in a task is influenced by their expectations of success (Wigfield & Eccles, 2000).

Regarding task value indicators, attainment value shows a moderate positive correlation with AI utilization (r_s=0.442), indicating that instructors who perceive AI integration as important to their professional identity are more inclined to adopt such technologies. Interest or intrinsic value demonstrates a stronger correlation (r_s=0.568), suggesting that personal enjoyment and interest in AI significantly drive its utilization. These observations are consistent with prior research highlighting the role of intrinsic motivation in technology adoption (Ryan & Deci, 2000). Conversely, utility value exhibits a negligible correlation with AI utilization (r_s=0.064), implying that perceiving AI as useful does not necessarily translate to its adoption in instructional practices. This finding aligns with studies indicating that utility value alone may not be a sufficient motivator for technology use (Eccles & Wigfield, 2002).

Notably, the cost indicator shows a strong positive correlation with AI utilization (R = 0.635), suggesting that higher perceived costs are associated with increased AI use. This counterintuitive result may reflect a complex relationship where instructors who invest significant effort and resources into understanding AI are more likely to implement it, despite the associated costs. This complexity is acknowledged in the expectancy-value-cost model, which considers cost as a multifaceted construct influencing motivation (Flake et al., 2015).

The negative association between expectancy and AI utilization aligns with findings by Ayaz and Yanartaş (2020), who observed that higher effort expectancy could reduce technology adoption intentions. This suggests that when instructors anticipate significant effort in using AI tools, their actual utilization may decline. In contrast, the positive correlations of interest/intrinsic value and cost with AI utilization are consistent with prior research. Studies have demonstrated that intrinsic motivation significantly enhances technology acceptance and usage (Davis et al., 1992; Venkatesh, 1999). Additionally, economic considerations, such as cost savings, serve as internal drivers for technology adoption by highlighting financial benefits (Sarrab et al., 2021).

Table 4. Predictors of AI Utilization among RT Instructors

	Observed Estimate	z	p-value	Remarks
Expectancy	-0.185	-1.24	0.22	Accept null
Task Value				
Attainment	0.278	1.73	0.08	Accept null
Interest/Intrinsic Value	0.390	2.21	0.03	Reject null
Cost	0.589	4.03	0.00	Reject null

R-Squared= 0.5853

In Table 4, the regression analysis suggests that AI Utilization is significantly influenced by several factors. Cost and Interest/Intrinsic both have significant positive effects on AI Utilization. On the contrary, Attainment shows a positive effect but with borderline significance. Expectancy shows a negative but insignificant effect, indicating it may not have a meaningful impact in this model. The model explains around 58.53% of the variability in AI Utilization (based on the R-squared value), which indicates a moderately good fit of the model to the data.

These findings are consistent with existing research on AI adoption in educational settings. For instance, a study by Li and Noori (2024) examined the factors influencing primary mathematics teachers' intentions to use AI in China. The study found that teachers' attitudes toward AI significantly impacted their intention to use AI, and contextual factors, such as institutional support and resource availability, played crucial roles in shaping these attitudes and directly influencing AI utilization. This aligns with our finding that Interest/Intrinsic Motivation positively influences AI Utilization. Furthermore, a study by Zhang et al. (2025) investigated teachers' adoption of AI technologies using a unified model of external and internal determinants. The research found that institutional support had both direct and indirect positive effects on teachers' intention to use AI, mediated by intrinsic motivation and self-efficacy. This supports our finding that Attainment (potentially related to institutional support and achievement) has a positive effect on AI Utilization, albeit with borderline significance.

Conclusion and Recommendations

This study concluded that Radiologic Technology instructors exhibit diverse motives for AI use, with intrinsic interest and utility value emerging as the strongest drivers of motivation. Conversely, cost and attainment had a lesser influence. A high level of AI utilization was observed, indicating widespread integration of AI tools in instructional practices. A significant relationship was found between AI use motives and actual AI utilization, where instructors with positive expectations and a strong perception of AI's usefulness were more likely to adopt these technologies. Among the motivational factors, intrinsic interest and utility value were the strongest predictors of AI utilization.

To enhance AI adoption, institutions should support professional development programs that nurture instructors' intrinsic interest and improve their AI competencies. Reducing financial barriers and providing institutional support will further encourage integration. Administrators are advised to supply necessary resources such as funding and training, recognizing the role of expectancy in promoting AI use. Future research should investigate the long-term effects of expectancy, incorporate both qualitative and quantitative approaches, explore clinical applications, and develop more refined tools to assess AI motives and utilization in radiologic education.

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