"Perceived Value of Generative AI and Student Motivation: The Mediating Role of Information Literacy in Educational Institution of Butwal Sub-Metropolitan City, Nepal"

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Abstract

This study aims to analyze the effect of Attainment Value, Intrinsic Value, Utility Value, the Perceived Value of Generative AI, and Student Motivation. It seeks to identify how different dimensions of Attainment Value, Intrinsic Value, Utility Value, and the Perceived Value of Generative AI influence Student Motivation. Moreover, the study examines the role of Information Literacy affecting the Perceived Value of Generative AI and Student Motivation. A quantitative approach was adopted, gathering responses from 275 master's students from Tribhuvan University-affiliated campuses in Butwal Sub-Metropolitan City, Nepal, using a structured questionnaire and a convincing sampling method. Data were analyzed using PLS-SEM software, including assessment of measurement items, model fit, IPMA, and bootstrapping techniques for hypothesis testing. The results revealed that Attainment Value is a major predictor of the Perceived Value of Generative AI. Likewise, Information Literacy plays a vital mediating role in the relationship between the Perceived Value of Generative AI and Student Motivation. It is evident that Attainment Value, Intrinsic Value, Utility Value, and the Perceived Value of Generative AI are major contributors to Student Motivation. Therefore, the management of master's programs at Tribhuvan University affiliated campuses in Butwal Sub-Metropolitan City, Nepal, should consider these aspects to enhance student motivation. By understanding and reformulating policies based on these factors, there is a higher possibility of improving student motivation.

Keywords: *Attainment Value, Intrinsic Value, Perceived Value of Generative AI, Student Motivation and Information Literacy.*

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I. Introduction

In a world where technological advancements are reshaping every facet of human life, education stands at the forefront of this transformation, grappling with both unprecedented opportunities and complex challenges. The emergence of Generative Artificial Intelligence (GenAI) tools such as ChatGPT has ignited a paradigm shift in how knowledge is accessed, processed, and disseminated, compelling educators and students alike to reconsider the very nature of learning. As digital natives increasingly interact with AI-powered platforms, the question is no longer whether these technologies will influence education, but how deeply they will redefine the learning experience and what this means for the next generation of professionals (Walczak & Cellary, 2023; Tlili et al., 2023).

The integration of technology into education is not a recent phenomenon. Early iterations of computer assisted instruction in the 1960s and 1970s laid the groundwork for the digital learning environments we see today (Luckin et al., 2016). However, the advent of GenAI powered by sophisticated machine learning and natural language processing algorithms has dramatically expanded the possibilities for personalized, adaptive, and interactive learning experiences. GenAI tools can generate human-like responses, provide instant feedback, and tailor content to individual learning needs, making them particularly attractive in diverse educational settings (Dai et al., 2023; Clune, 2019). Yet, as technology has evolved, so too have the debates surrounding its appropriate use, ethical considerations, and potential impact on foundational academic skills.

The rapid adoption of GenAI in education has sparked both enthusiasm and concern among educators, policymakers, and researchers. On one hand, GenAI holds promise for enhancing student engagement, fostering critical thinking, and supporting differentiated instruction (Koohi-Moghadam & Bae, 2023; Chan, 2023). On the other hand, significant apprehensions remain regarding the risk of diminishing interpersonal learning interactions, over-reliance on technology at the expense of deep learning, and the potential erosion of essential information literacy skills (Walczak & Cellary, 2023; Tlili et al., 2023). These concerns are particularly pronounced in management education, where the ability to critically evaluate information, make informed decisions, and communicate effectively are core competencies for future leaders (Yilmaz & Karaoglan Yilmaz, 2023).

Despite the theoretical benefits of GenAI, several practical challenges hinder its positive impact on student motivation and learning outcomes. Chief among these is the risk of academic dishonesty, as students may be tempted to use AI-generated content inappropriately, undermining the development of original thought and critical analysis (Lim et al., 2023; Mills et al., 2023). Additionally, disparities in information literacy skills can create inequities in how students leverage GenAI, with some benefiting more than others due to varying levels of digital competence (Hacker et al., 2023). The lack of clear pedagogical frameworks for integrating GenAI further complicates efforts to maximize its educational value while mitigating potential drawbacks (Yilmaz, Maxutov, et al., 2023).

While literature offers valuable insights into the general integration of GenAI in education, significant gaps remain particularly regarding how management students perceive and are motivated by these technologies within the unique context of their discipline. Most existing studies have either focused on broad educational outcomes or examined GenAI through the lens of specific technological applications, often overlooking the nuanced ways in which institutional culture, curriculum design, and disciplinary expectations shape student experiences (Aronson et al., 2023; Epstein et al., 2023). Moreover, there is a paucity of research exploring the mediating role of information literacy in this relationship, especially in non-Western contexts such as India, where rapid digitalization intersects with diverse educational traditions (Bowles & Kruger, 2023; Wang, Hua, et al., 2023).

This study seeks to address these gaps by investigating the perceived value of GenAI, its influence on student motivation, and the critical role of information literacy among management students in India. By employing a mixed methods approach, the research aims to generate actionable insights for educators and policymakers seeking to harness the potential of GenAI while safeguarding the integrity and efficacy of management education. Ultimately, the findings will inform the development of targeted pedagogical strategies and training programs, equipping students with the skills necessary to thrive in a technology driven workforce and ensuring that educational institutions remain responsive to the evolving demands of the digital age (Ajibade & Muchaonyerwa, 2023; Sayyad Abdi et al., 2023).

Objective of the Study

- To examine the effect of attainment value, intrinsic value, utility value on Perceived value of Generative AI.
- To analyze the perception of the respondents with regard to the construct of the study by examining their average response level.
- To determine which factors, act as necessary conditions for the Student Motivation identifying the minimum levels that must be present for the outcome to occur.
- To analyze the Mediating effect of Information Literacy on the relationship between Perceived Value of Generative AI and Student Motivation.

II. Literature Review

Attainment Value and Perceived Value of Generative AI.

Theoretically, Attainment Value refers to the importance students place on mastering a task or technology because it aligns with their identity or personal goals. According to Expectancy-Value Theory (EVT), individuals are motivated to engage in tasks that they perceive as relevant to their self-concept and social recognition (Eccles & Wigfield, 2002). When students view GenAI as an achievement-related tool that contributes significantly to their academic success, their perceived value of the technology increases, promoting engagement. This suggests a positive association between Attainment Value and Perceived Value, as students who see GenAI as crucial for their achievement are more likely to regard it as valuable.

Empirical studies support this relationship. For example, Dai et al. (2023) emphasized that students' perception of GenAI as a tool for academic achievement enhances their perceived utility and overall value of technology. Similarly, Yilmaz and Karaoglan Yilmaz (2023) found that students' perception of the importance of AI tools in achieving learning objectives directly influences how they perceive the usefulness and value of these tools. Furthermore, these findings indicate that when students recognize the attainment-related benefits of GenAI, their motivation to utilize such technology increases, highlighting the significance of Attainment Value in shaping perceptions.

Additionally, the integration of GenAI into educational processes reinforces the notion that students' success-oriented motivations bolster their perceived value of technology. The more students associate GenAI with successful learning outcomes and attainment of academic goals, the more likely they are to perceive it as valuable in their educational journey.

H1: There is a significant relationship between Attainment Value and Perceived Value of Generative AI.

Intrinsic Value and Perceived Value of Generative AI.

Intrinsic Value pertains to the internal satisfaction, enjoyment, and interest derived from using GenAI in the learning process. According to Self-Determination Theory (Deci & Ryan, 1985), intrinsic motivation significantly influences individuals' engagement and perceived value of activities, including technology use. When students find using GenAI intrinsically rewarding such as discovering new insights, enjoying problem-solving, or experiencing personal interest they are more likely to perceive the technology as valuable, which enhances their willingness to integrate it into their learning routines.

Empirical evidence substantiates this relationship. Vohra and Sinha (2022) reported that students who experience higher intrinsic motivation towards AI-enabled activities tend to perceive greater value in technology, considering it more engaging and meaningful. Similarly, research by Yilmaz and Karaoglan Yilmaz (2023) highlights that intrinsic motivation positively influences perceptions of AI tools, leading students to see them as more valuable for their personal and academic growth. These studies indicate that intrinsic interest and enjoyment in using GenAI are key drivers of perceived value, reinforcing the importance of intrinsic motivation in educational technology adoption.

Furthermore, the perception of GenAI as an engaging and interesting tool contributes to fostering positive attitudes and sustained use. When students find the process of employing GenAI intrinsically satisfying, their perceived utility and overall value of the technology are likely to increase, promoting deeper engagement and motivation.

H2: There is a significant relationship between Intrinsic Value and Perceived Value of Generative AI.

Utility Value and Perceived Value of Generative AI.

Utility Value refers to the extent to which students perceive GenAI as useful for achieving specific academic tasks and real-world applications. Theoretically, according to the Expectancy-Value Theory (Eccles & Wigfield, 2002), perceived utility enhances motivation by emphasizing the usefulness of a task or tool in fulfilling practical goals. When students recognize that GenAI can effectively support their learning activities, improve efficiency, or solve complex problems, their perceived value of the technology increases.

Empirical studies support this association. Yilmaz and Karaoglan Yilmaz (2023) found that students' perceptions of AI tools' practical usefulness significantly influence their perceived value, which in turn affects their motivation to use such tools. Similarly, Dai et al. (2023) demonstrated that students who acknowledge the utility of GenAI in academics and future careers tend to regard it as highly valuable, fostering greater engagement. Moreover, O'Reilly et al. (2021) emphasized that when students see concrete benefits such as timesaving, problem-solving, or enhanced learning outcomes, their perceived value of AI technologies rises, motivating continued use and exploration.

Furthermore, the recognition of utility value extends beyond immediate academic benefits, including applications in future professional scenarios, thus reinforcing perceived value. When students perceive that GenAI offers practical advantages aligned with their goals, they are more likely to find the technology worthwhile and integrate it into their learning practices.

H3: There is a significant relationship between Utility Value and Perceived Value of Generative AI.

Perceived Value of Generative AI and Student Motivation.

Theoretical foundations, such as the Expectancy-Value Theory (Eccles & Wigfield, 2002), posit that perceived value plays a critical role in motivating individuals toward specific behaviors. When students perceive GenAI as valuable whether in terms of enhancing learning, engaging with content, or achieving academic success they are more likely to demonstrate increased motivation to utilize these technologies in their educational endeavors.

Empirical research supports this linkage. Dai et al. (2023) demonstrate that students' perceptions of the usefulness and benefits of GenAI directly influence their motivation to interact with AI tools. Similarly, Gill et al. (2023) highlights that positive perceptions of AI's transformative effects on education can foster higher levels of student motivation, as students feel more encouraged and confident in using these tools to support their learning objectives. Vohra and Sinha (2022) further emphasize that when students find AI technologies engaging and worthwhile, their intrinsic motivation to learn and experiment with these tools significantly increases.

Additionally, studies suggest that perceived value not only increases initial motivation but also sustains ongoing engagement. When students believe that GenAI adds meaningful benefits such as personalized support, problem-solving capabilities, or efficiency they are more likely to develop an intrinsic motivation to explore, utilize, and depend on these tools for their academic growth.

H4: There is a significant relationship between Perceived Value of Generative AI and Student Motivation.

Perceived Value of Generative AI and Information Literacy.

Theoretical frameworks such as the Technology Acceptance Model (TAM) and the Expectancy-Value Theory (Eccles & Wigfield, 2002) suggest that user's perceptions of technology are closely tied to their skills and confidence in handling information. When students possess higher levels of information literacy defined as the capacity to effectively find, evaluate, and apply information they are more likely to recognize the potential benefits of GenAI, thus perceiving it as more valuable in supporting their learning processes.

Empirical studies reinforce this connection. Rai et al. (2021) found that students with stronger information literacy skills tend to have more positive perceptions of digital tools and AI technologies, viewing them as more beneficial and trustworthy. Similarly, Yilmaz and Karaoglan Yilmaz (2023) note that students proficient in information literacy are better equipped to critically engage with AI-generated content, which enhances their perception of technology's usefulness and relevance, thereby increasing its perceived value.

Moreover, the ability to discern credible from non-credible information and to utilize AI-generated data effectively contributes directly to perceived utility and satisfaction with GenAI.

Students with limited information literacy may perceive AI tools as unreliable or overwhelming, thereby reducing their perceived value of such technologies. Consequently, strengthening information literacy skills can foster more favorable perceptions, encouraging greater engagement and trust in GenAI.

H5: There is a significant relationship between Perceived Value of Generative AI and Information Literacy.

Information Literacy and Student Motivation.

Theoretical perspectives such as the Self-Determination Theory (Deci & Ryan, 1985) propose that competence one's perceived ability to effectively handle tasks, including information management enhances intrinsic motivation. When students possess strong information literacy skills, they perceive themselves as more competent in navigating digital information environments, which can increase their confidence and motivation to participate actively in learning activities.

Empirical research supports this association. Rai et al. (2021) identified that students with higher information literacy levels are more confident in engaging with digital tools and resources, leading to increased motivation to learn. Similarly, the work of Yilmaz and Karaoglan Yilmaz (2023) indicates that students proficient in information literacy display higher motivation levels to explore and utilize AI-driven educational tools, because they feel more competent and assured in their understanding and use of digital information.

Additionally, information literacy fosters critical thinking and autonomous learning, which are key drivers of motivation. When students can effectively evaluate sources and synthesize information, they tend to experience greater satisfaction and interest in their learning process. Conversely, students with limited information literacy may feel overwhelmed or skeptical about digital content, which can diminish their motivation to engage with technological learning tools.

H6: There is a significant relationship between Information Literacy and Student Motivation.

Mediating role of Information Literacy on the relationship between Perceived Value of Generative AI and Student Motivation.

Theoretical frameworks such as the Expectancy-Value Theory (Eccles & Wigfield, 2002) suggest that the perceived value of technology influences motivation primarily when individuals have the requisite skills and confidence to utilize it effectively. In this context, Information Literacy Student's ability to locate, evaluate, and apply information acts as a facilitator that enhances the perceived utility and relevance of AI tools, thereby boosting motivation.

Empirical evidence supports the mediating role of information literacy. Rai et al. (2021) found that students with higher information literacy skills are more likely to perceive digital and AI tools as valuable because they can critically engage with content and derive meaningful insights. These perceptions, in turn, positively influence their motivation to learn and use such technologies. Similarly, Yilmaz and Karaoglan Yilmaz (2023) demonstrated that students' information literacy skills significantly affect their motivation to adopt AI-based tools, as better literacy skills increase perceived utility and confidence.

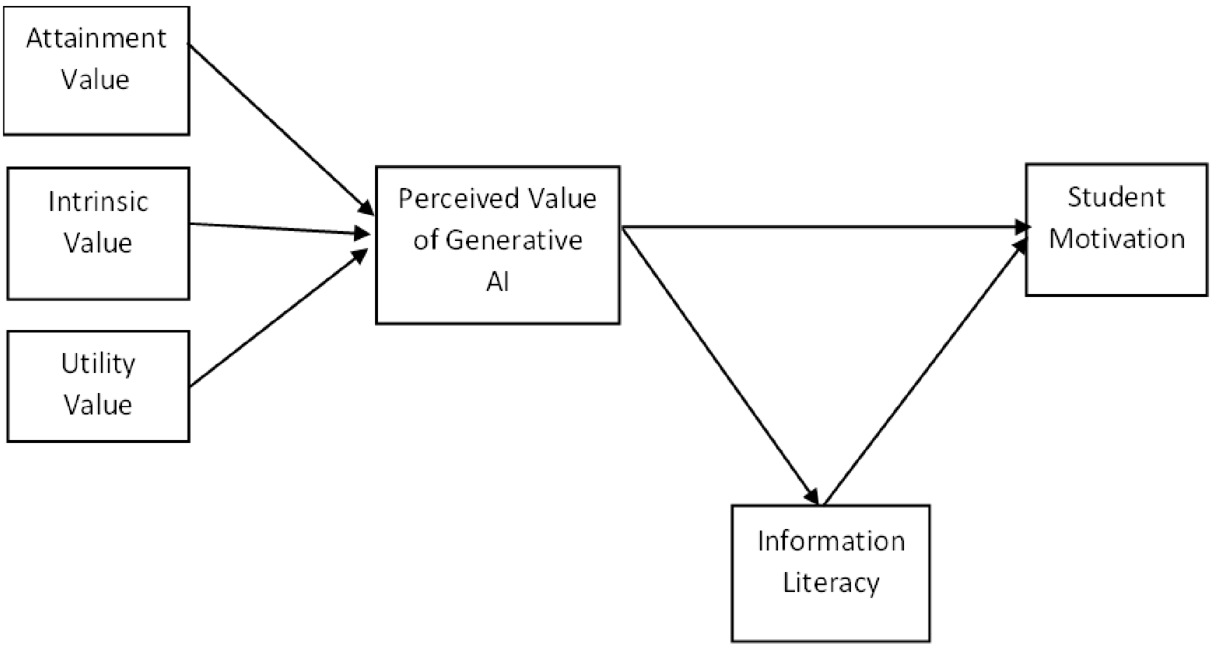
Moreover, the mediating effect is rooted in the idea that information literacy enhances cognitive and affective engagement with AI tools. When students recognize that they can effectively evaluate and utilize generative AI, their perception of its value increases, leading to heightened motivation. Conversely, a lack of information literacy may weaken this relationship, as students may view AI tools as unreliable or overly complex, reducing their motivation despite recognizing some benefits of the technology.

H7: There is a mediating role of Information Literacy on the relationship between Perceived Value of Generative AI and Student Motivation.

Theoretical Framework

The theoretical framework of the study is outlined below:

Figure 1 - Theoretical Framework



Note. Adapted from (Jos, 2024)

III. Research Methodology

Research Design

A research design is a structured plan that guides data collection and analysis, shaping the study (Cooper & Schindler, 2003). This study adopts Descriptive Research Design and Explanatory Research Design to achieve its objectives.

Descriptive Research Design systematically presents characteristics, behaviors, or phenomena without altering variables. It identifies trends, patterns, and relationships within a population (Creswell, 2014). Explanatory research design is a quantitative approach used to investigate cause-and-effect relationships between variables by testing hypotheses and analyzing the strength and direction of associations (Creswell & Creswell, 2018; Saunders et al., 2019). Likewise, Kerlinger (1986) highlights ex post facto research, where past independent variables are analyzed to assess their effects on dependent variables (Kerlinger, 1986; Pant, 2012, p. 117). Common statistical methods include the Spearman Rank Order Coefficient, Phi Correlation Coefficient, Regression, t-test, Chi-square, and Analysis of Variance (Isaac, 1978; Pant, 2012, p. 118).

By combining descriptive and explanatory research designs, this study effectively examines variable relationships and their impact (Kerlinger, 1986), ensuring a structured and systematic approach.

Population and sample size

The population of this research study comprises all respondents within the research area. In this study, the chosen research area is Butwal Sub-Metropolitan City, and the population consists of all master's management students in different Tribhuvan University affiliated campuses located in Butwal. The total number of students in this campus is 702 Therefore, the population of the study is identified as 702. The details of the campus and their respective number of students are presented in Table 1.

Table 1 - *Total master's Students of Tribhuvan University affiliated Campuses in Butwal*

S. No	Name of Campuses	Number of Students
1	Lumbini Banijya Campus	357
2	New Horizon College	47
3	Siddhartha Gautam Buddha Campus	124
4	Butwal Multiple Campus	174
	Total	702

Sample is a part of a population or subset of population and denoted by n. The total sample size for this study has been obtained using the formula developed by yamane (1967). In case of population size is known, the Yamane formula for determining the sample size is given by:

n= N/1+Ne2 Where, n= sample size, N= Population size, and e= Margin of error (MOE), e=0.05 based on research condition. Thus, the sample size of the study is n = 255

Sampling Method

The sampling method is chosen to select sample respondents from the overall population for data collection. In this context, the simple random sampling method is specifically employed to approach the sample respondents. Given that the study focuses on the perceived value of generative AI and students' motivation in educational institution in Butwal Sub-metropolitan city, the simple random sampling technique is deemed appropriate. This choice is made because the number of male students is relatively low, allowing for the identification and random selection of individuals from the list of male students to mitigate bias among respondents.

Nature and Sources of Data Collection

This study primarily relies on quantitative data**,** which were collected from primary sources. A structured questionnaire was designed to gather first-hand information directly from respondents.

Survey Instrument

A self-structured questionnaire was used as the survey instrument for data collection. It was developed based on operational definitions from previous literature. The questionnaire employs a seven-point Likert scale (7 = Strongly Agree, 6 = Agree, 5 = Somewhat Agree, 4 = Neutral, 3 = Somewhat Disagree, 2 = Disagree, and 1 = Strongly Disagree) to gather responses from participants.

A set of questions was designed to measure each independent, dependent, and mediating variable, totaling 30 items. To ensure clarity and accuracy, a pilot test was conducted by distributing the questionnaire to a sample of 10 respondents. Out of 292 distributed questionnaires, 275 were fully completed, yielding a response rate of 94.18 %**.**

Statistical Tools

The study employed various statistical tools appropriate to the nature of the collected data. Descriptive statistics, including mean and standard deviation (SD), were calculated to summarize and interpret respondents' answers. Analytical procedures included the assessment of measurement items, evaluation of model fit, Importance-Performance Map Analysis

(IPMA), and bootstrapping techniques to test the proposed hypotheses regarding the relationship between Perceived value of Generative AI and Student Motivation.

Operational Definition

Attainment value reflects students' perception that using generative AI (e.g., ChatGPT) aligns with their academic identity and competence, measured via Likert-scale agreement with statements like "Using generative AI helps me achieve excellence" (Eccles & Wigfield, 2002). Intrinsic value denotes inherent satisfaction derived from AI interactions (e.g., "I find using generative AI intellectually stimulating") (Ryan & Deci, 2000). Utility value captures perceived practical benefits for academic/career goals (e.g., "Generative AI saves time on assignments") (Wigfield & Eccles, 2000). Perceived value of generative AI represents holistic cost-benefit assessments (e.g., "AI improves learning despite ethical concerns"), averaged across multi-item scales (Venkatesh et al., 2012). Information literacy (mediator) is operationalized as self-reported ability to ethically locate, evaluate, and synthesize AI-generated information (e.g., "I can critically verify AI outputs") using adapted scales (Kurbanoglu et al., 2006). Student motivation (dependent variable) reflects self-directed academic drive, measured through items like "I seek challenges when using AI" from validated motivation scales (Vallerand et al., 1992).

IV. Results and Analysis

Measurement Items Assessment

Table 2 - *Assessment of measurement scale items*

Variables	Items	Outer loadings	VIF	Mean	Standard deviation
	AV1	0.751	1.821	4.76	1.779
	AV2	0.805	2.72	5.131	1.503
Attainment Valu	AV3	0.81	2.549	5.127	1.685
	AV4	0.879	3.886	5.909	1.483
	AV5	0.798	3.113	6.218	1.363
	IV1	0.828	2.144	5.127	1.685
	IV2	0.796	2.022	5.185	1.803
Intrinsic Value	IV3	0.85	2.291	5.469	1.505
	IV4	0.773	1.805	5.789	1.532
	IV5	0.792	1.766	5.182	1.578
	UV1	0.9	3.215	4.753	1.895
	UV2	0.882	3.096	4.356	1.985
Utility Value	UV3	0.842	2.452	4.371	2.082
	UV4	0.817	2.277	3.891	1.955
	UV5	0.918	4.145	4.233	1.975
	SM1	0.895	3.232	5.655	1.43
	SM2	0.905	3.687	5.138	1.715
Student Motivation	SM3	0.786	2.371	5.022	1.77
	SM4	0.855	2.595	5.149	1.846
	SM5	0.827	2.249	5.582	1.451

Information Literacy	**IL1**	**0.82**	**1.936**	**5.564**	**1.537**
	IL2	**0.809**	**2.38**	**5.724**	**1.522**
	IL3	**0.874**	**2.989**	**5.593**	**1.531**
	IL4	**0.859**	**3.652**	**4.931**	**1.741**
	IL5	**0.77**	**2.73**	**4.593**	**1.744**
Perceived Value of Generative AI	**PV1**	**0.873**	**2.993**	**5.96**	**1.415**
	PV2	**0.911**	**3.945**	**5.8**	**1.509**
	PV3	**0.913**	**4.194**	**5.687**	**1.648**
	PV4	**0.726**	**1.818**	**5.015**	**1.793**
	PV5	**0.775**	**1.742**	**5.505**	**1.717**

Note. Derived from SmartPLS 4 Software

Table 2 presents the standardized outer loading and Variance Inflation Factor (VIF) of the scale items employed to measure the variables pertinent to this investigation. In accordance to Sarstedt et al. (2017), the outer loading of an item must exceed 0.708 to signify a substantial contribution of that item in assessing the associated variable. Therefore, all 30 scale items are preserved for subsequent analysis. Furthermore, the VIF values for each item are less than 5, thereby indicating no multicollinearity within the scale items (Sarstedt et al., 2014).

Most of the mean values are on the higher side of the scale representing agreeableness towards each statement. For standard deviation values are small indicating less deviation in responses. Therefore, the data is suitable for further analysis.

Quality Criteria Assessment

Table 3 - *Construct Reliability and Validity*

Variables	Alpha	CR (rho_a)	CR (rho_c)	AVE
Attainment Value	0.869	0.878	0.905	0.655
Information Literacy	0.885	0.891	0.916	0.685
Intrinsic Value	0.868	0.872	0.904	0.653
Perceived Value of Generative AI	0.896	0.904	0.924	0.711
Student Motivation	0.908	0.916	0.931	0.73
Utility Value	0.922	0.932	0.941	0.762

Note. Derived from SmartPLS 4 Software

Table 3 contains the values of Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) to evaluate the convergent validity of the variables employed in this study. The Cronbach's Alpha coefficients for all items exceed the threshold of 0.705, signifying the adequate contribution of each scale item in the assessment of related constructs (Bland &

Altman, 1997). Furthermore, the CR values for rho_A and rho_C surpass the minimum criterion of 0.70, denoting a robust measure of internal consistency (Saari et al., 2021; Hair et al., 2022). The AVE values also exceed the pivotal threshold of 0.50, suggesting that each variable accounts for more than 50 percent of the explained variance. This finding confirms the establishment of convergent validity (Hair et al., 2022). Subsequently, the outcomes depicted in the table as mentioned above satisfy all requisite of quality criteria measures.

Discriminant Analysis

Table 4 - *Heterotrait-Monotrait ratio of correlations (HTMT) Matrix*

Variables	Attainment Value	Information Literacy	Intrinsic Value	Perceived Value of Generative AI	Student Motivation	Utility Value
Attainment Value						
Information Literacy	0.577					
Intrinsic Value	0.592	0.880				
Perceived Value of Generative AI	0.836	0.737	0.812			
Student Motivation	0.801	0.831	0.722	0.808		
Utility Value	0.483	0.447	0.572	0.54	0.475	

Note. Derived from SmartPLS 4 Software

Table 4 contains the HTMT ratio of the correlation matrix, which evaluates the discriminant validity of the latent variables. The values of the HTMT ratio vary from 0.447 to 0.880. The HTMT ratio values need to remain below the critical threshold of 0.85; nevertheless, a range extending up to 0.90 is deemed acceptable, as posited by Henseler et al. (2015). Consequently, the presence of discriminant validity is confirmed among the reflective constructs (Hair & Alamer, 2022).

Table 5 - *Fornell-Larcker Criterion*

Variable	Attainment Value	Information Literacy	Intrinsic Value	Perceived Value of Generative AI	Student Motivation	Utility Value

Attainment Value	**0.809**					
Information Literacy	0.728	**0.827**				
Intrinsic Value	0.633	0.781	**0.808**			
Perceived Value of Generative AI	0.749	0.812	0.726	**0.843**		
Student Motivation	0.728	0.821	0.664	0.744	**0.855**	
Utility Value	0.439	0.418	0.522	0.505	0.452	**0.873**

Note. Derived from SmartPLS 4 Software

Table 5 displays the Fornell-Larcker Criterion, an important discriminant validity assessment in a structural equation model (SEM) (Fornell & Larcker, 1981). This criterion is satisfied when the average variance extracted (AVE) for every construct is higher than the squared correlation between that construct and any other construct in the model. The diagonal entries, the square root of AVE of every construct, are to be higher than the off-diagonal values for their corresponding columns and rows. As evident in Table 4, diagonal values of Attainment Value (0.809), Information Literacy (0.827), Intrinsic Value (0.808), Perceived Value of Generative AI (0.843), Student Motivation (0.855), and Utility Value (0.873) are all higher than their inter-construct correlations. This means the measurement model's discriminant validity is assured, implying that each construct is unique and taps into a distinct segment of variance (Hair et al., 2010). This ensures that the constructs do not overlap and that the measures are measuring what they should measure.

Model Fit Assessment

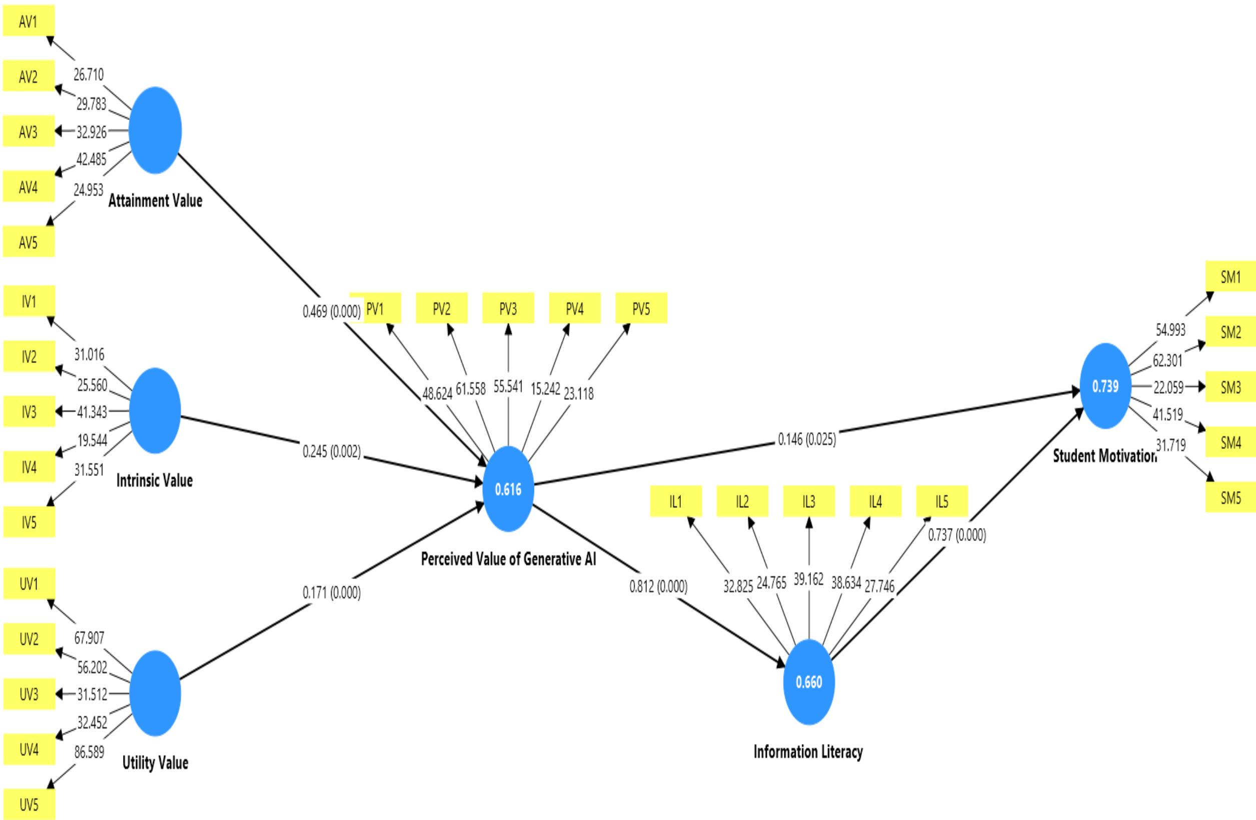
The SRMR indices evaluate the model's explanatory efficacy. The model's SRMR value is 0.085, below the acceptable threshold of 0.10 (Bollen & Stine, 1992). This finding suggests that the model exhibits adequate explanatory capability.

Moreover, the effect sizes of Attainment Value on Perceived Value of Generative AI shows 0.175 is strong, Information Literacy on Student Motivation shows 0.708 is Strong, Intrinsic Value on Perceived Value of Generative AI shows 0.043 is weak, Perceived Value of Generative AI on Information Literacy shows 1.939 is strong, Perceived Value of Generative AI shows on Student Motivation is 0.028 is weak, Utility Value on Perceived Value of Generative AI shows 0.055 is weak effect (Cohen, 1988).

Finally, the r-square values corresponding to Information Literacy, Perceived Value of Generative AI and Student Motivation are 0.66, 0.616 and 0.739 respectively. This signifies that Information Literacy, Perceived Value of Generative AI and Student Motivation possess robust predictive ability (Hair et al., 2013).

Structural Equation Model

Figure 2 - *Path Relationship Diagram*



Note. Derived from SmartPLS 4 Software

Table 6 - *Hypotheses Testing Using Bootstrapping*

Hypotheses	**β**	**Mean**	**STDEV**	**Confidence interval 2.50%**	**97.50%**	**T statistics**	**P values**	**Decision**
H1: Attainment Value -> Perceived Value of Generative AI	0.47	0.471	0.073	0.327	0.613	6.42	0	Accepted
H2: Intrinsic Value -> Perceived Value of Generative AI	0.25	0.245	0.079	0.091	0.401	3.116	0.002	Accepted
H3: Utility Value -> Perceived Value of Generative AI	0.17	0.17	0.035	0.103	0.239	4.881	0	Accepted
H4: Perceived Value of Generative AI -> Student Motivation	0.15	0.149	0.064	0.033	0.284	2.28	0.023	Accepted

H5: Perceived Value of Generative AI -> Information Literacy	0.81	0.812	0.036	0.733	0.872	22.715	0	Accepted
H6: Information Literacy -> Student Motivation	0.74	0.734	0.061	0.604	0.841	12.097	0	Accepted

Note. Derived from SmartPLS 4 Software

Information Literacy

R-square: 0.660 and R-square adjusted: 0.658

Perceived Value of Generative AI

R-square: 0.616 and R-square adjusted: 0.611

Student Motivation

R-square: 0.739 and R-square adjusted: 0.737

Figure 2 and Table 6 report the results of a bootstrapping analysis performed with 10,000 subsamples, which examine decisions regarding the proposed hypotheses. Hypotheses H1, H2, H3, H5, and H6 have achieved acceptance at a significance threshold of 0.05. There is positive and significance impact of Attainment value, Intrinsic Value and Utility Value on Perceived Value of Generative AI, Perceived Value of Generative AI on Student Motivation and Information Literacy, Information Literacy on Student Motivation.

Table 7 - *Mediating Effect*

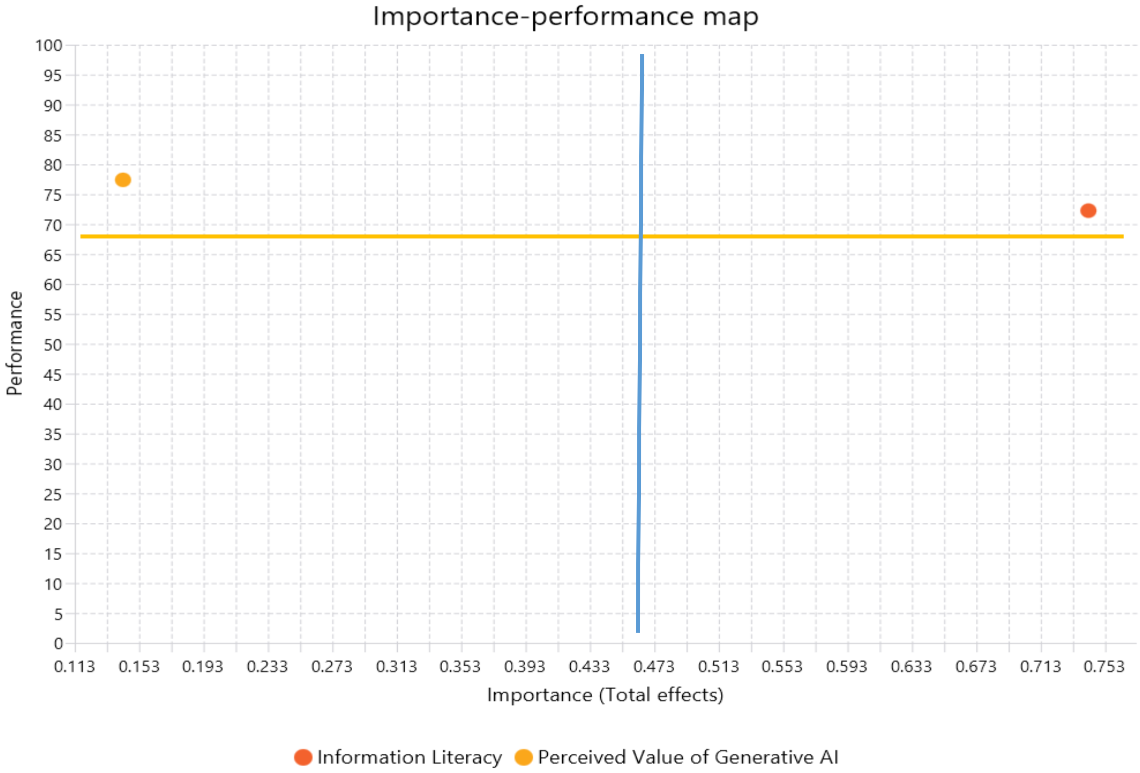
Hypotheses	**β**	**Mean**	**STDEV**	**Confidence interval**		**T statistics**	**P values**	**Decision**
				2.50%	**97.50%**			
Perceived Value of Generative AI -> Information Literacy -> Student Motivation	0.599	0.595	0.049	0.496	0.689	12.144	0	Accepted

Note. Derived from SmartPLS 4 Software

Table 7 also reports the mediating effects results, which indicates that information literacy has a positive and significant mediating effect on the relationship between Perceived Value of Generative AI and Student Motivation.

Table 8 - *Importance Performance Map Analysis*

Variables	LV performance	Importance
Information Literacy	72.258	0.742
Perceived Value of Generative AI	77.407	0.143
Mean	**74.8325**	**0.4425**



Note. Derived from SmartPLS 4 Software

Table 8 shows the total effects of Information Literacy and Perceived Value of Generative AI on Student Motivation for the unstandardized effects. These effects are the same as the unstandardized weights of ordinary least square regression modelling (Hair et al. 2010). Furthermore, the performance of Student Motivation was calculated as 72.696.

Notably, we derived the four quadrants successfully based on the mean values of the constructs' importance and performance value. As per Fig. 3, if we increase 1 unit in Information Literacy from 72.258 to 73.258, Student Motivation increases from 72.696 to 73.438. Similarly, if we increased 1 unit in performance of Perceived Value of Generative AI from 77.407 to 78.407, then Student Motivation grew to increase from 72.696 to 72.839. Therefore, out of the two determinants of Student Motivation, the most critical factor was noted to be Information Literacy.

Table 9 - *Necessary Condition Analysis (NCA)- Bottleneck Value*

	LV scores - Student Motivation	LV scores - Attainment Value	LV scores - Information Literacy	LV scores - Intrinsic Value	LV scores - Perceived Value of Generative AI	LV scores - Utility Value
0.00%	18%	NN	NN	NN	NN	NN
10.00%	26%	NN	24%	25%	NN	NN
20.00%	34%	NN	24%	31%	NN	NN
30.00%	43%	36%	38%	34%	NN	NN
40.00%	51%	51%	46%	36%	31%	NN
50.00%	59%	51%	52%	36%	31%	NN
60.00%	67%	51%	52%	44%	31%	NN
70.00%	75%	51%	52%	44%	31%	NN
80.00%	84%	54%	52%	50%	31%	NN
90.00%	92%	54%	60%	55%	31%	23%
100.00%	100%	54%	60%	55%	31%	23%

Note. Derived from SmartPLS 4 Software

Table 9 represents Bottleneck value of latent variable using necessary condition analysis (NCA). To achieve 18% of Student Motivation, no factors are necessary. Further, to achieve 26% of Student Motivation, 24% of Information Literacy and 25% of Intrinsic Value are necessary. To achieve 34% of Student Motivation, 24% of Information Literacy and 31% of Intrinsic Value are necessary. To achieve 43% of student motivation, 36% of Attainment value, 38% of Information Literacy and 34% of Intrinsic Value are necessary. To achieve 51% of student motivation, 51% of Attainment value, 46% of Information Literacy,36% of Intrinsic Value and 31% of Perceived Value of Generative AI are necessary. To achieve 59% of student motivation, 51% of Attainment value, 52% of Information Literacy, 36% of Intrinsic Value and 31% of Perceived Value of Generative AI are necessary. To achieve 67% of student motivation, 51% of Attainment value, 52% of Information Literacy, 44% of Intrinsic Value and 31% of Perceived Value of Generative AI are necessary. To achieve 75% of student motivation, 51% of Attainment value, 52% of Information Literacy, 44% of Intrinsic Value and 31% of Perceived Value of Generative AI are necessary. To achieve 84% of student motivation, 54% of Attainment value, 52% of Information Literacy, 50% of Intrinsic Value and 31% of Perceived Value of Generative AI are necessary. To achieve 92% of student motivation, 54% of Attainment value, 60% of Information Literacy, 55% of Intrinsic Value, 31% of Perceived Value of Generative AI and 23% of Utility Value are necessary. Also, to achieve 100% student motivation, 54% Attainment value, 60% of Information Literacy, 55% of Intrinsic Value, 31% of Perceived Value of Generative AI and 23% of Utility Value are necessary.

Findings of the Study

The findings of study indicate that Attainment value, Intrinsic Value and Utility Value positively and significantly impact on Perceived Value of Generative AI. The findings of study indicate that Perceived Value of Generative AI positively and significantly impact on Information Literacy. The study finding indicates that the Mediating variable of Information Literacy has positive and significant mediating effect in the relationship between Perceived Value of Generative AI and Student Motivation.

V. Discussion

The present study's findings align with and extend the existing literature on the role of value perceptions and information literacy in the adoption and motivational outcomes of generative AI within educational settings. Specifically, the results indicate that attainment value, intrinsic value, and utility value each exert a positive and significant influence on the perceived value of generative AI. This is consistent with expectancy-value theory, which posits that students' beliefs about the importance (attainment value), enjoyment (intrinsic value), and usefulness (utility value) of a task directly shape their engagement and adoption behaviors. Recent research underscores that when Students Perceive Generative AI as relevant to their academic goals, it is enjoyable to use, and practically beneficial, their overall valuation of such technology increases, fostering greater openness and engagement.

Furthermore, the study reveals that the perceived value of generative AI significantly predicts information literacy. This finding is supported by emerging literature suggesting that students who recognize the value in AI tools are more likely to develop the skills and critical awareness necessary to effectively locate, evaluate, and utilize information core components of information literacy. As generative AI becomes increasingly integrated into educational contexts, students' positive perceptions of its value appear to motivate deeper engagement with digital literacy practices, enhancing their capacity to discern credible information and use AI responsibly.

Crucially, the study identifies information literacy as a significant mediator in the relationship between perceived value of generative AI and student motivation. This mediating effect suggests that while valuing generative AI is important, its impact on motivation is amplified when students possess strong information literacy skills. This supports recent findings that information literacy not only enables students to maximize the benefits of AI tools but also strengthens their intrinsic and extrinsic motivation by fostering a sense of competence, autonomy, and confidence in navigating complex digital environments. In the context of educational institutions in Butwal Sub-Metropolitan City, Nepal, these insights highlight the importance of integrating information literacy training alongside the adoption of generative AI to fully realize its motivational and educational benefits.

VI. Conclusion and Implications.

Conclusion

This empirical study conducted in educational institutions of Butwal Sub-Metropolitan City, Nepal, offers valuable insights into the relationships among attainment value, intrinsic value, utility value, perceived value of generative AI, information literacy, and student motivation. The findings reveal that attainment, intrinsic, and utility values significantly and positively influence the perceived value of generative AI. Additionally, the perceived value of generative AI positively impacts information literacy, which in turn mediates the relationship between perceived value and student motivation. These results highlight the critical role of information literacy in enhancing the motivational effects of generative AI adoption among students, emphasizing the need to integrate both value-based and literacy-based interventions in educational settings.

However, this study has several limitations. The cross-sectional design restricts the ability to draw causal inferences, and the use of convenience sampling limits the generalizability of the findings to the broader student population in Nepal or other contexts. Moreover, reliance on self-reported data may introduce biases such as social desirability or inaccurate recall. The study's focus on a specific geographic and cultural context also suggests that the results might be influenced by local factors, which may not apply universally.

Future research should consider longitudinal or experimental designs to better establish causality and track changes over time. Expanding the sample using randomized sampling methods across diverse educational institutions and regions would improve the representativeness of findings. Additionally, exploring other potential mediators or moderators, such as digital readiness, teacher support, or institutional policies, could deepen understanding of the mechanisms influencing student motivation in relation to generative AI. Incorporating qualitative approaches like interviews or focus groups may also provide richer insights into students' experiences and perceptions. Comparative studies across different cultural and educational contexts would help distinguish universal patterns from context-specific dynamics. Addressing these limitations and pursuing these directions will strengthen the theoretical and practical contributions of future research on generative AI in education.

Implications

Theoretically, this study enriches the understanding of how the Expectancy-Value Theory, Self-Determination Theory, and Technology Acceptance Model intersect in the context of generative AI adoption within Nepali educational institutions. By empirically demonstrating that attainment value, intrinsic value, and utility value significantly shape the perceived value of generative AI, the research affirms and extends expectancy-value and motivation frameworks to emerging technologies. Furthermore, the identification of information literacy as a critical mediator highlights the importance of digital competencies in translating positive technology perceptions into enhanced student motivation, offering a nuanced perspective on how motivational and cognitive factors jointly influence technology-driven learning environments.

Practically, these findings suggest that educational institutions in Nepal and similar contexts should prioritize strategies that not only promote the perceived value of generative AI but also systematically develop students' information literacy skills. Integrating targeted training on both the effective use of AI tools and critical information evaluation into curricula can amplify student motivation and learning outcomes. Additionally, policymakers and educators are encouraged to design interventions that foster both intrinsic and extrinsic motivational factors, ensuring that technology adoption is both meaningful and sustainable in the local educational landscape.

VII. References

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