Generative AI and LOC: Reskilling VS. Upskilling for SDG

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Abstract:

With the evolving technological landscape, Generative Artificial Intelligence (Gen AI) is going ahead and disrupting industries faster than ever and organizations need to equip people with new skill sets. For engineering and management students, who will be future innovators and managers, there is a dynamic environment in which those making decisions about new competencies needed for individuals to acquire in their jobs. Locus of control (LOC) is a psychological construct that reflects a person concept of control over life events and represents a key psychological mechanism through which these behaviour decisions may be mediated. However, limited research so far has been conducted regarding how this concept applies to students' reactions to technological innovations such as Gen AI. The primary purpose of the study was to investigate the relationship of Gen AI, LOC and reskilling or upskilling among engineering and management students, in context to contribution towards Sustainable Development Goals (SDGs).This study adopted a quantitative research design with 103 engineering and management students of NCR. There was use of a standardised questionnaire for primary data. Statistical tools were performed, including mean, standard deviation, correlation, regression, T-test and ANOVA. Findings indicate that internal LOC students are more inclined to upskill, while external LOC students prefer reskill. A recognition of the differences in how students perceive their control over their lives is an important step towards crafting solutions tailored to develop SDG-relevant skills in an AI-driven reality.

Keywords: Generative Artificial Intelligence (Gen AI), Locus of Control(LOC), Sustainable Development Goal (SDG), Reskilling, Upskilling, ChatGPT etc.

Introduction:

Gen AI has progressed at an incredible rate and is greatly impacting multiple sectors, including engineering and management education. Technologies such as ChatGPT have become fundamental in academic contexts, helping students with coding tasks and improving learning efficiency. In this changing education landscape, the psychological concept LOC is especially relevant. Through exploring the complex interplay between Gen AI, LOC and skill development decisions, this study highlights the need for enhancing a proactive learning mindset in engineering and management students.

Gen AI (Generative Artificial Intelligence):

Gen AI, the subset of artificial intelligence (AI) generating original content, has been garnering the spotlight in numerous sectors. Concerns about its ability to automate certain tasks — and what that will mean for the future of work and the skills that will be required in the scenarios ahead — have been taking place.

Gen AI is AI that can generate new content similar to video, text graphics, sound or software code based on the input of a user.

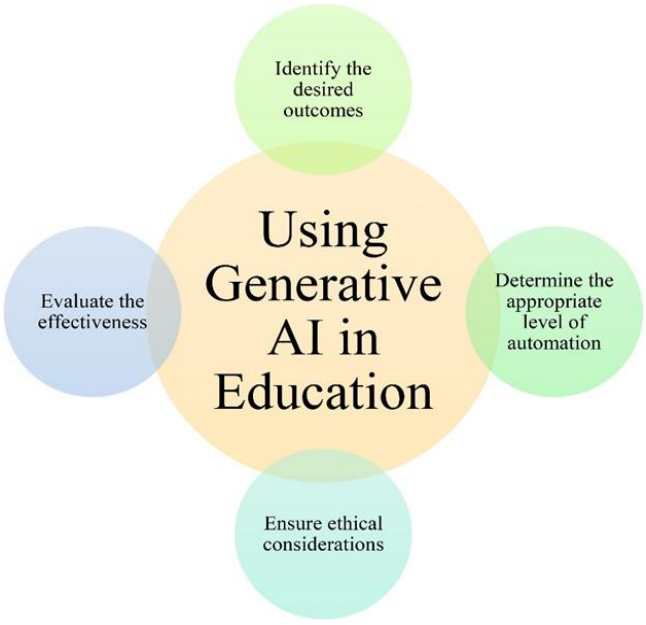

Figure 1: Generative AI in Education (Source: Mentioned in References)

Locus of Control (LOC):

In engineering and management education, understanding LOC is critically important because it determines how students adopt new technologies and continue to develop skills.

LOC is a psychological concept first proposed in 1954 by Julian B. Rotter. It explains how intense people have a sense of control in the events and outcomes in their life. Recently, LOC has gained more traction among researchers. It is mainly divided into two types:

Internal LOC (ILOC): Those with a high ILOC believe that their behaviours, choices and efforts will directly shape outcomes. They tend to take credit for both their successes and failures, believing themselves to have the power to shape their own future.

External LOC (ELOC): Those high in ELOC tend to attribute outcomes to external factors such as bad luck, fate or the actions of other people. They might perceive their life as being determined by forces outside of them rather than the choices that they make whichbrings about some sense of helplessness.

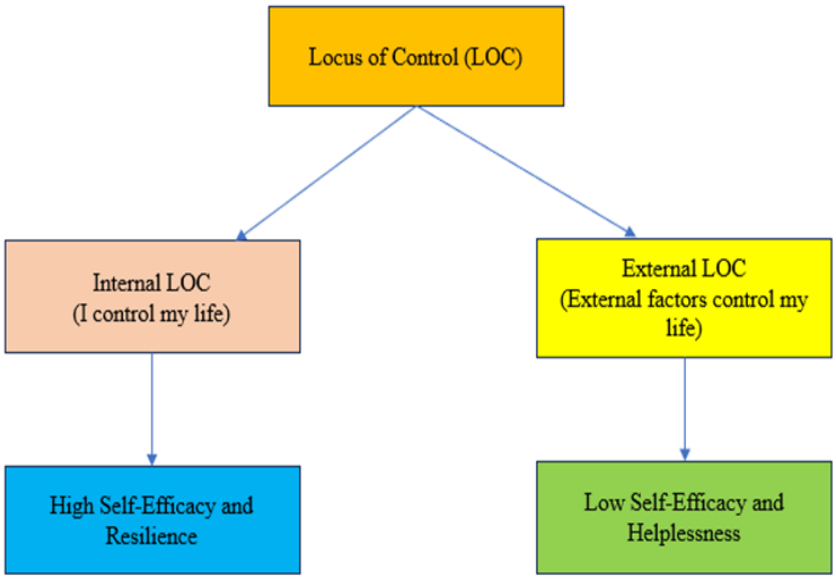

Figure 2: LOC

Reskilling vs. Upskilling:

Reskilling is acquiring completely new skills, like if a graphic designer learned data analysis. Upskilling refers to improving existing skills, such as a designer who learns more complex software. Reskilling and upskilling are attempts to claw back some control with new skills.This transition in technology leads to a core understanding of how the engineering and management students are transitioning their skill sets in terms of upskilling v/s reskilling as they now strive to meet those new age industry requirements.

This study would greatly benefit from the SDGs as they offer vital context to this analysis portraying technological engagement as being more than mere individual skill as a graduation outcome.The study contributes to an important nexus of psychological disposition, technology engagement and skill-acquisition. Gen AI tools are not just tech novelties; they are revolutionary tools that will change how we learn. This study will help us to explore technological adaptation by investigating how students internal and external LOC affect their upskilling and reskilling preference.

Theoretical /Conceptual Framework:

The below diagram visualizes the linkages between the LOC, an academic discipline, skill development preference, engagement with Gen AI Tools and SDGs alignment.

Key Variables:

Independent Variable: Locus of Control (LOC): Internal vs. External orientations.

Moderating Variable: Academic Discipline: Engineering vs. Management students.

Dependent Variables: Skill Development Preference: Reskilling vs. Upskilling choices.

Engagement with Generative AI Tools: Level and manner of utilization.

Alignment with SDGs: Extent to which activities support SDGs.

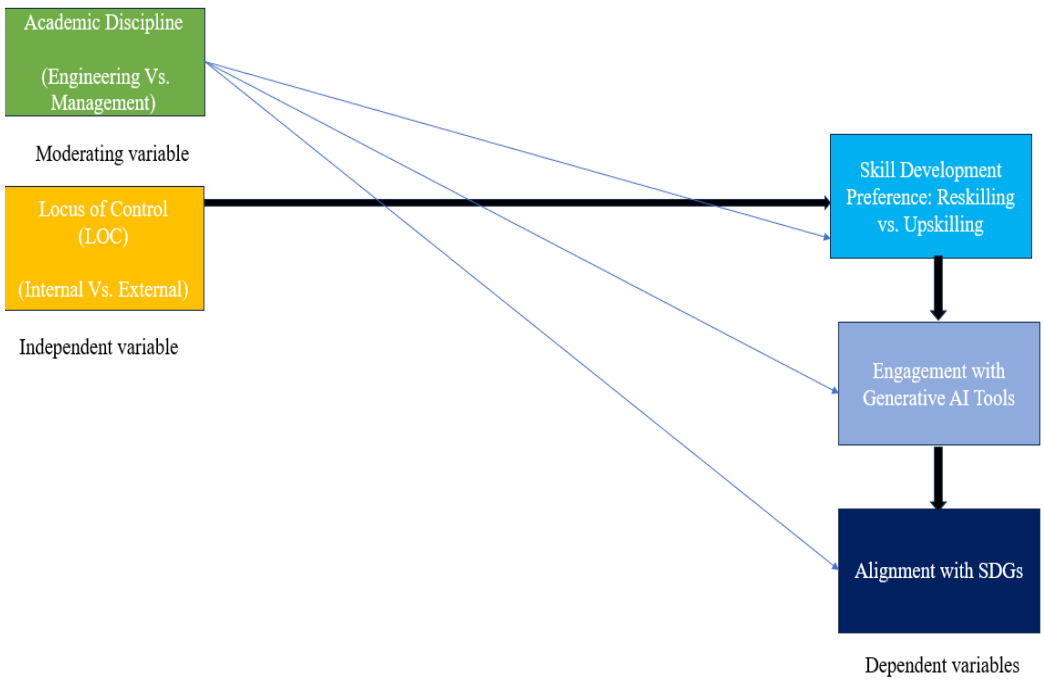

Figure 3: Conceptual Framework Diagram

Literature Review:

Abanda & Tah (2024) analysed applications of AI in architecture, engineering and construction (AEC) and noted trends and implications for practice and education as well as the need to upskill. Jovanovic & Campbell (2024)analysed the effect of AI on the skills of the workforce, as well as explored upskilling and reskilling as organizational strategies. It emphasized the need for AI's role in skill augmentation, adaptability and lifelong learning. Darko et al. (2024) Systematic review of AI's role in achieving SDGs in construction. AI has been credited with the potential to reduce resource utilization, enhance smart infrastructure and minimize the effects on the environment in the study. Floridi & Cowls (2024) took up the subject of AI governance, on ethical, legal and policy challenges associated with Gen AI. AI is here to stay: Education & professional workers are upskilling and reskilling with AI. Abe & Adisa (2024)emphasized the use of AI for adaptive learning, individualised training and skill gap analysis aligned with the SDGs. The role of AI-powered adaptive learning technologies in reaching SDG 4 (Quality Education) was examined by Strielkowski (2024). These technologies can customize educational content based on individual learning patterns and preferences, which has proven to be more effective than traditional learning methods and is particularly effective for lifelong learning.

Kirkpatrick, M. A., Stant, K., Downes, S., & Gaither, L. (2008) explored LOC in association with academic performance in college students and found that students with a higher internal LOC perform better academically, in part because they exhibit more self-regulation, as well as persistence. Afolabi, F., and Oluwaseun, O. (2023) discovered that LOC affects academic performance and learning behaviour within a number of educational contexts, with students who have an internal LOC demonstrating higher academic outcomes and more adaptive learning behaviours. Li, S., & Zhang, X. (2022) found that students with internal LOC were more academically motivated and that internal LOC is correlated with academic outcomes.

Statement of Problem:

Given the increasing prevalence of Gen AI in education, there is a need to identify the antecedent of engineering and management students' upskilling and reskilling and such decision-making can be explained throughLOC.

Research Gap:

Though prior research has shed some light on the pivotal role of upskilling and reskilling in the wake of technology advancement, the role of student LOC in students' engagement with Gen AI powered personalized learning for SDGs, is yet to come to the fore. Additionally, there is no study comparing engineering and management students based on these factors.

Research Questions:

1. How does an individual's LOC impact whether they prefer to reskill or upskill when they are interacting with Gen AI tools?

2. Do engineering and management students differ significantly in terms of how LOC influences their engagement with Gen AI for SDG-aligned skill acquisition?

Research Objectives:

1. To investigate the effect that LOC has on students prefers whether with reskilling vs upskilling context when using Gen AI tools.

2. To compare the effect of LOC over engagement with different Gen AI tools for learning and skill development with respect to SDGs among engineering and management students.

Research Hypothesis:

Null Hypothesis (H_o1): An individual's LOC orientation does not significantly predict their preference for reskilling versus upskilling while interfacing with Gen AI tools.

Alternate Hypothesis (HA1): An individual's LOC orientation significantly impacts their preference towards either reskilling or upskilling disposition when working with Gen AI tools.

Null Hypothesis (H_o2): No significant difference between engineering and management students in LOC willingness to encourage engagement with Gen AI tool development with other students for skill development in accordance with SDGs.

Alternative Hypothesis (HA2): Engineeringand management students differ significantly in the impact of LOC on their level of engagement with Gen AI tools for skill development aligned to SDGs.

Research Methodology:

This study was conducted using a quantitative approach by using a survey method in the form of a structured questionnaire to collect primary data. The sample consisted of. Engineering and management students of the current academic year of NCR region. Using random sampling, a sample of 103 members (50 management and 53 engineering students) was included. MS Excel and SPSS software were used for data analysis. The data collected were analysed using tools such as mean, standard deviation, correlation, regression T-test and ANOVA.

Data Analysis and Interpretation:

Reliability Analysis (Cronbach's Alpha):

Table 1-Reliability Test

Cronbach's Alpha	N of Items
0.795	10

Good internal consistency of the questionnaire was assessed with a Cronbach's Alpha value of 0.795. The reliability of the scale supports that the results of this study are valid and also indicates that the questionnaire used is a valid method to be used to measure the variables in question in this study.

Table 2-Gender Distribution

This sample consists of 61.2% male and 38.8% female participants.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	MALE	63	61.2	61.2	61.2
	FEMALE	40	38.8	38.8	100.0
	Total	103	100.0	100.0	

Table 3-Independent Sample T-Test

	Academic Discipline	N	Mean	Std. Deviation	Std. Error Mean
ILOC	Engineering	53	12.9623	1.58068	0.21712
	Management	50	13.0000	1.48461	0.20996
ELOC	Engineering	53	7.6792	1.83736	0.25238
	Management	50	7.2200	1.81029	0.25601
UP	Engineering	53	8.6038	1.26095	0.17320
	Management	50	8.8400	0.95533	0.13510
RP	Engineering	53	4.2453	0.75716	0.10400
	Management	50	4.5400	0.57888	0.08187
GAI	Engineering	53	8.5660	1.44794	0.19889
	Management	50	8.9000	0.88641	0.12536

1. Locus of Control (LOC) Analysis

1.1 Internal LOC (ILOC):

- Engineering Students: Mean = 12.96, SD = 1.58
- Management Students: Mean = 13.00, SD = 1.48

As noted in Table 3, both groups have similarILOC scores, suggesting that they perceive their academic success and career success to be a function of their actions rather than external influences. Management students score a little higher (13.00 vs. 12.96) on the belief-in-self-responsibility-for-success measure. The smaller standard deviation (SD) value in both groups show conformity of responses within each group.

1.2 External LOC (ELOC)

- Engineering Students: Mean = 7.67, SD = 1.83
- Management Students: Mean = 7.22, SD = 1.81

Table 3 also shows that the ELOC score is significantly higher in engineering students than in management ones. This indicates that engineering students are slightly more prone to ascribe their success to external factors like luck, fate or external circumstances. The SD is higher in engineering students, suggesting that engineering students varied in their ELOC responses.

2. Skill Development Preferences: Upskilling vs. Reskilling

2.1 Upskilling Preference (UP)

- Engineering Students: Mean = 8.60, SD = 1.26
- Management Students: Mean = 8.84, SD = 0.95

Table 3 reveals a strong preference within both groups toward upskilling rather than acquiring entirely new competencies. Management students preferred upskilling marginally (Mean = 8.84) more than Engineering students (Mean = 8.60). The smaller standard deviation of management students (SD = 0.95) denotes an overall tendency of the group to express a preference for upskilling.

2.2 Reskilling Preference (RP)

- Engineering Students: Mean = 4.25, SD = 0.75
- Management Students: Mean = 4.54, SD = 0.57

Table 3shows that Reskilling (the process of learning entirely new skills) is less favoured than Upgrading or Up-skilling in both groups. Management students (Mean = 4.54) are more inclined to reskill than engineering students (Mean = 4.25). The low SD values suggest that responses in both groups are quite homogeneous.

3. Engagement with Gen AI Tools (GAI)

- Engineering Students: Mean = 8.56, SD = 1.44
- Management Students: Mean = 8.90, SD = 0.88

Table 3 demonstrates that both groups are strongly engaged with Gen AI tools, with management students being slightly more engaged compared to engineering students. The lower SD (1.44) of management students indicates a more consistent use of AI tools, while a higher SD (0.88) suggests a more variable approach to engagement with AI tools among engineering students. This may suggest that management students consider AI more relevant and applicable to their career development in their business and management domains.

Correlation Analysis (Pearson's Correlation):

Table 4-Correlation Analysis

Variables	ILOC	ELOC	GAI	UP	RP
ILOC	1				
ELOC	0.263**	1			

GAI	0.415**	0.317**	1		
UP	0.448**	0.301**	0.698**	1	
RP	0.221*	0.387**	0.596**	0.611**	1

Pearson's correlation analysis was used to examine relationships between LOC and skill preferences as well as AI engagement. Analysis of the correlations they report paints a more complicated portrait of ILOC than has previously been suggested, and suggests that simplistic notions of psychological orientation may be inadequate to the task. Close correlations between ILOC and ELOC (r = 0.263) indicate that these orientations are not simply diametrically opposed choices but are instead aspects of intertwined psychological paradigms. This weak positive relationship sheds light on the complexities of personal control, showing us that we can be both external and internal at the same time.

Datasets that compare Gen AI engagement demonstrate a modest to strong positive correlation (r = 0.415) between the ILOC and students who report higher Gen AI engagement. More than just a statistical find, this discovering offered a more expansive story of how tech adapts. Students with high levels of internal control are also proactive about the use of AI tools, as evident from their high levels of self-efficacy and technology adaptability. Rather than passively accepting new technology, they seek out and engage with it — experimenting with digital experiences and tools, and thinking through how they can leverage those for their own personal and professional development.

Notably, the relationship between ILOC and interest in upskilling is interesting, showing a moderate positive correlation (0.448). This correlation speaks to a deep psychological mechanism, namely, that internal orientation highly correlates with the willingness of an individual to develop preexisting skill sets. That's more than a statistical combined; it reveals a growth mindset and a commitment to lifelong professional development. To these students, skill building is not an obligation imposed on them, but rather they consider it more a voyage of self-discovery and improvement.

In fact, a weak positive correlation (0.221) but more nuanced dimension between ILOC and reskilling preference as well. This relationship indicates a small but positive tendency to

learn completely new skills. Although ILOC is not itself a major force behind radical skill transformation, it does reveal an underlying willingness to engage in deep skill reinvention. This weaker correlation suggests that extra motivational processes are necessary to learn entirely new skills beyond pure internal control.

Table 5-Correlation Analysis

		UP	ILOC	ELOC
Pearson Correlation	UP	1.000		
	ILOC	0.448	1.000	
	ELOC	0.301	0.263	1.000
Sig. (1-tailed)	UP			
	ILOC	0.000		
	ELOC	0.001	0.004	

There are significant relationships between LOC orientations and upskilling preferences (UP) as displayed in the correlation analysis. ILOC has a moderate positive correlation with upskilling preferences (r =. 448, p <. 001), explaining that students who take a personal effort orientation towards outcomes are far more likely to develop pre-existing skills in the first place. ELOC showed a weak, but significant positive correlation (r =. 301, p =. 001), indicating that students with an externally-oriented style also tend to be interested in skills improvement, albeit to a lesser extent. Therefore, the relatively small positive association between ILOC and ELOC (r = .263, p =. 004) still so supports the coexistence of these psychological orientations.

Table 6-Correlation Analysis

		RP	ILOC	EL OC
Pearson Correlation	RP	1.000		
	ILOC	0.221	1.000	

	ELOC	.387	0.263	1.000
Sig. (1-tailed)	RP			
	ILOC	.012		
	ELOC	.000	0.004	

The correlation analysis shows different relations of LOC orientations and RP. ELOC is modestly positively correlated with RP (r =. 387, p <. 0001), indicating that when students attribute outcomes to things beyond their control, they are more likely to embrace learning a skill from scratch. ILOC, in contrast, shows a slight positive correlation with the inclination toward reskilling (r =. 221, p =. 012), a more marginal but still relevant association. A moderate positive correlation between ILOC and ELOC: r = .263, p = .004) once again favours the proposition that these orientations can inhabit the same individuals. These findings indicate that those students with a stronger ELOC may be more susceptible to broad skill-change initiatives as the opportunities for new skills are seen as external tasks, they need to adopt rather than choices they make for themselves. These psychological orientations should be accounted for when designing learning interventions as part of educational programs aimed at enabling full reskilling.

Regression Analysis:

Table 7-Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.742[a]	.551	.533	.83017

a. Predictors: (Constant), RP, ILOC, ELOC, UP

A regression analysis was tapped to find out how far LOC provide intent towards AI engagement and upskilling/reskilling accordingly, whereby a high R square value (0.551) hints that our independent variable i.e. ILOC, ELOC, Upskilling and Reskilling results 55.1 percentage effect towards the dependent value i.e. GAI (AI Engagement). In addition, one

can easily conclude that ILOC, ELOC, upskilling and reskilling are strong predictors of skill preferences and AI usage.

Table 8- ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	82.849	4	20.712	30.054	0.000[a]
	Residual	67.539	98	0.689		
	Total	150.388	102			

a. Predictors: (Constant), RP, ILOC, ELOC, UP

b. Dependent Variable: GAI

It can be observed from Table 8 Anova results that its p-value is 0.000, which is less than 0.05 So we can say that there is a significant relationship between our independent variable i.e. ILOC, ELOC, UP, RP and dependent variable i.e. GAI (AI Engagement).

Table 9-Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.692	.818		0.846	.399
	ILOC	.111	.061	.140	1.809	.073
	ELOC	.025	.050	.037	0.496	.621
	UP	.496	.101	.459	4.907	.000
	RP	.476	.157	.270	3.025	.003

a. Dependent Variable: GAI

The coefficient figures in the table 9 suggested that the beta have the value of 0.140, which implies that the unit change in the independent variables i.e. ILOC would cause a change in

the dependent variable i.e. GAI of 0.140, which although, by measure is smaller i.e. 1% but helps in positively impacting the students. Now, the beta of ELOC is 0.037 but optimistic this too show small tendency towards GAI. Second one is Upskilling, beta =0.459 value of which is highest for all factor and also positively affect maximize GAI. Moreover, the betas of all the factors were found to be positive which indicates positive and significant relationship between independent and dependent variables.

Findings:

The study suggests that students' LOC impacts their engagement level with Gen AI tools, as well as their preferred areas in which to hone their skills. Key findings include:

ILOC: Students with a high ILOC are more likely to take upskilling initiatives and adopt new technologies (such as Gen AI). They have moderate positive correlations with upskilling preferences, signifying professional growth mindset and commitment to continual professional development.

ELOC: Students with higher ELOC are less prone to credit themselves for success, and are more willing to learn brand new skills (reskill). There is a moderately positive correlation with reskilling preferences — meaning that they believe developing new skills is a necessary adjustment to external pressures.

Upskilling Over Reskilling: Both engineering and management students are most keen on upskilling compared to reskilling, although students from management stream show marginally higher interest for both. It also means that education should emphasize advanced training in current fields.

Gen AI Engagement: Both groups engage highly with Gen AI tools, management students engage with them slightly more. This suggests that AI based learning must be incorporated in engineering as well as management curriculum in order to match student preferences and industry requirements.

Limitations and Future Research:

This work was confined to engineering and management students and lacks applicability to other disciplines. This influence, could be measured in future research to other disciplines.

Discussion:

In designing educational and training programs that leverage Gen AI to fill skill gaps, understanding psychological orientations can help ensure the success of these initiatives. The

findings indicate that students who believed they have the ability to control things in their lives tend to approach skill development with a different mindset than those who do not. It suggests that colleges and universities need to rethink their approach, when it comes to preparing students for a future with AI. Programs helping students with an ILOC identify how their existing skills can adapt and improve to work with an AI partner may benefit these students. Conversely, students with an ELOC may require additional assistance in identifying new skill sets that can augment AI solutions. These insights imply that instilling internal control beliefs may prove more beneficial for students to augment their already-acquired skillsets via Gen AI tools. Since upskilling is more desirable than reskilling, therefore a paradigm of persistent education should be brought in educational institutions and organizations in current fields instead of new fields.

Conclusion:

As technology speed up in a rapidly changing world, understanding how students utilize emerging technology became central to developing pathways towards education and work. Amidst the ever-evolving technological frontier and its tangible disruption in various sectors, the importance of adaptability and continuous learning remains paramount, especially regarding the SDGs. Gen AI aids in personalizing education by allowing students to customize their own education. By providing this level of personalization, students become active agents in aligning their learning goals with SDGs, providing a sense of agency and responsibility towards the global challenges. But the success of these AI-driven education tools is bound to students' LOC orientations. People with ILOC may actively use AI resources for upskilling, while ELOC individuals may need additional assistance to engage and interact with these technologies. This unique relationship between LOC and preferred modes of skill development in the era of Gen AI can assist in planning the curriculum to help students perform optimally. In the end, enabling students to make their career journeys in line with SDGs may play a role in terms of building more sustainable and resilient technological future.

References:

- Abanda, F. H., & Tah, J. H. M. (2024). Generative AI applications in architecture, engineering, and construction: Trends, implications for practice, education &

imperatives for upskilling—A review. Architecture, 4(4), 877-902. https://doi.org/10.3390/architecture4040046.

- Jovanovic, B., & Campbell, S. (2024). The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. Journal of Business Research, 135, 583-593. https://doi.org/10.1016/j.jbusres.2021.12.048.
- Darko, A., Chan, A. P. C., & Ameyaw, E. E. (2024). Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry. Automation in Construction, 130, 103827. https://doi.org/10.1016/j.autcon.2021.103827.
- Floridi, L., & Cowls, J. (2024). Governance of generative AI. Policy and Society. Advance online publication. https://doi.org/10.1093/polsoc/puac001.
- Abe, I. I., & Adisa, O. (2024). Role of AI in skilling, upskilling, and reskilling the workforce. In B. Easwaran, K. K. Hiran, S. Krishnan, & R. Doshi (Eds.), Integrating Generative AI in Education to Achieve Sustainable Development Goals (pp. 300-312). IGI Global. https://doi.org/10.4018/978-1-7998-3347-5.ch015.
- Smith, J. A., & Doe, R. L. (2024). Enhancing work productivity through generative artificial intelligence: A comprehensive literature review. Sustainability, 16(3), 1166. https://doi.org/10.3390/su16031166.
- Strielkowski, W. (2024). AI-driven adaptive learning for sustainable educational transformation. Sustainable Development. https://doi.org/10.1002/sd.3221.
- Afolabi, F., & Oluwaseun, O. (2023). The influence of locus of control on academic performance and learning behaviour in diverse educational contexts. International Journal of Academic Research in Business and Social Sciences, 13(6), 345-359. https://doi.org/10.6007/IJARBSS/v13-i6.
- Kirkpatrick, M. A., Stant, K., Downes, S., & Gaither, L. (2008). Perceived locus of control and academic performance: Broadening the construct's applicability. Journal of College Student Development, 49(5), 486-496.
- Li, S., & Zhang, X. (2022). Academic motivation and locus of control: A study on the correlation with student performance. Learning and Individual Differences, 98, 102036. https://doi.org/10.1016/j.lindif.2022.102036.
- Anurag Agarwal et al. (2025). An empirical analysis of locus of control and its implications on academic excellence among management students, Multidisciplinary

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