From Deskilling to Reskilling: Understanding Student Adaptation to Generative AI In Higher Education

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***Abstract*—The widespread adoption of generative artificial intelligence (AI) technologies like ChatGPT prompts significant inquiries regarding their effects on skill acquisition and educational results in higher education. This study investigates the impact of augmentative vs substitutive AI utilization on skill adaption mechanisms—deskilling, upskilling, and reskilling—and how these mechanisms subsequently affect learning outcomes. The study utilized a quantitative, cross-sectional survey with 122 higher education students from various fields, applying descriptive statistics, correlation analysis, multiple regression, and moderation analysis. Research indicates that the use of augmentative AI substantially fosters upskilling and reskilling, hence improving analytical capabilities and flexibility, but substitutive use correlates with deskilling. Upskilling and reskilling positively correlate with learning performance, but deskilling negatively impacts it when accounting for other factors. Contextual variables (task complexity, time constraint) did not significantly influence these associations, demonstrating their resilience across learning settings. The paper provides a mechanism-based paradigm for comprehending AI-mediated learning and presents consequences for educators, institutions, and politicians aiming for responsible AI integration.**

***Index Terms*—Deskilling, Generative AI, Higher Education, Learning outcomes, Reskilling, Skill Adaptation, Upskilling.**

I. INTRODUCTION

The rapidly evolving advancement in generative artificial intelligence (AI)—notably big language models like ChatGPT—has profoundly transformed teaching methodologies in higher education. Students are progressively using these tools for writing assistance, concept elucidation, idea creation, and problem-solving, establishing generative AI as a significant entity in modern educational settings. Although these advancements present potential to improve learning efficiency and accessibility, they have also ignited discussions about their effects on students' skill acquisition and long-term educational results.

The current study offers diverse viewpoints. Generative AI is seen both as a formidable support mechanism for personalizing learning and enhancing information acquisition, and as a possible menace to academic integrity, cognitive engagement, and vital competencies such as critical thinking and autonomous problem-solving. The divergent perspectives indicate that the educational influence of AI cannot be comprehended just via the analysis of usage frequency; it is important to consider the manner in which students engage with these tools during their learning experiences.

A developing corpus of literature differentiates between augmentative and substitutive types of AI utilization. Augmentative use pertains to AI that supports cognitive processes while the student is actively involved; substitutive use transpires when AI supplants learner effort by immediately providing answers, hence diminishing prospects for skill development. The notions of deskilling—diminution of skills due to less practice—upskilling, and reskilling are associated with these patterns. Despite an increase in theoretical discourse, empirical investigations concurrently analysing all three processes within a cohesive higher education framework are still a few.

This study investigates how generative AI deployment patterns affect skill adaptation and, hence, affect learning outcomes in higher education students. The paper presents a mechanism-based paradigm for comprehending AI-mediated learning by explicitly modelling deskilling, upskilling, and reskilling, so establishing a basis for evidence-based instructional and policy decisions.

II. LITERATURE REVIEW

Generative AI in Higher Education: Generative AI systems that can generate human-like prose and provide real-time feedback have emerged as appealing academic assistance tools [9]. Students are progressively dependent on ChatGPT for writing aid, conceptual elucidation, research help, and issue resolution [13]. Initial study prioritized efficiency and convenience, however contemporary studies underscore issues related to academic integrity, excessive dependence, and diminished cognitive engagement [3]. Academics increasingly contend that the educational implications of generative AI should be assessed not just by its frequency of use but by the manner in which it is incorporated into learning methodologies.

Augmentative and Substitutive AI Use: Research differentiates between augmentative (complementary) and substitutive ways of artificial intelligence utilization. Augmentative usage aids learners by improving comprehension and providing cognitive scaffolding, while substitutive use diminishes learner engagement by minimizing student participation [2]. This contrast corresponds with overarching educational technology theories indicating that learning results are contingent upon whether technology enhances or detracts from cognitive engagement. AI-based technologies are more effective in enhancing learning when utilized as cognitive supports rather than as automated solution providers [6].

Deskilling, Upskilling, and Reskilling: Deskilling, upskilling, and reskilling delineate the impact of AI engagement on learners' skill profiles. Deskilling denotes the deterioration of current abilities resulting from cognitive dumping; upskilling signifies the augmentation of existing competences; reskilling pertains to the acquisition of new skills necessary for adaptation to changing demands [6]. Excessive dependence on AI may diminish critical thinking and autonomous reasoning [8] whereas introspective interaction with AI might enhance analytical and metacognitive abilities [15]. Effective engagement with AI necessitates new competencies—prompt formulation, output evaluation, and critical judgment—indicating a need for reskilling rather than skill degradation [13].

Skill Adaptation and Learning Outcomes: Meta-analytic data demonstrate that ChatGPT enhances learning outcomes when instructional guidance promotes meaningful engagement [10]. Nevertheless, these investigations frequently fail to elucidate the reasons behind the enhancement or decline of results. Contemporary researchers contend that skill adaptation procedures function as essential mediation mechanisms connecting AI utilization to learning outcomes [3]. Results enhance when learners acquire new abilities via AI-assisted practices, and deteriorate when AI replaces effort.

Contextual Factors: Task complexities, time pressures, and task type have been suggested as possible moderators of technology-enhanced learning. AI tools may prove more effective for intricate analytical tasks when utilized under structured instructional circumstances [2]; however, some academics contend that learners establish consistent patterns of AI interaction that endure across various contexts, thereby reducing the impact of task-specific conditions [7]. The empirical data on this moderating role is unclear.

Research Gap and Study Contribution: Despite the increasing interest in generative AI, there is a paucity of research distinguishing between augmentative and substitutive usage patterns, and integrated models that concurrently analyse deskilling, upskilling, and reskilling are notably rare. Previous studies have concentrated on direct learning outcomes, neglecting the methods via which AI utilization affects performance. This paper presents and experimentally evaluates a complete framework that connects generative AI usage patterns to skill adaption mechanisms and learning outcomes in higher education, therefore enhancing the mechanism-driven knowledge of AI-mediated learning.

III. CONCEPTUAL FRAMEWORK AND HYPOTHESES

Building on previous research and established theories of deskilling [4], upskilling, and reskilling [14], the study presents a conceptual framework (Figure 1) that connects generative AI usage patterns—augmentative and substitutive—to three mechanisms of skill adaptation, which subsequently affect learning outcomes. Contextual task factors, including job complexity, deadlines, and task type, are included as possible moderators.

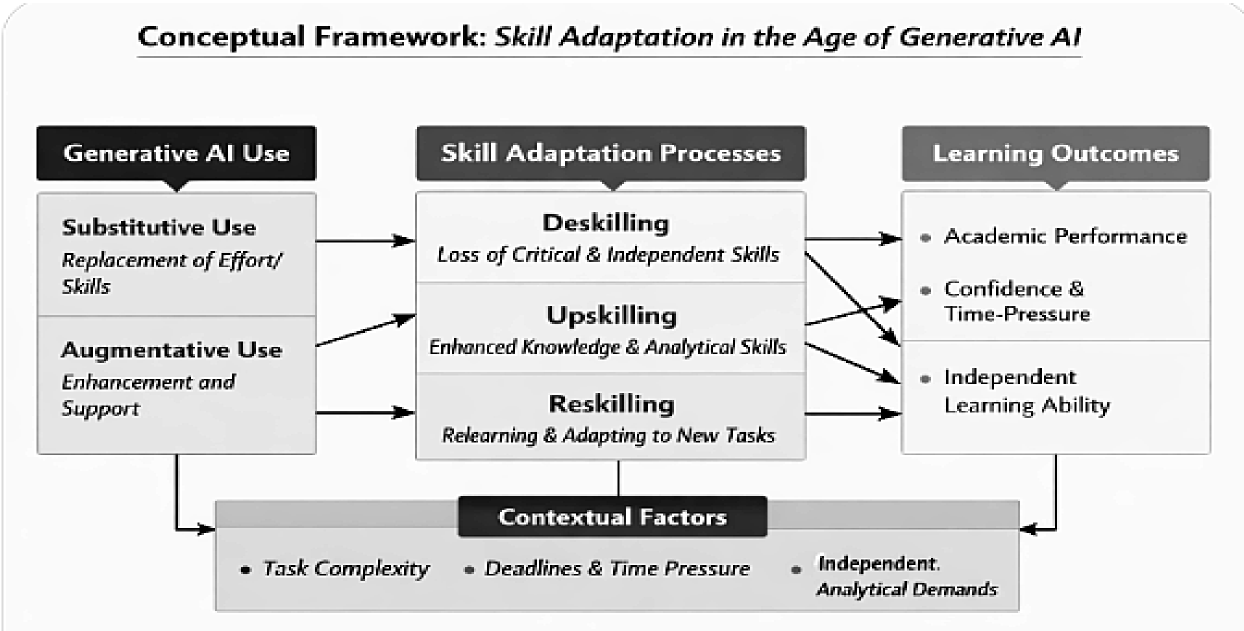

Figure I. Conceptual framework: Skill adaptation in the age of generative AI. Contextual factors moderate the relationships between AI use patterns and skill adaptation outcomes.

HYPOTHESES

H1: Generative AI use significantly influences skill adaptation, with augmentative use leading to upskilling and reskilling, and substitutive use contributing to deskilling.
H1a: Augmentative AI use positively predicts upskilling.
H1b: Substitutive AI use positively predicts deskilling.

H2: Increased reliance on ChatGPT is associated with reduced confidence in independent problem-solving and critical thinking.

H3: Frequent augmentative use of ChatGPT for analytical tasks enhances students' ability to structure arguments and analyse topics.

H4: Students who use ChatGPT to revisit or relearn academic concepts demonstrate higher adaptability to new learning tasks.

H5: Task complexity, time pressure, and task type moderate the relationship between generative AI use and skill adaptation.

H6: Upskilling and reskilling through ChatGPT use are associated with improved learning performance and confidence

IV. METHODOLOGY

Research Design and Sample

A quantitative, cross-sectional survey approach was utilized to investigate students' attitudes and usage habits of generative AI at a certain moment. The target market consisted of higher education students enrolled in undergraduate, postgraduate, and doctorate programs across several academic areas. A non-probability convenience sampling method produced 122 valid replies following data screening. The sample included students across age groups (18–21: 17.2%; 21–25: 54.9%; 25–30: 18.9%; above 30: 9.0%), gender (male: 61.5%; female: 38.5%), education level (undergraduate: 27.9%; postgraduate: 59.8%; doctoral: 12.3%), and discipline (commerce: 55.7%; arts: 15.6%; science: 15.6%; engineering: 9.0%; others: 4.1%). Participation was voluntary and anonymity was assured.

Instrument and Measures:
A structured questionnaire utilizing Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) assessed four construct categories: (1) AI Dependence Patterns—substitutive and augmentative usage; (2) Skill Adaptation Mechanisms—deskilling, upskilling, and reskilling; (3) Learning Performance Outcomes—confidence, academic grades, and independent learning capability; and (4) Contextual Factors—task characteristics, deadlines, and the balance between creativity and analytical demands. Items were designed based on available literature and corresponded with accepted conceptual meanings. All constructs exhibited adequate internal consistency (Cronbach's $\alpha > 0.70$), so affirming the trustworthiness of the instrument. Data were analysed using SPSS via a sequential methodology: (1) screening for missing values, normality, and multicollinearity; (2) descriptive statistics; (3) Pearson correlation analysis; (4) multiple regression analysis to examine the direct effects of AI utilization on skill adaptation (H1a–H4) and the impact of skill adaptation on learning performance (H6); and (5) interaction-based moderation regression employing mean-centered predictors to evaluate H5. Regression analysis was used over structural equation modelling due to the sample size (N = 122) and the focus on predictive and moderating connections among observable variables.

V.RESULTS

Reliability and Descriptive Statistics
All constructs demonstrated acceptable reliability (α: Substitutive Use = 0.79; Augmentative Use = 0.83; Deskilling = 0.76; Upskilling = 0.81; Reskilling = 0.78; Contextual Factors = 0.74; Learning Performance = 0.86). Descriptive statistics (Table 1) showed that students reported high augmentative use relative to moderate substitutive use. Upskilling and reskilling were higher than deskilling, suggesting that students perceive more positive than negative skill adaptation.

Table I: Descriptive Statistics

Construct	Mean	SD
Substitutive AI Use	2.86	0.93
Augmentative AI Use	3.79	0.84
Deskilling	3.02	0.90
Upskilling	3.73	0.87
Reskilling	3.61	0.91
Contextual Factors	3.60	0.87
Learning Performance	3.42	0.95

Correlation Analysis
Pearson correlations (Table 2) revealed that substitutive AI use was positively associated with deskilling (r = 0.54), while augmentative use was positively associated with upskilling (r = 0.61) and reskilling (r = 0.67). Learning outcomes showed strong positive correlations with upskilling (r = 0.51) and reskilling (r = 0.74), and a moderate positive correlation with deskilling (r = 0.35) at the bivariate level—a pattern explained further in Section 5.3.

Table II: Correlation Matrix

Variable	1	2	3	4	5	6
1. Substitutive Use	1					
2. Augmentative Use	0.46	1				
3. Deskilling	0.54	0.32	1			
4. Upskilling	0.42	0.61	0.29	1		
5. Reskilling	0.42	0.67	0.31	0.72	1	
6. Learning Outcomes	0.50	0.61	0.35	0.51	0.74	1

Note. Bold values $p < 0.05$; all correlations significant at $p < 0.01$ unless otherwise noted.

Regression Analysis: AI Use and Skill Adaptation (H1a–H4):
Multiple regression analyses with deskilling, upskilling, and reskilling as dependent variables (Table 3) showed that substitutive AI use significantly predicted deskilling ($\beta = 0.43$, $p < 0.001$, $R^2 = 0.34$), while augmentative AI use strongly predicted both upskilling ($\beta = 0.72$, $p < 0.001$, $R^2 = 0.56$) and reskilling ($\beta = 0.76$, $p < 0.001$, $R^2 = 0.49$). These

findings support H1a, H1b, H2, H3, and H4, confirming that the educational impact of generative AI depends on how it is integrated into learning processes rather than usage frequency alone.

Table III: Regression Results — AI Use Predicting Skill Adaptation

Predictor	Deskilling (β)	Upskilling (β)	Reskilling (β)
Substitutive AI Use	0.43***	—	—
Augmentative AI Use	—	0.72***	0.76***
R^2	0.34	0.56	0.49
Adjusted R^2	0.32	0.55	0.49
F-value	20.22***	50.39***	116.10***

*Note. Standardised beta coefficients; *** $p < 0.001$; — = not included in model.*

Regression Analysis: Skill Adaptation and Learning Performance (H6)

A multiple regression analysis indicated that reskilling ($\beta = 0.52$, $p < 0.001$) and upskilling ($\beta = 0.41$, $p < 0.001$) considerably improved learning performance, with $R^2 = 0.63$ (Table 4). The use of substitutive AI, acting as a proxy for deskilling, was inversely correlated with performance ($\beta = -0.18$, $p = 0.016$), suggesting that patterns of usage that replace cognitive effort detrimentally affect academic results. These findings validate H6 and illustrate that positive skill adaptation is the principal mechanism by which AI utilization leads to learning improvements. The moderate positive bivariate correlation between deskilling and learning outcomes ($r = 0.35$) indicates a simultaneous occurrence of short-term performance improvements (e.g., quicker task completion) alongside a decline in skills; multivariate regression elucidates that the net effect of deskilling on outcomes is negative when upskilling and reskilling are accounted for.

Table IV: Regression Results — Skill Adaptation Predicting Learning Performance

Predictor	β	t-value	p-value
Upskilling	0.41	5.87	0.000
Reskilling	0.52	7.14	0.000
Substitutive AI Use (Deskilling proxy)	−0.18	−2.45	0.016
$R^2 = 0.63$; Adjusted $R^2 = 0.61$; $F = 66.42$, $p < 0.001$			

Note. Standardised beta coefficients reported.

Moderation Analysis: Contextual Factors (H5)

While both AI use ($\beta = 0.43$, $p < 0.001$) and contextual factors ($\beta = 0.32$, $p = 0.004$) had significant main effects, moderation analysis using interaction-based regression revealed no significant interaction effect between AI use and contextual factors on skill adaptation ($\beta = 0.08$, $t = 0.94$, $p = 0.348$; $R^2 = 0.34$). As a result, H5 was not supported. This implies that the main factors influencing skill adaption results are AI usage patterns rather than situational task variables.

Hypothesis Testing Summary:

Table V: Hypothesis Testing Summary

H	Statement	Key Result	Decision
H1a	Augmentative use → Upskilling	$\beta = 0.72$, $p < 0.001$	Supported
H1b	Substitutive use → Deskilling	$\beta = 0.43$, $p < 0.001$	Supported
H2	Reliance on ChatGPT reduces independent problem-solving confidence	Substitutive use predicts deskilling	Supported
H3	Augmentative use enhances analytical/structuring abilities	$\beta = 0.72$, $p < 0.001$	Supported
H4	Using ChatGPT to relearn concepts improves adaptability	$\beta = 0.76$, $p < 0.001$	Supported

H5	Contextual factors moderate AI use → skill adaptation	Interaction $p = 0.348$	Not Supported
H6	Upskilling and reskilling improve learning performance	$R^2 = 0.63$, $p < 0.001$	Supported

VI. DISCUSSION

The results offer strong proof that generative AI's impact on educational attainment varies and is heavily reliant on usage patterns. Augmentative AI use exhibited strong positive effects on upskilling ($\beta = 0.72$) and reskilling ($\beta = 0.76$), confirming that when students use ChatGPT as a supportive learning tool—for concept clarification, feedback, or idea refinement—they develop stronger analytical thinking and adaptability. These results align with augmentation-oriented models of AI-enhanced learning emphasising AI's role in extending cognitive capacity rather than replacing it [2], and with evidence that positive outcomes arise when pedagogical guidance encourages active engagement [13; 10]. The strong reskilling effects further suggest that effective AI interaction itself demands new competencies—prompt formulation, evaluation of outputs, metacognitive regulation—thereby expanding rather than eroding skill repertoires [13; 6].

In contrast, the employment of substitutive AI strongly predicted deskilling ($\beta = 0.43$), as students indicated diminished confidence in autonomous problem-solving and critical thinking. This reflects prevalent apprehensions regarding cognitive offloading and excessive dependence on automation [8;9] and corresponds with the 'levelling effect' recognized by Brynjolfsson [5], in which AI assists users in generating satisfactory results while potentially diminishing profound expertise over time. The findings emphasise that deskilling is not an unavoidable result of AI utilization, but rather arises from specific use behaviours that undermine significant cognitive involvement [2].

The study illustrates that skill adaptation mechanisms are the primary pathway connecting AI use to learning performance, in addition to divergent skill outcomes ($R^2 = 0.63$). Performance was substantially improved by both upskilling and reskilling, while substitutive use had a detrimental impact on outcomes after accounting for other mechanisms. This mechanism-focused explanation expands upon previous research that evaluated the direct performance impact of AI [10] by elucidating the mechanisms by which those outcomes are generated. This response to the call for more process-oriented approaches in AI-in-education research and the transition from binary narratives of benefit versus harm [3] is warranted.

Contextual factors did not moderate the AI use–skill adaptation relationship, as anticipated. This non-significant moderation implies that students establish habituated AI engagement patterns that endure across task contexts, rendering utilization orientation the primary determinant of skill outcomes. This lack of moderation does not diminish the study's contribution; rather, it emphasizes the robustness of the main effects and emphasizes learner agency and AI literacy as critical factors in AI-mediated learning [6;9]. In general, the results challenge deterministic assumptions regarding the educational influence of AI and establish skill adaptation as a critical explanatory mechanism.

VII. IMPLICATIONS

Theoretical Implications

The literature on technology-enhanced learning is furthered by this study, which introduces skill adaptation—deskilling, upskilling, and reskilling—as a fundamental explanatory mechanism for the impact of AI on educational outcomes. The findings endorse a usage-contingent perspective, which posits that learning outcomes are contingent upon the cognitive integration of technologies rather than solely on the characteristics of contextual tasks. The study provides a more comprehensive and mechanism-driven model than previous direct-effects approaches by empirically distinguishing between the three skill adaptation processes and linking them to outcomes [3; 10].

Practical Implications

Rather than limiting generative AI, educators ought to advocate for its augmentative application—directing students to utilize AI for elucidation, feedback, and skill development instead of just work replacement. Tasks necessitating autonomous reasoning in conjunction with AI assistance, as well as reflective activities wherein students evaluate AI-generated outputs, can maintain critical thinking while utilizing AI's potential. Incorporating AI literacy modules into curricula—focused on quick formulation, output assessment, and responsible usage—would facilitate students in establishing reskilling routes while preserving cognitive autonomy.

Policy Implications

Higher education institutions ought to transcend restrictive AI regulations and implement guided-use frameworks that differentiate between permissible augmentative usage and detrimental substitutive use. Institutional norms must be supplemented by faculty development programs to assist educators in identifying deskilling and formulating suitable remedies. Policymakers at the national level should contemplate integrating AI competence development into higher education initiatives to guarantee that graduates acquire adaptable abilities for AI-enhanced studying and employment settings.

VIII. LIMITATIONS AND FUTURE RESEARCH

This research possesses many limitations. Initially, it depends on self-reported survey data gathered at a singular moment, constraining causal inference and rendering it vulnerable to response bias. Secondly, convenience selecting from certain fields and institutions may limit generalizability. Third, skill adaptation constructs assessed by Likert scales may fail to encapsulate the whole intricacy of these processes. The study concentrated on ChatGPT, and the results may not be entirely applicable to other generative AI systems.

Future research should employ longitudinal designs to analyse the evolution of skill adaptation over semesters and investigate whether deskilling effects are transient or enduring. Cross-cultural comparative research would elucidate how institutional circumstances and cultural norms influence patterns of dependence on AI. Utilising mixed-methods approaches that integrate surveys with interviews or classroom observations would yield deeper insights into students' real experiences. Utilising structural equation modelling with bigger samples would provide a more thorough examination of the suggested framework, encompassing mediation pathways. Experimental treatments, like AI literacy modules and reflective assignment designs, would facilitate the identification of techniques to optimise upskilling and reskilling while minimizing deskilling. Future study should expand beyond academic achievement to investigate the impact of AI-driven skill adaptation in higher education on employability and workplace preparation.

IX. CONCLUSION

This study investigated the impact of generative AI use on skill adaptation and learning outcomes in higher education students. The findings reveal a split impact dependent on usage patterns: augmentative AI usage considerably fosters upskilling and reskilling, hence improving academic performance and confidence, but substitutive use leads to deskilling and adversely affects outcomes. Skill adaptation mechanisms identified as the essential pathways connecting AI utilization to learning performance, although contextual task factors did not significantly alter these associations. Generative AI is not intrinsically advantageous or detrimental; its educational efficacy is determined by whether students utilize it to augment or supplant cognitive involvement. This research positions skill adaptation as a fundamental process, offering a sophisticated, evidence-based comprehension of AI-mediated learning in higher education and establishing a basis for informed pedagogical practices and policy decisions in an increasingly AI-integrated educational environment.

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