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The Impact of Generative AI on Intrinsic Learning Motivation and Perceived Learning Outcomes

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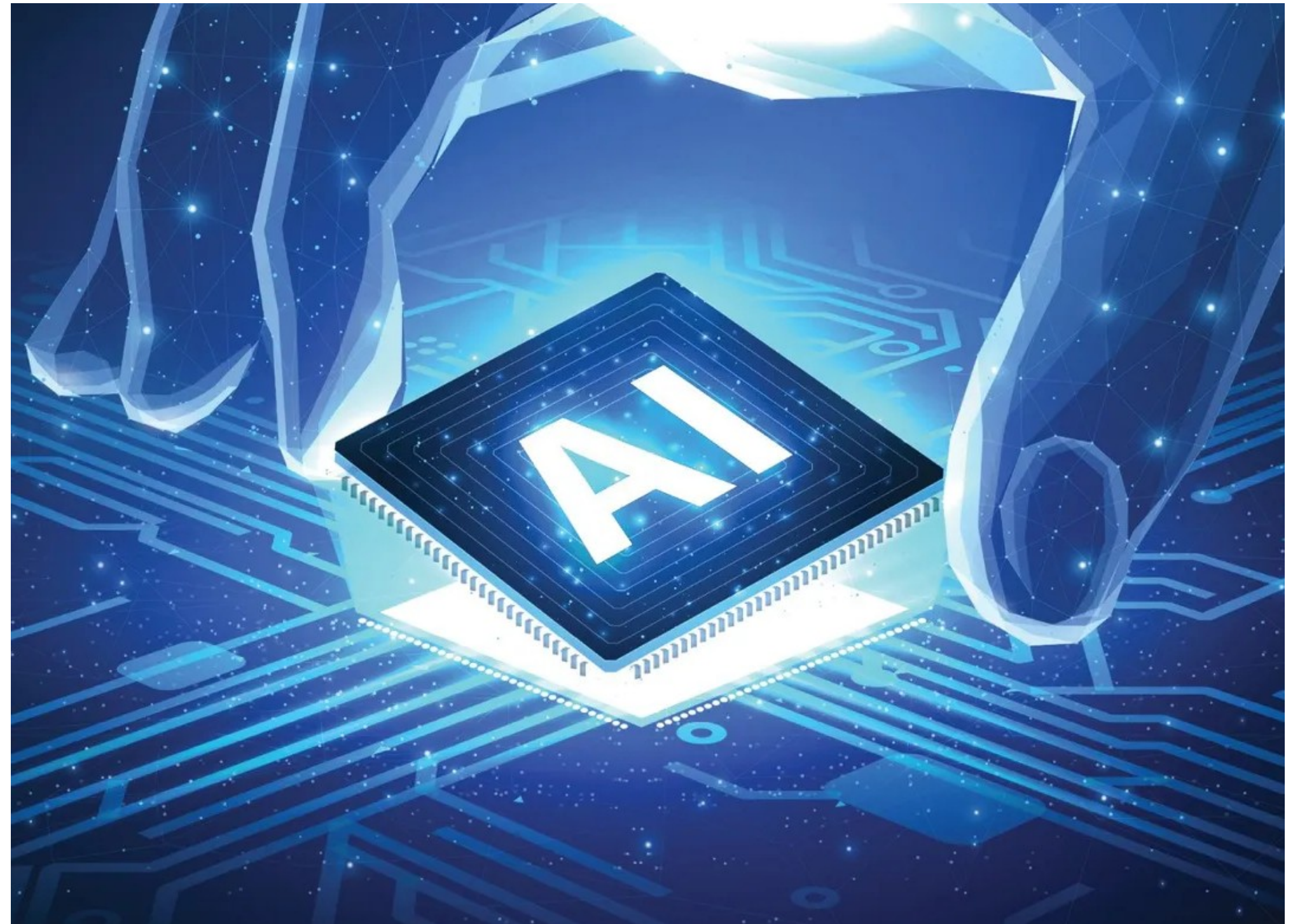
[National Economics University] · [Vietnam]

Paper [30] · Track [1] · Room [A] · [15:35 – 16:00], 28 August 2026



Overview

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- 2 Theoretical background and hypothesis
- 3 Methodology
- 4 Results
- 5 Discussion
- 6 Conclusion



01

Introduction

More capable GenAI always improve learning outcomes?

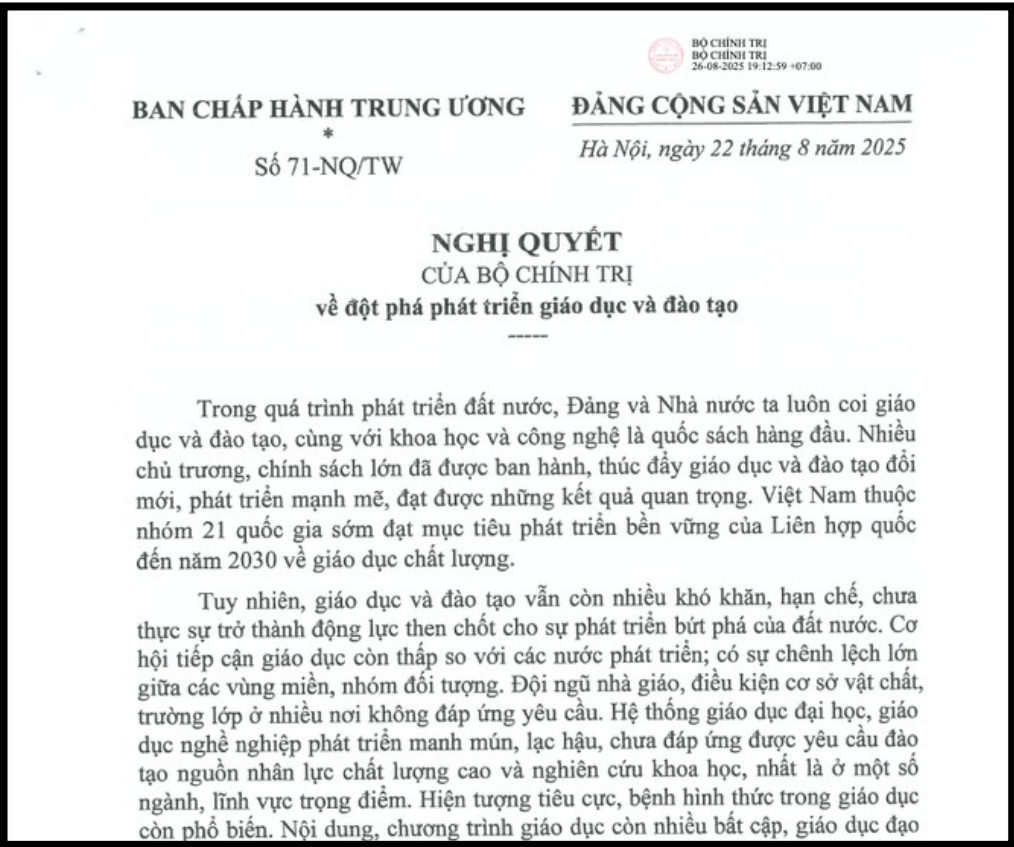
~16.3% of global population uses GenAI for learning and work (Microsoft, 2025)

GenAI is becoming increasingly capable: summarizing, writing code, and solving problems within seconds (S. Panke, 2025)

This trend is increasingly in **Vietnam's higher education digital transformation, demands technical proficiency for workforce competitiveness** (Resolution No. 71-NQ/TW, 2025)

While **GenAI can do more** for students, **goals of education** are still **developed learners' actual own knowledge, skills, attitudes, and ability to learn independently**

Does a more capable GenAI always help students develop better? Or could it, in some cases, reduce their motivation and learning outcomes?



What has been tried, and the gap

Benefits

↑ **Money, time, and cognitive effort**
(M. Hmoud et al., 2024)

↑ **Self-efficiency**
(N. N. Ye, 2025)
(Y.-J. Chen et al., 2025)

Drawbacks

↑ **Learning motivation, critical thinking, and social interaction**
(S. Wu et al., 2025)

Higher academic scores

≠

Actual knowledge application

(Y. Fan et al., 2024)

Positive learning experience

≠

Academic growth

(L. Fan et al., 2025)

Two Main Approaches:

Approach 1: Inheriting **TAM** to examine **Perceived Ease of Use, Perceived Usefulness & attitudes, behavioral intentions to use GenAI**

(N. T. T. Thúy et al., 2024), (N. T. P. Anh and T. N. Ghi, 2025)

Approach 2: GenAI's effects on the **learning process: motivation, engagement, higher-order thinking, self-efficiency and academic performance**

(R. Yilmaz and F. G. K. Yilmaz, 2023)

Previous works: GenAI → one general technology

Learner's experience → different characteristics of the technology



Shift in perspective: unified technology → multi-dimensional learning experience



Lacks an integrated framework examines & connecting these characteristics to learning outcomes via intrinsic motivation

Research questions:

RQ1

How do the different multidimensional characteristics of GenAI (PU, PEOU, PC, PA, PP) relate to students' intrinsic learning motivation?

RQ2

Does intrinsic learning motivation serve as a mediating mechanism linking the GenAI experience with perceived learning outcomes?

RQ3

Do these relationships change depending on the learner's GenAI proficiency?

02

Theoretical background & Hypothesis

Integrating **TAM factors** with **three representative characteristics of GenAI** :

Perceived Usefulness (PU)

Perceived Creativity (PC)

Perceived Accuracy (PA)

Perceived Ease of Use (PEOU)

Perceived Personalisation (PP)

Perceived Learning Outcomes: students' **own evaluation** of the knowledge, skills, and attitudes

Our study mainly draws on two theories:

Self-Determination Theory (SDT): Intrinsic motivation is supported when three needs are satisfied: autonomy, competence, and relatedness

Expectancy-Value Theory (EVT): Stronger motivation encourages students to invest more effort and remain engaged in learning

GenAI Proficiency: learners' **ability** to **critically evaluate, communicate, collaborate, and effectively work with GenAI**

Research model

Base on SDT, 5 GenAI characteristics are associated with ILM by supporting learners' psychological needs:

- **PU & PA:** Strengthen **competence**
- **PEOU:** Support **competence** and **autonomy**
- **PC:** Enhance **autonomy** and **competence**
- **PP:** Support **autonomy** and **relatedness**.

Based on EVT: ILM is expected to positively relate to PLO

GP is a moderator that may change how these characteristics relate to ILM

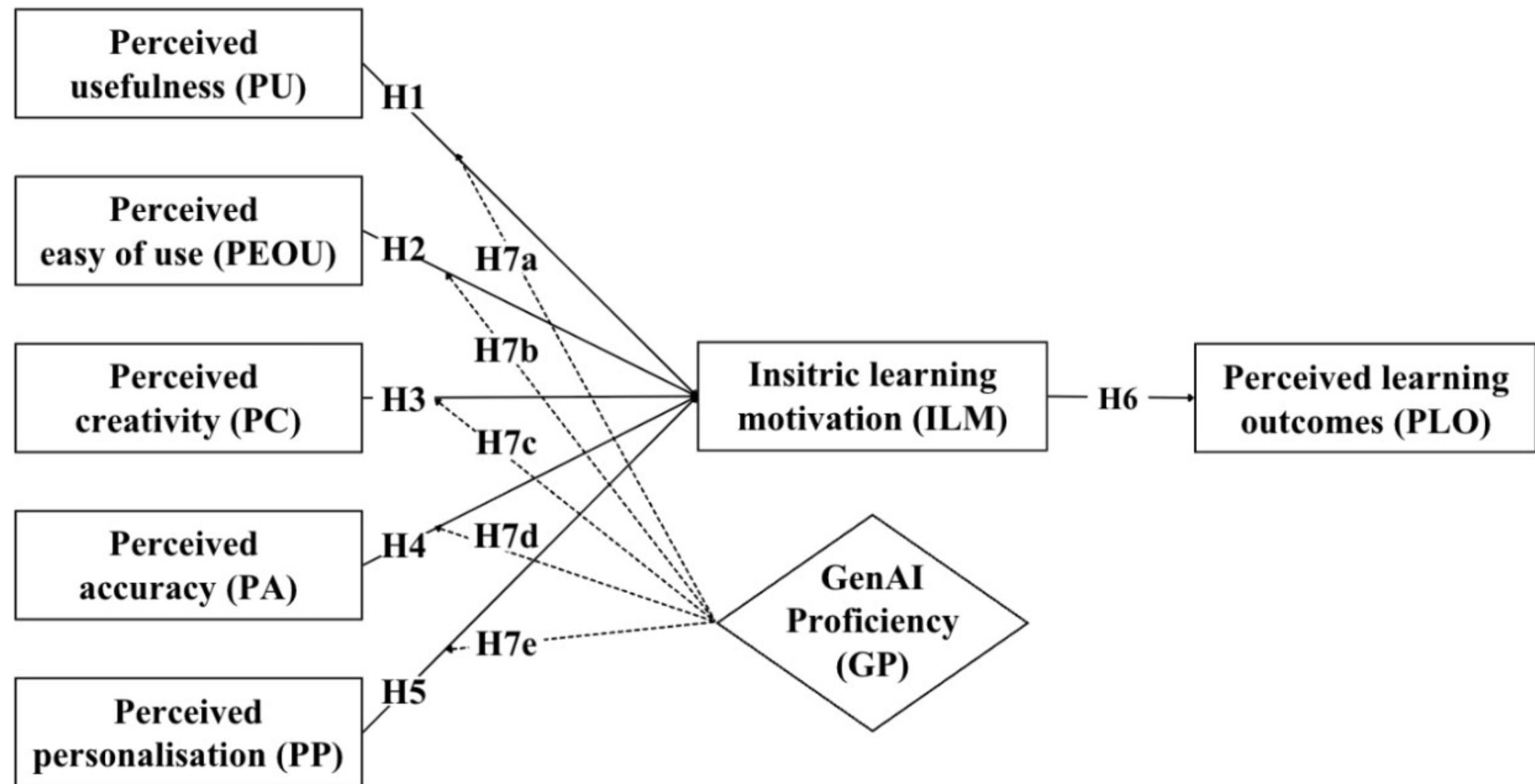


Fig. 1. Proposed Research Model

H1: PU is associated with ILM

H2: PEOU is associated with ILM

H3: PC is associated with ILM

H4: PA is associated with ILM

H5: PP is associated with ILM

H6: ILM is associated with PLO

H7a: GP moderates the impact of PU on ILM

H7b: GP moderates the impact of PEOU on ILM

H7c: GP moderates the impact of PC on ILM

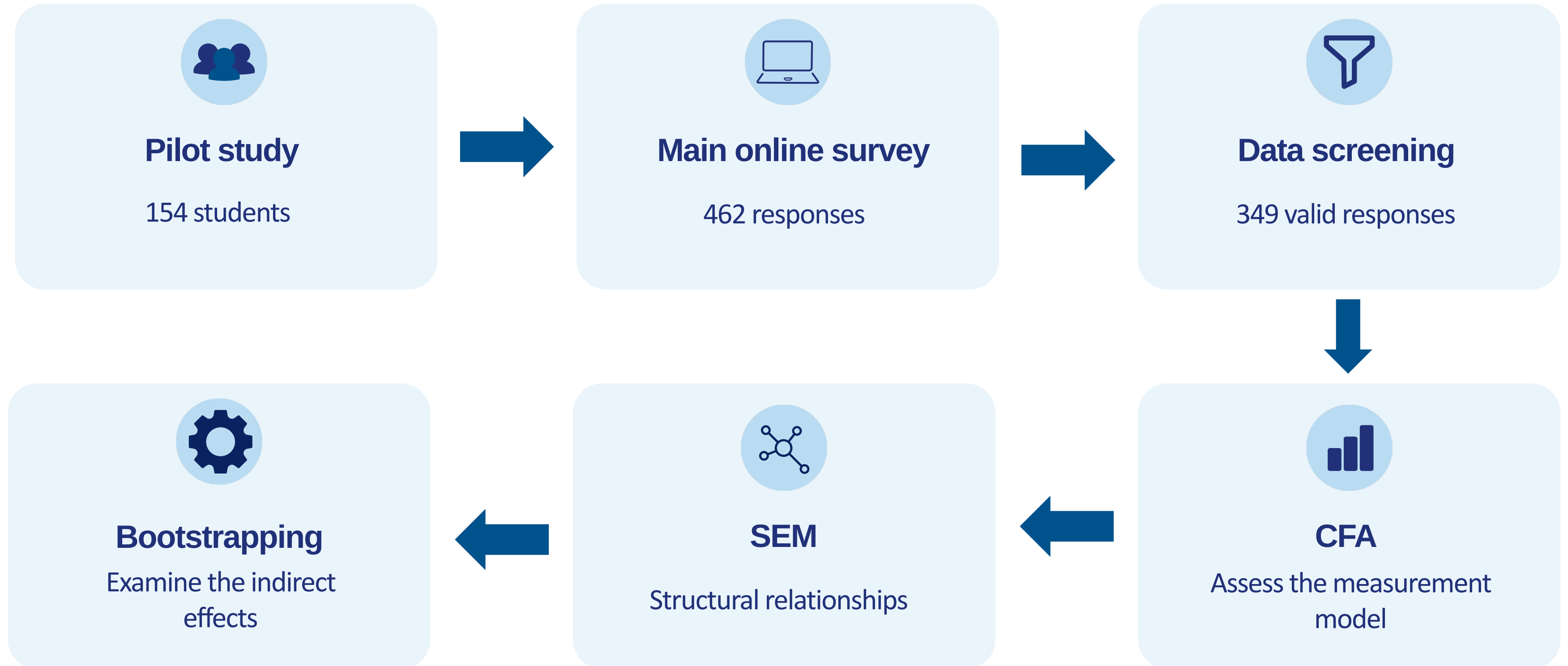
H7d: GP moderates the impact of PA on ILM

H7e: GP moderates the impact of PP on ILM

03

Methodology

Research design

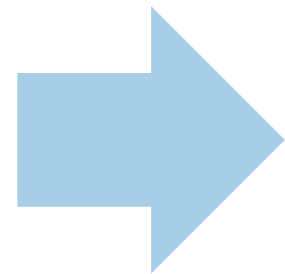


Study method, participants, measures & analytical tools

1

Stage 1: Pilot Study

Pilot Study (n = 154): Conducted with students who had used at least one GenAI tool for learning purposes
→ To test question clarity, scale suitability, and initial reliability



2

Stage 2: Formal Study

Formal Study (n = 462): Online survey distributed across social media, digital learning communities, academic groups, and university-issued student emails in Vietnam. Conducted over three weeks. Yielded **349/ 462 valid responses**

PARTICIPANT

Primarily Gen Z students from higher education institutions in Vietnam, gender fairly balanced & mainly from urban areas

MEASUREMENT SCALES & ANALYTICAL TOOLS

- **Measurement:** Adapted scales, 5-point Likert scale
- **Data analysis:** SPSS 26 & AMOS 24
- **Method: CFA:** Assess the measurement model, reliability, and validity → **SEM:** Test the proposed structural relationships and hypotheses → **Bootstrapping (5,000 resamples):** Test indirect effects

04

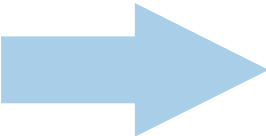
Results



The overall model fit also met the recommended criteria.

Table 1. Model Fit Indices Results

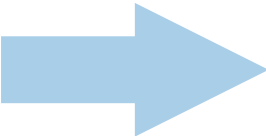
	Index	Assesment
CMIN/DF	1.315	Very good (<2)
GFI	0.928	Good (> 0.9)
CFI	0.983	Very good (> 0.9)
TLI	0.981	Very good (> 0.9)
RMSEA	0.030	Very good (< 0.05)



CFI = 0.983
TLI = 0.981
RMSEA=0.030
→ The measurement model provided a robust foundation to proceed with the structural model testing

Table 2. Reliability, Convergent Validity, and Discriminant Validity Results

Factor	Cronbach's Alpha	CR, AVE, MSV			Fornell & Lacker						
		CR	AVE	MSV	PU	PEOU	PC	PA	PP	ILM	PL
PU	0.867	0.872	0.633	0.154	0.796						
PEOU	0.901	0.904	0.702	0.029	0.091	0.838					
PC	0.873	0.874	0.698	0.272	-0.126	-0.095	0.836				
PA	0.881	0.886	0.723	0.100	0.057	0.043	-0.134	0.850			
PP	0.853	0.855	0.663	0.154	0.295	0.039	-0.141	0.202	0.814		
ILM	0.844	0.844	0.576	0.272	0.393	0.169	-0.522	0.317	0.392	0.759	
PL	0.925	0.924	0.708	0.175	0.143	0.062	-0.217	0.128	0.198	0.418	0.841



Cronbach's Alpha > 0.7
Factor loadings > 0.6
CR > 0.7
AVE > 0.5
MSV < AVE
→ All constructs achieved satisfactory reliability, convergent validity, and discriminant validity.

Overall, five of the six direct hypotheses were supported

Table 3. Hypothesis Testing Results

	Hypothesis	β	P-Value	Result
H1	PU $\rightarrow$ ILM	0.254	0.000	Supported
H2	PEOU $\rightarrow$ ILM	0.088	0.074	Rejected
H3	PC $\rightarrow$ ILM	-0.424	0.000	Supported
H4	PA $\rightarrow$ ILM	0.197	0.000	Supported
H5	PP $\rightarrow$ ILM	0.217	0.000	Supported
H6	ILM $\rightarrow$ PL	0.418	0.000	Supported

- #1. Positive associations with ILM: PU ($\beta = .254$) > PP ($\beta = .217$) > PA ($\beta = .197$)
- #2. No significant association: PEOU ($\beta = .088$, $p = .074$)
- #3. Negative association with ILM: PC ($\beta = -.424$)
- #4. Positive association with PLO: ILM ($\beta = .418$)

Indirect Effects and the Mediating Role of Intrinsic Learning Motivation

- **Significant indirect effects:** PU, PP, PA, PC → ILM → PLO
- The indirect effect of PEOU was not statistically significant.

Table 4. Results of the Indirect Effects Analysis through the Mediating Variable ILM

Indirect Path	β	P-Value (BC)	Conclusion
PU → ILM → PL	0.106	0.000	Supported
PP → ILM→PL	0.091	0.000	Supported
PA → ILM→ PL	0.082	0.000	Supported
PEOU → ILM→ PL	0.037	0.059	Not supported
PC → ILM→ PL	-0.177	0.000	Supported

The Moderating Role of AI Proficiency

- **Creativity → IM:** Negative effect weakens with higher AI proficiency.
- **Accuracy → IM:** Effect becomes less important with higher AI proficiency.

Table 5. Moderation Result

	Estimate	S.E.	C.R.	P
ILM ← INTpu	-.100	.054	-1.848	.065
ILM ← INTpeou	.036	.055	.659	.510
ILM ← INTpc	.131	.048	2.757	.006
ILM ← INTpa	-.147	.050	-2.942	.003
ILM ← INTpp	-.082	.049	-1.658	.097

05

Discussion



What the results mean

What we found

- Usefulness, personalization, and accuracy actively drive intrinsic motivation.
- Ease of use is now a basic expectation for Gen Z, not a direct motivator.
- Excessive AI creativity turns active learners into passive selectors.

What it means

- Supports Self-Determination Theory (competence, autonomy & relatedness).
- Tools must deliver actual learning value beyond just a good UX.
- Educators must balance AI assistance to preserve student ownership.

GenAI motivates when it builds competence, but over-automating creativity risks turning active creators into passive consumers.

What the results mean

What we found

- High proficiency weakens the negative impact of excessive AI creativity.
- Low proficiency increases reliance on accurate AI outputs for motivation.
- Intrinsic motivation mediates the overall educational value of GenAI.

What it means

- Students need skills to guide, evaluate, filter, and control AI-generated content., not just use it.
- Proficiency shifts learners from dependent users to autonomous directors.
- Value depends on psychological engagement, not just tech capabilities.

GenAI proficiency doesn't just make AI better; it gives learners the control needed to maintain autonomy and motivation.

What this study does not settle

Limitations

- **Sample Bias:** The study focuses predominantly on Gen Z undergraduates, limiting generalizability to broader populations. 
- **Disciplinary Aggregation:** Does not clearly classify students by academic majors; perceptions are pooled from various universities. 
- **Subjective Metrics:** Findings rely heavily on self-perceived assessments rather than objective learning outcomes. 
- **Cross-sectional Nature:** Cannot definitively prove long-term causal relationships. 

Next steps

- Broaden the demographic scope to test findings across different learner profiles.
- Run one-way ANOVA and analyze by group to examine how perceptions differ across academic disciplines.
- Incorporate objective academic metrics (e.g., GPA, test scores) to verify perceived outcomes.
- Employ longitudinal or experimental designs to establish clear causal mechanisms.

06

Conclusion



Three things to take away

01

Multidimensional Experience

GenAI is more than a single tool; it is a complex learning experience.

02

The Role of Motivation

Intrinsic motivation is the crucial bridge between AI features and learning outcomes.

03

Proficiency Dictates Experience

GenAI is more than a single tool; it is a complex learning experience.

Practical Implications

- **Beyond Access & Prompts:**

Universities must teach students to critically evaluate, verify, and strategically guide AI, not just use it.

- **Human-Centered Design:**

System evaluation should prioritize designs that preserve learner autonomy and active cognitive engagement over raw technological power.

OUR FINDINGS SUGGEST THAT:

*"The key question is not just how to develop AI that can do **more**, but how to use AI to help learners do **more**."*

GenAI should be used to extend human capacity while preserving learners' autonomy, motivation, and active agency.

Thank you

Questions welcome

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