Artificial Intelligence Learning Experiences and Behavioral Intentions: A Causal Analysis of Generation Z Students in Industrial Education Programs

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***Abstract*—Artificial Intelligence (AI) technology has significantly changed education by improving agility, flexibility, and access to knowledge. Students, especially in higher education including those in Industrial Education, engage with AI, influencing their perceptions and behaviors. This research aims to explore the causal relationships between AI learning experiences (Stimulus: S; AI Accuracy Experience: ACC, AI Insight Experience: INS, and AI Interactive Experience: INT) and perceptions, attitudes (Organism: O; Perceived Usefulness of AI: PU, Perceived Ease of Use of AI: PEOU), and Attitude toward AI Use: ATT), and intentions to use AI (Response: R; Behavioral Intention to Use AI: BEH) among Industrial Education students, using the Stimulus-Organism-Response model (SOR model) framework. This study utilized a quantitative methodology with a sample of 300 undergraduate Industrial Education students in Thailand. Data was collected via a 21-item questionnaire using a 5-point scale (IOC = 0.670–1.000; Cronbach's α = 0.841–0.917) and analyzed using descriptive statistics and Structural Equation Modeling (SEM) in Jamovi version 2.4.1.1. The research findings reveal that Industrial Education students' intention to use AI (BEH) is directly influenced by their attitude towards AI (ATT), with a coefficient (β) of 0.103*($p < 0.050$). Their intention is also indirectly affected by their experience with AI (ACC, INS, INT) through their perceptions (PU, PEOU) and attitude (ATT), with coefficients (β) of 0.106* ($p < 0.050$) and −0.307**($p < 0.010$). The model aligns well with the empirical data. The research indicates that AI experience, perception, and attitudes are interconnected factors influencing the intention to use AI in learning. This emphasizes the need for learning systems that enhance AI experiences, and foster awareness and positive attitudes, ultimately benefiting students in industrial education and beyond. These findings can guide policy and curriculum development in the AI-driven learning and Industry 4.0 contexts.**

***Keywords*—Artificial Intelligence (AI) learning usage experience, perceived usefulness of AI, perceived ease of use of AI, attitude toward AI use, behavioral intention to use AI, Stimulus-Organism-Response (SOR) model**

I. Introduction

Over the last decade, Artificial Intelligence or Artificial Intelligence (AI) has risen to center stage, becoming a crucial innovation that is fundamentally reshaping the fabric of society, the global economy, and our everyday lives [1–3]. AI not only serves as a tool to support human work, but has also evolved into an adaptable technology that has spread through every sector, including industry, health, service industry, and education [4, 5]. This transition clearly signals that the education system cannot continue in its traditional form. Instead, it must adapt to a new learning paradigm in which AI becomes a vital mechanism in support of teaching and learning.

The consequences of this structural transformation in education are evident in at least four key dimensions [2, 3]: (1) learning structures that shift from traditional to digital, personalized, and lifelong learning formats; (2) pedagogical structures that reimagine teachers from knowledge transmitters to facilitators and learning coaches; (3) assessment structures that shift from standardized tests to AI-powered analytical assessments that can reflect real-time results; and (4) policy and infrastructure structures that emphasize investment in data and digital skills to support modern learning, particularly in the field of industrial education where learners need to develop technical and operational skills to meet the demands of the Industry 4.0 workforce. These factors make AI skills and digital ethics an urgent need for learners and educational institutions alike [6, 7].

For Generation Z undergraduate students in Industrial Education in Thailand—youths growing up as "Digital Natives in the digital world"—the application of AI in the learning process directly impacts their digital experiences and behaviors [8–10]. With their high level of digital familiarity and skills, Generation Z can fluently use AI-powered platforms to create and manage their own learning, particularly by simulating manufacturing processes, designing, using CAD/CAE, and solving engineering problems in virtual labs—a key context in industrial education. It presents an academic challenge to obtain an in-depth understanding of how AI learning experiences influence the perceived usefulness of AI, perceived ease of use, attitudes toward AI use, and intentions with regard to using AI in the development of higher education students. Knowledge gained from such studies will not only fill theoretical gaps but also have the potential to inform policymaking and those involved in learning system design in such a way as to effectively support future learners.

Despite the widespread adoption of AI in education [11, 12], research on its actual impact on learner experiences and behavior remains limited. Most research concentrates on infrastructure and technical aspects, while user behavior, especially among Generation Z university students has not been adequately studied. In the absence of empirical evidence, educational institutions and policymakers struggle to build effective, sustainable AI learning ecosystems.

Consequently, this research sought to investigate the causal relationships between AI learning experiences and their impact on perceived usefulness and perceived ease of use of AI, as well as attitudes towards AI usage and the intention to use AI among Generation Z Industrial Education students in Thailand. The study aimed to build and test a causal model utilizing Structural Equation Modeling (SEM) techniques to explore how three dimensions of AI learning experiences—accuracy and precision of AI (ACC), depth of AI (INS), and user Interaction Experience (INT)—affect perceived usefulness of AI (PU), perceived ease of use of AI (PEOU), and attitudes toward AI use (ATT). Moreover, it examined whether these factors affect students' current intentions to use AI (BEH).

From a review of research, it was found that most studies on the variables relating to AI use for learning at the higher education level still rely on technology acceptance frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) and [2, 5, 6, 10, 13], which can explain AI usage behavior in terms of usability perceptions such as usefulness and ease of use.

However, the TAM and UTAUT frameworks have significant limitations, namely their inability to clearly explain variables such as how the learning experience students receive from directly using AI affects the formation of attitudes and intentions to use it. This is especially true in the context of those Generation Z students who focus on practical learning, such as in Industrial Education students, where AI functions as part of the learning environment rather than just as a technological tool.

Furthermore, the aforementioned research [2, 5, 6, 10, 13] also focuses on measuring AI acceptance in an abstract sense. Moreover, it neglects various dimensions of the AI learning experience such as AI Accuracy and Accuracy Experience (ACC), AI Insight Experience (INS), and user Interaction Experience (INT). These are important components that determine how learners Perceive the Usefulness (PU), Ease of Use (PEOU), and Attitude Towards AI Use (ATT), and ultimately whether they develop an intention to continue using it (BEH).

This research gap is clearly visible in the context of Thailand, especially in the field of industrial education, which is in the process of transitioning into the digital learning era under the Thailand 4.0 policy, emphasizing the readiness of the technological infrastructure, as well as the forms of AI learning, which differ significantly from that found in developed countries [9, 11].

This situation has led Generation Z students in Thailand to begin using AI for learning research, analysis, and practical application. This helps to explain and build a deeper understanding of the causal relationship between the three dimensions of AI learning experience variables.

In conclusion, this research has a theoretical strength that distinguishes it from previous work: the integration of the Stimulus-Organism-Response model (SOR) framework with the three dimensions of AI Learning Experience (ACC, INS, INT) with Perceived Variables (PU, PEOU) and Attitudinal Variables (ATT) to explain the Behavioral Intention (BEH) variable, specifically focusing on Generation Z Industrial Education students in Thailand. This not only overcomes the limitations of the TAM/UTAUT framework but also expands knowledge by applying a psychological framework to the context of AI learning, a focus of research that is relatively limited. The research questions are as follows:

RQ1: How do the three dimensions of AI learning experience, namely ACC, INS, and INT, influence PU and PEOU among Generation Z Industrial Education students?

RQ2: How do PU and PEOU influence ATT among Generation Z Industrial Education students?

RQ3: How does ATT among Generation Z Industrial Education students influence their BEH in Industrial Education?

II. Literature Review

A. SOR Model

The SOR model conceptual framework has roots in the field of environmental psychology. It was first proposed in 1974 by Mehrabian and Russell [14–16] to explain the mechanisms by which external stimuli influence individuals' internal states and lead to behavioral responses. This framework is based on the psychological assumption that "human behavior is not solely driven by direct stimuli, but undergoes internal, rational, and emotional processing before decision-making".

However, Bunea *et al.* [16] and Sivasothey *et al.* [17] further explained that the SOR model can be applied to effectively evaluate an individual's hierarchical thought processes, beginning with the reception of external stimuli (Stimulus: S). Individuals then engage in an internal interpretation and understanding process (Organism: O), which ultimately leads to an appropriate response (Response: R) to the stimuli they receive. This conceptual framework is therefore an important mechanism for understanding the causal relationships among the environment, psychological states, and expressed behaviors, consistent with research perspectives on technology acceptance and the study of technology user behavior. The SOR model conceptual framework is summarized in Fig. 1.

In Fig. 1, it can be seen that the conceptual framework of the SOR model comprises three important elements that are horizontally linked:

S is external stimuli or environmental factors that have the potential to capture attention, generate perception, or elicit cognitive and emotional reactions. In the AI context for learning, a stimulus presents three dimensions of interaction quality and user experience: ACC, INS, INT. All of these serve as the starting point for the ongoing cognitive and behavioral process [18].

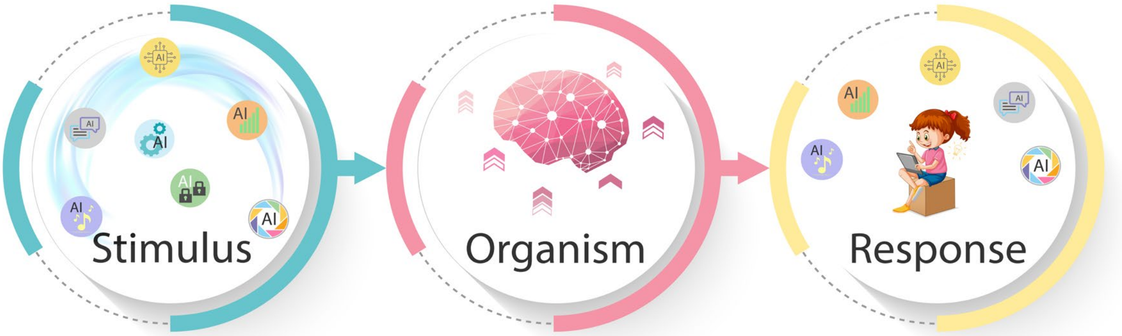


Fig. 1. SOR model.

O represents an individual's internal state after exposure to a stimulus, encompassing both cognitive and emotional dimensions such as perceived usefulness, evaluation of usefulness (usefulness), perceived ease of use (ease of use), attitudes toward use (attitudes), and psychological readiness. These factors serve as important mediators that directly connect external stimuli to response behavior [19].

R presents response behavior or behavioral intention, which emerges from an individual's internal evaluation. This research emphasizes explicitly the intention to continue using AI for learning and its acceptance as part of future educational strategies [20–22].

In summary, the conceptual framework of the SOR model not only focuses on the relationships among stimuli, internal states shaped by attitudes toward AI use, and response behaviors, but also illustrates the step-by-step process of individual decision-making. It makes it particularly suitable for examining the behavioral intentions to use AI in learning.

Thus, the SOR model conceptual framework is well-suited for this study, as it clarifies and enhances our understanding of the causal relationship among three dimensions of AI learning experiences: ACC, INS, INT, PU, PEOU, ATT, and BEH among Generation Z university students majoring in Industrial Education. The researchers selected the model for the following reasons:

(1) The SOR model's conceptual framework is comprehensive in terms of explaining the process of linking from the experience of using AI for learning to the behavioral intention to use it. That is, it can explain the transition from external stimuli, namely the variable of experience of using AI for learning, through the internal evaluation process, namely the variable PU, the variable PEOU, and the variable ATT, to the behavioral response, namely the variable of BEH systematically, with theoretical support.

(2) This model is highly flexible in terms of its application to emerging technologies, particularly AI for learning, which are rapidly changing contexts. This flexibility allows it to comprehensively account for external factors—technological stimuli—and internal psychological factors (PU and PEOU).

(3) The SOR model's conceptual framework has been supported by previous research with regard to technology acceptance and user behavior. It has been consistently adopted as a primary framework due to its ability to clearly explain the causal relationship between user experience and user behavior [23, 24].

For these reasons, the selection of the SOR model framework for this study is theoretically appropriate, as it can systematically explain causal relationships. Furthermore, applying research findings to policy design and AI-based learning models is appropriate for Generation Z learners in the Industrial Education field.

B. AI Learning Experiences

In the SOR model framework, the stimulus (S) variable represents external factors that influence a person's internal state (O) and lead to behavioral responses (R). Particularly in the context of digital learning, an important stimulus is the experience of using AI for learning, which is a key mechanism that determines how learners will perceive and accept the use of new technologies. From a review of the literature, it was found that the experience of using AI for learning can be classified into three dimensions: ACC, INS, INT. These are crucial drivers of PU, PEOU, ATT, and BEH among the target population [25–28].

1) AI accuracy experience

AI Accuracy Experience (ACC) refers to an AI's ability to provide accurate, reliable, and relevant answers or recommendations with regard to learners' needs. This accuracy not only builds trust but also directly affects students' PU and PEOU in industrial education [25, 26]. The literature review indicates that the ACC contributes to more favorable attitudes toward AI and boosts the likelihood of continued usage [27, 28]. Based on this evidence, the researchers suggest the following hypotheses:

H1: AI Accuracy Experience: ACC affects PU among the target population.

H2: AI Accuracy Experience: ACC influences the PEOU of AI among the target population.

2) AI insight experience

AI Insight Experience (INS) refers to AI's ability to analyze in such a way as to provide deep learning-based insights and feedback that helps learners systematically understand content and make effective learning decisions. Accurate and appropriate insights not only increase PU and PEOU, but also influence ATT and BEH. The review of the literature found that in-depth experiences with AI are a key factor in increasing learners' appreciation of AI and their acceptance of long-term use [25, 27, 29–31]. Therefore, the researchers suggest the following hypotheses:

H3: In-depth experiences with AI: INS affect the PU of the target population.

H4: In-depth experiences with AI: INS affect the PEOU of target population.

3) AI interactive experience

AI Interactive Experience (INT) refers to the interaction between learners and AI systems to provide real-time feedback. AI is, therefore, a virtual assistant that adapts itself to user behaviors. Smooth, efficient interactions help learners feel engaged and satisfied with their learning. From the literature review, INT directly affects PU, PEOU, ATT, and BEH [25, 27, 29–31]. Therefore, the researchers suggest the following hypotheses:

H5: User Experience Interaction: INT influences the PU among the target population.

H6: User Experience Interaction: INT significantly influences the PEOU for the target population.

From the above review of the literature, it is concluded that the three dimensions of AI learning experience (ACC, INS, and INT) act as the main stimuli that stimulate the Organism, namely, PU, PEOU, and ATT, which then lead to the response in the form of BEH. The integration of the three dimensions of AI learning experience reflects the complex dynamics of the decision-making process for using AI technology among the target population, and is an important reason why the SOR model's conceptual framework is appropriate for this study.

C. Perceptions and Attitudes toward Use

According to the SOR model framework, the Organism variable represents the internal state of a person that occurs after exposure to stimuli (S). It plays a mediating role in conveying the impact of the three main dimensions of AI learning experience variables (ACC, INS and INT) to the internal state of a person (O), which consists of PU, PEOU, and ATT, which reflects both the cognitive and affective dimensions of the learner [32–36].

1) Perceived usefulness of AI

Perceived Usefulness of AI (PU) shows belief on the part of the learner as to the ability of AI to enhance learning efficiency and improve academic performance. The literature review focuses on the significance of PU as a crucial mediator that links the experience of utilizing AI for learning through three key dimensions: ACC, INS, and INT. ATT mediate this relationship and BEH [34, 37–41]. Furthermore, Zhou *et al.* [39] found that PU has a direct impact on ATT and BEH. From these findings, the researchers suggest the following hypothesis:

H7: The perceived usefulness of AI: PU influences ATT among the target population.

2) Perceived ease of use of AI

Perceived Ease of Use of AI (PEOU) refers to learners' perception that AI is easy to use and requires little effort. The literature review indicates that the PEOU is shaped by experiences with AI in learning, primarily through three dimensions: accessibility (ACC), instructor support (INS), and interaction (INT) [42–45]. Furthermore, PEOU affects ATT and BEH [34]. Consequently, the researchers suggest the following hypothesis:

H8: Perceived ease of use of AI (PEOU) influences the ATT of the target population.

3) Attitude toward AI use

Attitude toward AI Use (ATT) refers to learners' positive or negative evaluation of AI use for learning. This is a practical outcome resulting from the PU and the PEOU. The review of the literature reveals that numerous studies confirm that ATT is a key variable influenced by PU and PEOU, which in turn influences BEH [19, 21, 22, 46, 47]. Furthermore, Haley *et al.* [20] found that students who perceived AI as helpful and easy to use tended to have positive attitudes toward its use. Allen *et al.* [45] indicated that positive attitudes directly influence BEH. Consequently, the researchers suggest the following hypothesis:

H9: Attitude toward AI use (ATT) influences the BEH of the target population.

D. Behavioral Intention to Use AI

According to the SOR model framework, the Response (R) variable refers to learners' behavioral intentions to use AI after completing the internal assessment (O). In this research, the Response variable is BEH, a downstream variable reflecting the learner's decision to accept AI as part of the learning process.

AI Use Intention (BEH) refers to learners' intention to use AI in their learning continuously. The literature review indicates that ATT has a direct influence on BEH [19, 21, 22, 46, 47]. Furthermore, Rathod *et al.* [43] noted that ATT acts as a mediator between PU and PEOU, significantly impacting BEH.

E. The Relationships between Stimulus, Organism, and Response

Under the SOR model framework, the relationship between Stimulus (S), Organism (O), and Response (R) can be clearly explained in a hierarchical causal manner, with the three main dimensions of AI learning experience variables (ACC, INS, and INT) acting as stimuli that stimulate learners' internal perceptions and evaluations at the Organism level, consisting of variables such as PU, PEOU, and ATT. These interpretation processes lead to the creation of a rational and emotional understanding of AI use.

When learners perceive AI as applicable (PU), easy to use (PEOU), and have a positive attitude (ATT) towards using AI, these psychological processes are reflected in the response, namely AI Use Intention (BEH). The review of the literature found that the path from Stimulus → Organism → Response is not just a correlational relationship, but a causal process that accurately explains technology adoption [19, 48, 49].

In summary, this hierarchical relationship demonstrates that stimuli from AI use experiences can be systematically transformed into internal evaluations at the Organism level and finally reflected as behavioral responses in the form of

BEH, which reflects the consistency of the SOR model's conceptual framework with the context of AI use with regard to the target population.

F. Ethical Dilemmas and Risks of AI in Higher Education

The expansion of AI applications in higher education has raised vital ethical concerns and perception of risk. Therefore, these aspects should be considered alongside the educational benefits. One major issue is algorithmic bias, as AI trained on historical data may use inaccurate datasets, resulting in low levels of accuracy or incorrect outcomes [21, 43, 47, 48]. This is particularly problematic when AI is used in personalized learning, making academic mentoring crucial for learners. In addition, learners need to be taught to be AI-savvy.

Another critical issue is data privacy and monitoring. AI learning platforms gather extensive data about learners, for example, with regard to learning behavior and personal information, leading to an increase in data ownership risks. It is important to require informed consent for suitable data use [24, 29, 35, 48]. Lack of clear oversight could lead to privacy violations.

Additionally, academics indicate the risk of over-reliance on the use of AI, resulting in a decrease in critical thinking skills and self-learning abilities, a drop in in-depth knowledge, impaired decision-making, and impacts on attitudes and motivation, all of which could affect learning and/or encourage plagiarism. These are considered negative impacts of AI [26, 33, 41, 48]. The digital divide is also a significant ethical issue, as unequal access to AI technology could create a gap between learners, especially in emerging economies such as Thailand [34–36, 48, 49].

The ethical risk aspect reflects the need to consider more than just the acceptance of technology in order to understand the role of AI in higher education. Under the SOR model, ethical concerns and perceived risk both influence learners' cognitive and emotional assessments of AI, which in turn can affect their attitudes and behavioral intentions when it comes to using it. Therefore, interpreting research findings on AI-based learning experiences should be based on the ethical and risk contexts of AI in higher education institutions.

G. Conceptual Model

Based on the above literature analysis, the researcher developed a conceptual model, referencing the SOR model framework, to explain the dynamics of AI use in learning among Generation Z students in Industrial Education programs.

Stimulus (S) represents the experience of using AI for learning, which consists of three dimensions: (1) ACC, (2) INS, and (3) INT. These three dimensions reflect the characteristics of the learner-AI interaction that have the potential to stimulate internal perception and evaluation.

Organism (O) consists of PU, PEOU, and ATT. PU and PEOU act as cognitive mediators, translating the impact of stimuli to internal evaluation processes, while ATT is an affective mediator, reflecting learners' attitudes toward AI use.

Response (R) represents the BEH, the end output that reflects the learner's intention to accept and continuously use AI to support learning.

In summary, this theoretical framework illustrates a causal pathway from Stimulus → Organism → Response that links AI use experiences (ACC, INS, and INT) to cognitive mechanisms (PU and PEOU) and attitudes (ATT), leading to AI use intention (BEH), which is consistent with the stated research hypotheses H1–H9. The theoretical framework is summarized in Fig. 2. This shows the causal relationship pathways developed based on the SOR model framework.

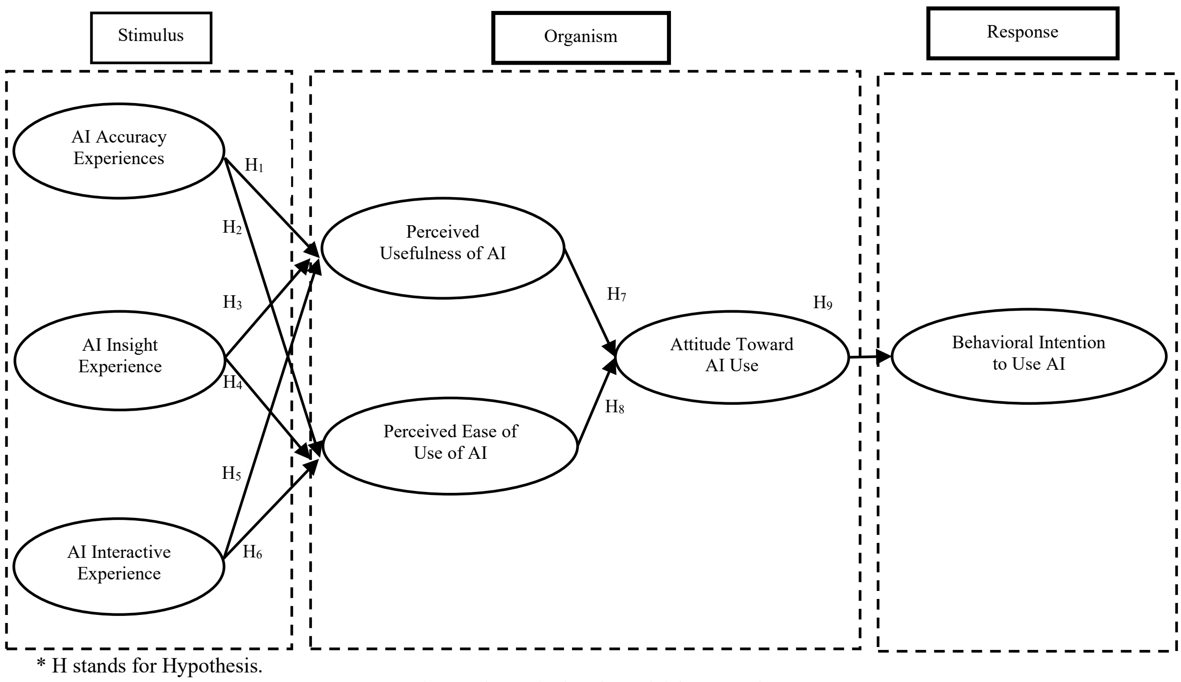


Fig. 2. Theoretical path model framework.

H. Theoretical Implications and Research Hypotheses

In summary, this research has integrated the SOR model's conceptual framework into the context of AI learning for Generation Z students in the Industrial Education. The variables of ACC, INS, and INT are considered as stimuli affecting Organisms, namely, PU, PEOU, and ATT. These stimuli are then reflected in the Response as the BEH variable. This conceptual framework not only broadens the application of the SOR model in digital education environments but also makes new contributions by linking AI user insights to explain learner behaviors causally. The results of the developed model are expected to have both theoretical (enhancing understanding of the causal mechanisms of AI adoption) and applied (serving as an empirical database for designing AI learning policies and systems suitable for new-generation learners).

III. Methodology

A. The Synthesis of the Latent Variable Items Involves the Following Steps

The researcher conducted a data search of the Scopus database to synthesize a list of latent variables under the conceptual framework of the SOR model by defining latent variables in terms of 3 main components: Stimulus (S)—the variable of experience with regard to using AI for learning (ACC, INS and INT), Organism (O)—the variable of perception and attitude (PU, PEOU and ATT), and Response (R)—the variable of intention to use AI (BEH). Selected from 124 related research studies, the researcher synthesized the studies using a 50% frequency criterion, following the approach of Suwanroj *et al.* [11]. Such an operation ensured that the selected variable list reflects both systematicity and theoretical validity (as shown in Tables 1 and 2).

Table 1. Results of latent variable synthesis

Latent Variable	Construct	Definitions	Sources
1. ACC	S	AI's ability to provide answers or recommendations that are accurate, reliable, and relevant to the learner's needs.	[25, 27, 29–31]
2. INS	S	AI's ability to analyze data and provide insights that support learner learning. This insight helps learners better understand content and make effective learning decisions.	[25, 27, 29–31]
3. INT	S	Interactions between learners and AI systems, such as real-time feedback, virtual assistants, or adaptive learning. Good interaction creates a sense of engagement, convenience, and satisfaction for learners.	[25, 27, 29–31]
4. PU	O	Learners' belief that using AI will improve learning efficiency and make learning work more effective.	[34, 37–40]
5. PEOU	O	The learner's convenience and ease in using AI without much effort.	[42–45]
6. ATT	O	Positive or negative feelings that learners have towards using AI for learning.	[19, 21, 22, 46, 47]
7. BEH	R	Learners' intention to use AI in the learning process.	[27, 49–51]

Table 2. Abbreviations of latent and observed variables

Latent Variable	Observed Variable	
1. ACC	ACC1	The results obtained from the AI that I use are often factually accurate.
	ACC2	AI results are often inaccurate or inaccurate. *(Reverse)*
	ACC3	When using AI, the results often do not need much editing or improvement.
2. INS	INS1	AI provides me with new insights or ideas that help me learn.
	INS2	Using AI did not improve my understanding of the material I was learning. *(Reverse)*
	INS3	The data or summaries from AI enhance my understanding and analysis.
3. INT	INT1	Interaction with AI is smooth and natural.
	INT2	Interactions with AI are often slow or irrelevant. *(Reverse)*
	INT3	I can easily adjust questions or give commands to the AI and get the desired results.
4. PU	PU1	Using AI helps me complete my work or schoolwork faster.
	PU2	AI doesn't improve my work quality or academic performance. *(Reverse)*
	PU3	AI is a tool that enhances my learning and work efficiency.
5. PEOU	PEOU1	Overall, using AI is easy for me.
	PEOU2	I feel that using AI is complicated and difficult. *(Reverse)*
	PEOU3	I can use the core functions of AI without having to rely on an assistant often.
6. ATT	ATT1	Overall, I have a positive attitude towards using AI for learning and work.
	ATT2	I am not very supportive of using AI to help with schoolwork. *(Reverse)*
	ATT3	I agree that the use of AI should be promoted in educational institutions.
7. BEH	BEH1	In the future, I intend to use AI as a tool to help me study and work regularly.
	BEH2	I do not expect to use AI in learning or work in the future. *(Reverse)*
	BEH3	I have an idea to recommend to my friends or juniors to use AI for learning.

B. Development of a Causal Relationship Model Based on the SOR Model Framework

1) Determining sample size

The study population comprised undergraduate students in Industrial Education at public and private higher education institutions across Thailand. The sample size determination was based on the Hair *et al.* [50] concept, which suggested that SEM analysis should consider the ratio of observed variables to sample units. There should be at least 10 sample units per observed variable, and the total sample size must be at least 200 to ensure stable Maximum Likelihood estimation. In addition, Hair *et al.* [50] suggested that when the sample size exceeds 400 units, some fit indices may be skewed, leading to a lower-than-actual model fit assessment.

Therefore, the researcher determined the sample size based on the aforementioned criteria and chose probability and stratified random sampling to cover both public and private higher education institutions across all regions. The sample size was determined at a ratio of 10 sampling units per observed variable. Since this research included 21 observation variables, a sample size of at least 210 participants was required. However, to increase statistical power and enhance the reliability of the analysis results, the researcher determined the total sample size to be 300 people, which is appropriate both theoretically and practically, and in line with the objectives of studying the causal relationship using SEM.

Data collection revealed the general characteristics of a sample of 300 undergraduate students in Industrial Education from public and private higher education institutions across Thailand—the sample comprised a range of gender and age. The majority of the sample was female (46%), followed by male (41.333%). Sexual and gender diversity accounted for 12.667%. The sample was concentrated among ages 17–20, representing 80.333% of the total dataset, reflecting the context of AI users at the early stages of higher education. Regarding familiarity with digital technology, including AI for learning, the majority (57.667%) reported regular and proficient use, followed by frequent and relatively fluent use (42.333%). The average Internet usage for learning was 10 hours per week (88%), followed by 7–9 h per week (12%), respectively. The summary is shown in Table 3.

Table 3. General characteristics of the respondents (*n* = 300)

Profile	Items	Number (f)	Percentage (pct)
Gender	Male	124	41.333
	Female	138	46.000
	LGBTQ alternative gender	38	12.667
Age	17	69	23.000
	18	52	17.333
	19	63	21.000
	20	57	19.000
	21	31	10.333
	22	28	9.333
The use of digital technology and AI in learning	Use it regularly and expertly	173	57.667
	Used frequently and quite fluently	127	42.333
Using the Internet for Studying	≥10 h or more	264	88.000
	7–9 h	36	12.000

2) *Research tools*

The research instrument used in this study was a 5-point Likert-scale questionnaire designed to assess all seven latent variables. It comprised 21 items, divided into seven reverse-coded and 14 positive items. This was done to reduce response bias and enhance data reliability.

The instrument was reviewed for content validity by three experts. The results revealed an index of consistency between the items and the Research Objectives (IOC) ranging from 0.670 to 1.000, indicating that the instrument is appropriate and adequately covers the variables to be measured.

Before using the instrument for actual data collection, the researcher conducted a tryout with 30 non-sample Generation Z university students from Industrial Education programs to test the instrument's reliability.

The results of the Cronbach's Alpha Coefficient test revealed that the instrument's reliability in terms of each of the seven latent variables ranged from 0.841 to 0.917, exceeding the recommended minimum criterion (> 0.700) set by Hair *et al.* [50] and Leekitchwatana [51]. The analysis also indicated that the discriminant power of all 21 observed variables ranged from 0.703 to 0.832, exceeding the criterion for all items [52, 53] and exceeding the recommended minimum criterion. This indicates that each item has discriminatory power that meets the criteria.

Furthermore, the results of the examination of the seven latent variable measurement models against empirical data from a sample of *n* = 300 using a single-factor confirmatory factor analysis (CFA) revealed that the developed seven latent variable measurement models were consistent with the empirical data, indicating that each observed variable truly measures the latent variable. The results of the examination of the seven latent variable measurement models are shown in Table 4.

Table 4. Results of latent variable measurement model examination (*n* = 300)

Latent Variable	χ^2	df	p value		χ^2/df		CFI		SRMR		RMSER		Result of consideration
			Criterion Standard [50]	Result	Criterion Standard [50]	Result	Criterion Standard [50]	Result	Criterion Standard [50]	Result	Criterion Standard [50]	Result	
ACC	0.240	3	>0.050	0.970	< 2	0.080	< 0.940	0.870	≤ 0.080	0.075	≤ 0.070	0.030	Passed
INS	0.621	3	>0.050	0.100	< 2	0.207	< 0.940	0.900	≤ 0.080	0.073	≤ 0.070	0.000	Passed
INT	0.546	1	>0.050	0.990	< 2	0.546	< 0.940	0.930	≤ 0.080	0.071	≤ 0.070	0.000	Passed
PU	0.845	3	>0.050	0.890	< 2	0.282	< 0.940	0.865	≤ 0.080	0.069	≤ 0.070	0.007	Passed
PEOU	0.998	2	>0.050	0.950	< 2	0.499	< 0.940	0.790	≤ 0.080	0.074	≤ 0.070	0.000	Passed
ATT	1.172	2	>0.050	0.973	< 2	0.586	< 0.940	0.813	≤ 0.080	0.065	≤ 0.070	0.005	Passed
BEH	1.346	3	>0.050	0.856	< 2	0.449	< 0.940	0.793	≤ 0.080	0.053	≤ 0.070	0.000	Passed

Table 5. Discriminant validity of Heterotrait-Monotrait Ratio (HTMT) (*n* = 300)

Variables	ACC	INS	INT	PU	PEOU	ATT
ACC						
INS	0.603					
INT	0.677	0.602				
PU	0.635	0.524	0.531			
PEOU	0.618	0.646	0.645	0.554		
ATT	0.643	0.643	0.607	0.586	0.591	
BEH	0.629	0.654	0.603	0.518	0.577	0.585

When considering the HTMT values of all latent variables, they were less than 0.900 [50] (Table 5), which confirmed that all latent variable items had appropriate discriminant validity. In summary, this research confirmed that the measurement model included all latent variables of high quality.

Furthermore, when considering construct validity, it was found that the standardized factor loadings of all 21 observed variables were in the range of 0.513–0.695, passing the standard criteria (≥0.500) [50], and the AVE values were in the range of 0.503–0.689, also passing the standard criteria (≥0.500), indicating that each observed variable can be used to measure the latent variable significantly and be conceptually consistent. The measurement model has good structural validity and convergent validity. This shows that the measuring instrument has appropriate quality for further causal analysis [50]. In terms of reliability, the Cronbach's Alpha (α) of each latent variable was between 0.701 and 0.818, and the Composite Reliability (CR) was between 0.714 and 0.735, both of which passed the standard criteria (≥0.700) [51–53] The aforementioned index values indicate that the instrument has good internal consistency, showing that each observed variable can measure the latent variable well and is reliable for all variables. Details are as shown in Table 6.

Therefore, it can be concluded that the research instruments have adequate quality in terms of content validity, discrimination power, discriminant validity, construct validity, and reliability, and is sufficient and appropriate for the research under consideration.

Table 6. Results of quality inspection of measuring instruments

Latent Variable	Item	Tryout n = 30							Sample Group n=300			
		Criterion Standard [50]	Cronbach's (α)	Reliability level	Application	Criterion Standard [50]	Item Reliability Correlation	Application	Cronbach's	CR	AVE	Factor Loadings
1. ACC	ACC1	≥0.700	0.917	very high	applicable	≥0.200	0.832	applicable	0.701	0.717	0.564	0.631
	ACC2					≥0.200	0.816	applicable				0.695
	ACC3					≥0.200	0.824	applicable				0.674
2. INS	INS1	≥0.700	0.912	very high	applicable	≥0.200	0.738	applicable	0.713	0.735	0.513	0.626
	INS2					≥0.200	0.794	applicable				0.617
	INS3					≥0.200	0.776	applicable				0.672
3. INT	INT1	≥0.700	0.864	very high	applicable	≥0.200	0.739	applicable	0.787	0.718	0.577	0.549
	INT2					≥0.200	0.724	applicable				0.668
	INT3					≥0.200	0.758	applicable				0.574
4. PU	PU1	≥0.700	0.892	very high	applicable	≥0.200	0.717	applicable	0.706	0.724	0.503	0.513
	PU2					≥0.200	0.736	applicable				0.557
	PU3					≥0.200	0.770	applicable				0.582
5. PEOU	PEOU1	≥0.700	0.841	very high	applicable	≥0.200	0.762	applicable	0.774	0.719	0.574	0.618
	PEOU2					≥0.200	0.753	applicable				0.684
	PEOU3					≥0.200	0.798	applicable				0.666
6. ATT	ATT1	≥0.700	0.913	very high	applicable	≥0.200	0.753	applicable	0.809	0.714	0.689	0.607
	ATT2					≥0.200	0.788	applicable				0.575
	ATT3					≥0.200	0.724	applicable				0.618
7. BEH	BEH1	≥0.700	0.905	very high	applicable	≥0.200	0.786	applicable	0.818	0.733	0.535	0.664
	BEH2					≥0.200	0.703	applicable				0.626
	BEH3					≥0.200	0.785	applicable				0.604

3) Data collection

The researcher collected data using an online questionnaire and sent it to the sample group at 17 public and private universities that host students in the Industrial Education program via e-mail. Data collection took place over 1 month (October 8, 2025–November 8, 2025). The data collection yielded 523 respondents. Before entering the analysis, the researcher checked the reverse-coded items and screened the data to eliminate discrepancies and increase reliability, resulting in a final sample of 300 people, in accordance with the research's preliminary agreement.

4) Data analysis

Data analysis was divided into two steps as follows:

Step 1: Descriptive data analysis was used to describe the general characteristics of the respondents, with results presented as frequencies and percentages.

Step 2: Inferential statistics were used to test the appropriateness and consistency of the research model. This was a SEM analysis using Jamovi 2.4.1.1, a statistical software program that supports advanced SEM and displays complete model fit indices. The steps were as follows:

(1) The Measurement Model was examined to test the reliability of the instruments. The Composite Reliability (CR) index of the observed variables must be at least 0.700, the Indicator Reliability (Outer Loading) index must be at least 0.500, and the Convergent Validity (AVE) index must be at least 0.500. The discriminant validity was also tested. Considering the HTMT Criterion value, they must not be higher than 0.900 [50–52], respectively.

(2) Analyze the path model to find the relationship between the independent latent variable (exogenous variable) and the dependent latent variable (endogenous variable) according to the conceptual framework of the SOR model.

IV. RESULT

Hair *et al.* [50] and Khontee and Poonputta [52] stated that the ability on the part of the model to predict the values of the dependent variables (Endogenous Variables) (Predictive Power) was considered in terms of the Cross-Validated Redundancy Index (Q^2), the Coefficient of Determination (R^2), and the Standardized Root Mean Square Residual (SRMR), respectively. The research results are as follows:

Table 7. Evaluation results of model's ability to predict the values of the dependent variables (Q^2, R^2) (n = 300)

Endogenous Variables	Q^2		R^2		Result of Consideration/Conclusion
	Criterion Standard [52]	Result	Criterion Standard [52]	Result	
PU	>0	0.305	> 0.500	0.573	Passed / Good
PEOU	>0	0.268	> 0.500	0.597	Passed / Good
ATT	>0	0.241	> 0.500	0.614	Passed / Good
BEH	>0	0.539	> 0.500	0.786	Passed / Good

Table 8. Evaluation results of model's ability to predict the values of the dependent variables (CFI, SRMR and RMSEA) (n = 300)

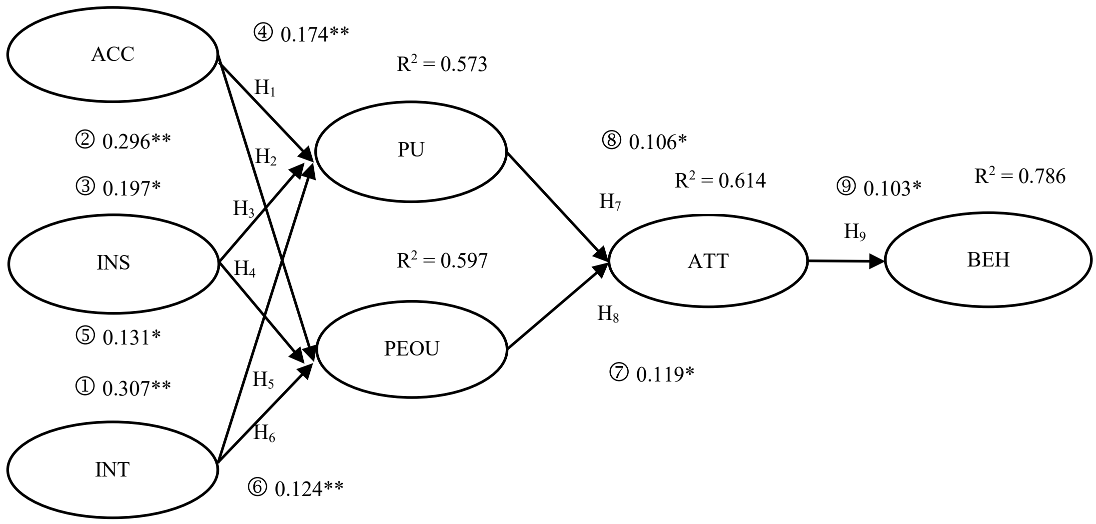
Goodness-of-fit index	Criterion Standard [50]	Result	Result of Consideration/Conclusion
CFI	>0.940	0.960	Passed / Good
SRMR	≤0.080 (with CFI above 0.940)	0.063	Passed / Good
RMSEA	<0.070 (with CFI of 0.940 or higher)	0.058	Passed / Good

From Table 7, it can be seen that the Q^2 value of the variable PU was equal to 0.305, PEOU was equal to 0.268, ATT was equal to 0.241, and BEH was equal to 0.539. The results indicate that the model had good predictive ability and the ability to explain the model's variance (Explanatory Power). The values of the Q^2 of all four dependent variables were greater than 0, indicating that the model had good predictive ability (Predictive Relevance).

Regarding the R^2 values, the R^2 values for the variable PU was 0.573, the variable PEOU was 0.597, the variable ATT was 0.614, and the variable BEH was 0.786. This indicates that the model has a good ability to explain the variance of the dependent variables (>0.50) [50, 53]. The results of the CFI, SRMR, and RMSEA tests are shown in Table 8.

From Table 8, the Comparative Fit Index (CFI) for this model was 0.960, which met the standard criteria (>0.940). The SRMR value for this model was 0.063, which met the standard criteria (≤0.080). The Root Mean Square Error of Approximation: RMSEA value of this model was equal to 0.058, which passed the standard criteria (<0.070). The SRMR and RMSEA values must be considered alongside the CFI value, and the results must meet the criteria set by Hair *et al*. [50]. It can be said that all three goodness indices (CFI, SRMR, and RMSEA) passed the standard criteria, indicating that the model is consistent with the empirical data. The aforementioned index values are presented in the Model, along with the path coefficient, as shown in Fig. 3.

From Fig. 3, the relationship path of the variables is presented as follows: The relationship path of the variable INT that affects the variable PU has the highest path coefficient, equal to 0.307. ① The relationship path between the variables ACC and PEOU is 0.296. ② The relationship path between the variable INS and the variable PU was 0.197. ③ The relationship path from the variable ACC to the variable PU was 0.174. ④ The relationship path from the variable INS to the variable PEOU was 0.131. ⑤ The relationship path from the variable INT to the variable PEOU was 0.124.⑥ The relationship path of the variable PEOU affecting the variable ATT was equal to 0.119. ⑦ The relationship path from the variable PU to the variable ATT was 0.106. ⑧ The relationship path from the variable ATT to the variable BEH, showed a value of 0.103. ⑨ The R^2 value of the latent variable BEH was 0.786, indicating that all six variables (ACC, INS, INT, PU, PEOU, and ATT) can explain the variance of the latent variable at 78.600 percent, which is at a high level [50, 52, 53] .The values of the various indices are presented in Table 9.



CFI = 0.960, SRMR = 0.063, and RMSEA = 0.058

* $p < 0.050$, ** $p < 0.010$

Fig. 3. Model and path coefficient.

Table 9. Hypothesis validation results ($n = 300$)

Hypotheses	Path	β	t-Value	p-value	95% CI (LL, UL)	Result
H1	④ ACC → PU	0.174	3.175	$p < 0.010$	[0.067, 0.281]	supported
H2	② ACC → PEOU	0.296	2.594	$p < 0.010$	[0.072, 0.520]	supported
H3	③ INS → PU	0.197	1.973	$p < 0.050$	[0.010, 0.393]	supported
H4	⑤ INS → PEOU	0.131	2.527	$p < 0.050$	[0.029, 0.233]	supported
H5	① INT → PU	0.307	3.214	$p < 0.010$	[0.120, 0.494]	supported
H6	⑥ INT → PEOU	0.124	3.482	$p < 0.010$	[0.054, 0.194]	supported
H7	⑧ PU → ATT	0.106	2.170	$p < 0.050$	[0.010, 0.202]	supported
H8	⑦ PEOU → ATT	0.119	2.458	$p < 0.050$	[0.024, 0.214]	supported
H9	⑨ ATT → BEH	0.103	1.964	$p < 0.050$	[0.019, 0.206]	supported

Source: t-Value > 1.960. [52]

From Table 9, the results in terms of hypothesis testing found that with regard to the nine research hypotheses, these were confirmed as follows: The factor INT had the most significant positive influence on PU ($\beta = 0.307$, $t = 3.214$, $p < 0.010$, 95% CI [0.120, 0.494], resulting in Hypothesis 5 being confirmed. ① The factor ACC experience had a positive influence on PEOU ($\beta = 0.296$, $t = 2.594$, $p < 0.010$, 95% CI [0.072, 0.520]), resulting in the confirmation of Hypothesis 2. ② The factor INS had a positive influence on PU ($\beta = 0.197$, $t = 1.973$, $p < 0.050$, 95% CI [0.010, 0.393], resulting in the confirmation of Hypothesis 3.③ The factor ACC had a positive influence on PU ($\beta = 0.174$, $t = 3.175$, $p < 0.010$, 95% CI [0.067, 0.281]), resulting in the confirmation of Hypothesis 1.④ The factor INS had a positive influence on PEOU ($\beta = 0.131$, $t = 2.527$, $p < 0.050$, 95% CI [0.029, 0.233]), resulting in the confirmation of

Hypothesis 4. ⑤ The INT had a positive influence on PEOU ($\beta = 0.124$, $t = 3.482$, $p < 0.010$, 95% CI [0.054, 0.194]), resulting in the confirmation of Hypothesis 6.⑥ The factor PEOU had a positive influence on ATT ($\beta = 0.119$, $t = 2.458$, $p < 0.050$, 95% CI [0.024, 0.214]), resulting in the confirmation of Hypothesis 8. ⑦ The factor PU had a positive influence on ATT ($\beta = 0.106$, $t = 2.170$, $p < 0.050$, 95% CI [0.010, 0.202]), resulting in the confirmation of Hypothesis 7.⑧ The factor ATT had a positive influence on BEH ($\beta = 0.103$, $t = 1.964$, $p < 0.050$, 95% CI [0.019, 0.206]) resulting in the confirmation of Hypothesis 9.⑨

V. Discussion

The results of this research reveal three key points that can be discussed in light of the research objectives. The details are as follows:

A. Relationship between AI Learning Experience and Perception

The SEM analysis results confirmed a significant causal relationship between AI learning experiences and learners' perceptions of AI technology. All three dimensions of experience (ACC, INS, and INT) directly influenced PU and PEOU.

Among the three dimensions, INT exhibited the highest positive influence on PU ($\beta = 0.307$, $t = 3.214$, $p < 0.010$, 95% CI [0.120, 0.494]), with a non-zero reliability interval. This suggests that learners value AI that provides interaction experience, analysis, and feedback, fostering confidence and motivation to learn. This significance suggests that when AI acts as a learning facilitator that can reflect deep understanding, learners will perceive its usefulness in terms of cognitive and intellectual value, as well as in terms of learning effectiveness.

Meanwhile, ACC positively influenced PEOU ($\beta = 0.296$, $t = 2.594$, $p < 0.010$, 95% CI [0.072, 0.520]), reflecting that data accuracy and system stability are important factors in making learners feel that AI is relatively easy and more reliable to use. When AI can respond accurately and quickly, learners can reduce their mental effort when using the tool, resulting in higher perceived usability, effort expectancy, and perceived ease of use.

These results are consistent with studies by Adwan & Aladwan [24], Yin and Qiu [26], Cao *et al.* [28], Nieves-Pavón *et al.* [29] and Yang *et al*. [30], which indicate that cognitive support was a key mechanism that significantly enhances the perceived usefulness and ease of use of AI technologies on the part of learners. These findings reinforce the view that the quality of AI learning experiences plays a key role in shaping positive perceptions of the technology, which serves as a crucial foundation for the sustainable adoption and use of AI in educational contexts.

B. Perception and Attitudes Affecting Usage Behavior

The results of the study confirmed that PU and PEOU had a significant positive influence on learners' ATT, especially perceived usefulness of AI ($\beta = 0.106$, $t = 2.170$, $p < 0.050$, 95% CI [0.010, 0.202]) and perceived ease of use ($\beta = 0.119$, $t = 2.458$, $p < 0.050$, 95% CI [0.024, 0.214]). This reflects that learners who view AI technology as a valuable, relatively easy-to-use tool are more likely to have a positive attitude towards its use in a learning context.

These results are consistent with the ideas of Liu and Ma [33], Albawwat and Frijat [35], Kelly *et al.* [36], Kim *et al.* [37] and Teodorescu *et al.* [38] which indicate that positive perceptions of usefulness and ease of use are the main drivers of positive attitudes towards technology. Furthermore, positive ATT also positively influenced BEH ($\beta = 0.103$, $t = 1.964$, $p < 0.050$, 95% CI [0.019, 0.206]), which was a statistically significant path, indicating that positive attitude plays an important role as a mechanism in predicting learners' future AI use behavior.

This interpretation reflects a psychological picture in which learners respond to technology, not only on functional grounds, but also through evaluations of its value and the positive experiences it provides, which in turn reinforce their trust and motivation to continue using it. Such findings have important practical implications for designing strategies to promote AI adoption in teaching and learning, focusing on learning experiences that enable learners to tangibly perceive its usefulness and ease of use through meaningful, authentic activities that align with real-life learning.

C. Suitability of Model and Theoretical Proposals

The analysis of the model validated the suitability of the SOR model's conceptual framework for explaining the application of AI in the learning environment of Industrial Education students in Thailand during the digital age. The Fit Indices (CFI = 0.960, SRMR = 0.063, and RMSEA = 0.058) were deemed acceptable, based on the standards set by Hair *et al.* [50], indicating a good fit with the empirical data. In addition, the R^2 value of the variable BEH = 0.786, indicating that it can explain the variance of learners' AI use behavior, which is considered to be at the Substantial Explanatory Power level [50, 52, 53]. These findings reinforce the view that the application of the SOR model to the study AI learning behavior is highly appropriate theoretically, consistent with the research of Huang [15] on the ability to clearly reflect the psychological mechanism linking learning experience (Stimulus) → cognitive and emotional processing (Organism) → usage behavior (Response). The model therefore does not only explain technology acceptance behavior, it also opens new perspectives on human-AI interaction in the experiential learning dimension, suitable for students in the field of Industrial Education in Thailand.

Although this research was conducted in the context of Thailand which may limit the ability to apply the findings to other countries or educational cultures directly, the study provides important theoretical findings regarding the mechanisms linking three dimensions of AI-based learning experience ACC, INS, and INT to PU, PEOU, ATT, and the BEH of Generation Z students in a digitally transitioning educational context, within the framework of the SOR model.

In the context of emerging economies and the process of driving digital and Industry 4.0 policies, Thailand is not merely a spatial case study but serves as a theoretical representative case for understanding the dynamics of AI-based learning in transitional education systems.

Although the SOR framework provides a systematic structure to link AI, experiences, perceptions, attitudes, and behavioral intentions, it importantly considers the specific background of the sample group and the educational setting when interpreting the research results. Learner engagement with AI may not depend solely on perceived usefulness and ease of use, but may also be influenced by emotional and contextual factors such as anxiety towards AI, levels of trust, institutional support, or learning culture. This may vary from country to country and field of study.

In theory, the validation of this model contributes to academia by suggesting ways to extend the SOR framework to include new variables that reflect the challenges of the AI era, such as AI ethics, trust in technology (AI Trust), and digital awareness (AI Literacy). This can enhance the model's capabilities to better align with the dynamics of future learner behavior.

Furthermore, the practical findings suggest guidelines for designing AI systems for high-quality, responsive learning (Accuracy and Insight) and promoting the development of AI literacy curricula to foster positive attitudes, trust, and sustainable AI use behaviors. This will serve as a crucial foundation for driving educational systems toward ethical, practical AI learning.

D. Limitations of the Research

This research has four limitations that should be mentioned:

Firstly, the referencing of the research results is limited because the sample group is Generation Z students in Industrial Education in the context of public and private higher education institutions in Thailand. Although the sample size determination is based on the concept of Hair *et al.* [50], the sample is specific, which may prevent the research results from being fully applicable to students in other fields in the country or to students of other cultures. However, although the Thai context limits the direct referencing of the research results to other countries, this research has taken place in a particular context that is significant and suitable for studying AI learning in the context of emerging economies which have specific characteristics in the transition to the digital industrial era, including the driving force of Industry 4.0 policy and the readiness of educational institutions. Therefore, in the context of Thailand, it is not just a spatial limitation, but a specific context that helps explain the dynamics of the acceptance and use of AI in education for Generation Z students in Industrial Education in Thailand, a country which is attempting to achieve a sustainable transition of manpower into the digital industrial era.

Secondly, this research used a cross-sectional data collection method, collecting data over a single time period. This makes it impossible to clearly examine long-term causal relationships. Although Structural Equation Modeling (SEM) was used to analyze causal paths, the lack of time-based data prevents the confirmation of long-term changes in the three dimensions of AI learning experience (ACC, INS, and INT), perception and attitude towards AI use (PU, PEOU, and ATT), and intention to use AI (BEH) among Generation Z students in Industrial Education Future research should utilize time-based designs or experiments to confirm the causal relationships found.

Thirdly, this research relies primarily on quantitative data from questionnaires, which, while effectively describing structural relationships between variables, have limitations in terms of reflecting the context and depth of learners' AI-based learning experiences. Quantitative research can show good statistical relationships but cannot fully explain the reasons, thought processes, and emotional experiences behind learners' behavior. The absence of qualitative data, such as from the use of in-depth interviews or focus groups, means that key issues that may influence learners' AI use such as anxiety, trust, motivation, curiosity, and institutional and social pressures, have not been adequately explained in the research model. Furthermore, other important factors that may influence AI use behavior such as digital literacy, AI anxiety, institutional support, or AI-related anxiety, which previous research [2, 10, 13] has indicated play a significant role in the AI-based learning experience, have not been included. Therefore, future research could employ a mixed-methods approach coupled with an expanded range of variables to more deeply explain and reflect the complexity of AI-based learning experiences in the higher education context.

Finally, questionnaires were employed to collect data in this research. These may be susceptible to respondent bias, such as students responding in a socially acceptable manner or making self-assessments that do not reflect actual behavior. Although the researchers performed quality control measures on the instrument and maintained the privacy of respondent data, the risk of bias remains. Future research may utilize behavioral data such as AI usage behavior, information from instructors or fellow students, to further confirm the research findings.

In summary, while this research provides valuable findings regarding three dimensions of AI-powered learning experiences namely, AI accuracy and precision experience (ACC), AI depth experience (INS), and user interaction experience (INT), influencing the perceived usefulness of AI (PU), perceived ease of use of AI (PEOU), attitudes toward AI use (ATT), and factors influencing the continued intention to use AI (BEH) on the part of Generation Z Industrial Education students in Thailand, the results are interpreted in light of these limitations. Therefore, to enhance the research's value and provide a deeper understanding of the context of AI-powered learning in various dimensions, future researchers should use diverse sample sizes, employ time-based research designs, incorporate qualitative research methods, and explore additional variables.

VI. CONCLUSION

The research confirms that experiences using AI for learning (S: ACC, INS, INT), combined with perceptions and attitudes towards AI (O: PU, PEOU, ATT), significantly influence the behavioral intention to use AI (R: BEH) among Industrial Education students within the SOR model framework. This result reflects that AI functions not merely as a technological tool, but as an intelligent instrument that stimulates analytical thinking, problem-solving, and creativity through interactive learning experiences, thereby shaping learners' perceptions, attitudes, and intentions with regard to use.

In terms of practice and policy, the research underlines the need for higher education institutions to develop an AI-driven learning ecosystem by integrating experiential learning, AI, and digital competency development, fostering technological ethics, and using hands-on learning to prepare learners for work and lifelong learning in the context of Industry 4.0 and an AI-driven society. Furthermore, instructors should design AI-powered learning activities that emphasize data accuracy, analytical depth, and the quality of interaction between learners and AI to enhance the perceived value and sustainable intention to use AI.

Theoretically, this research demonstrates the potential of the SOR model to explain the causal mechanisms of AI-driven learning in higher education. This research can be extended to other disciplines such as the humanities, health sciences, and social sciences, to compare the dynamics of AI adoption across contexts, to test the consistency of models and to enhance the applicability of research findings in a wider range of contexts, using a mixed-methods research approach. To lead to a better overall understanding, further research should be conducted into the emotional, cognitive, and contextual aspects of AI usage. This kind of investigation could help create more detailed and practical models that better explain how AI learns.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

T.S.: First Author. He is responsible for the research and manuscript writing (research design, literature review, research conduct, data analysis, research conclusions, and manuscript preparation). A.S, P.N., P.L., and K.K.: Co-author. They reviewed the accuracy of this research (research design, literature review, research conduct, data analysis, research conclusions, article editing, translation, proofreading, English grammar check, and manuscript preparation together with the First Author). B.C.: Co-author and Corresponding Author. O.S., O.A., S.I., and T.A.: Co-author and Data collection. K.K.: Co-author, Translation, proofreading, English grammar check, and manuscript preparation. The authors declare that they have reviewed and edited the final results as appropriate and take full responsibility for the content of the published article. The researchers reviewed the manuscript jointly and approved the final version before publication.

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References

[1] C. K. Y. Chan and K. K. W. Lee, "The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers?" *Smart Learning Environments*, vol. 10, no. 60, pp. 1–23, Nov. 2023. doi: 10.1186/s40561-023-00269-3

[2] C. R. Guerra-Tamez, K. K. Flores, G. M. Serna-Mendiburu, D. C. Robles, and J. I. Cortés, "Decoding Gen Z: AI's influence on brand trust and purchasing behavior," *Frontiers in Artificial Intelligence*, vol. 7, pp. 1–14, Mar. 2024. doi: 10.3389/frai.2024.1323512

[3] S. Namboothiri, T. Varghese, M. Jacob, S. Job, and J. Cyriac, "Integrating Artificial Intelligence with NHEQF descriptors for pedagogical excellence," *Higher Education for the Future*, vol. 12, no. 1, pp. 27–50, Nov. 2024. doi: 10.1177/23476311241290894

[4] N. Imjai, S. Aujirapongpan, J. Jutidharabongse, and B. Usman, "Impacts of digital connectivity on Thailand's Generation Z undergraduates' social skills and emotional intelligence," *Contemporary Educational Technology*, vol. 16, no. 1, pp. 1–21, Jan. 2024. doi: 10.30935/cedtech/14043

[5] P. Nakapthom, J. Srichroen, J. Pitanon, O. Chompu, K. Chinnapha, K. Boonnag, K. Pitchayadejanant, and M. Mambelli, "Perception of customer experience towards customer loyalty in online food delivery services in Thailand: Exploring in Generation Z," *Rajabhat Chiang Mai Research Journal*, vol. 25, no. 1, pp. 164–174, Apr. 2024. doi: 10.57260/rcmrj.2024.266141

[6] Y. T. Le, H. Shiyu, J. Y. Darren, and H. C. Kang, "Artificial intelligence-enabled adaptive learning platforms: A review," *Computers and Education: Artificial Intelligence*, vol. 9, pp. 1–12, Dec. 2025. doi: 10.1016/j.caeai.2025.100429

[7] C. Park and V. W. Harris, "The impact of family relationship quality on youth's career decision-making self-efficacy: The mediating role of youth's positive decision-making skills," *Family Journal*, vol. 32, no. 2, pp. 222–229, Jan. 2024. doi: 10.1177/10664807231225216

[8] Y. A. Alshumaimeri and A. K. Alshememry, "The extent of AI applications in EFL learning and teaching," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 653–663, 2024. doi: 10.1109/TLT.2023.3322128

[9] B. Gutiérrez-Caneda, J. Vázquez-Herrero, and X. López-García, "AI application in journalism: ChatGPT and the uses and risks of an emergent technology," *Profesional de la Information*, vol. 32, no. 5, pp. 1–16, 2023. doi: 10.3145/epi.2023.sep.14

[10] S. Na, S. Heo, S. Han, Y. Shin, and Y. Roh, "Acceptance model of artificial intelligence (AI)-based technologies in construction firms: Applying the technology acceptance model (TAM) in combination with the technology–organisation–environment (TOE) framework," *Buildings*, vol. 12, no. 2, pp. 1–17, Jan. 2022. doi: 10.3390/buildings12020090

[11] T. Suwanroj, O. Saeung, P. Leekitchwatana, and K. Kaewkamjan, "Qualifications framework of essential learning outcomes for computer innovation and digital industry professionals," *International Journal of Information and Education Technology*, vol. 13, no. 2, pp. 266–278, Feb. 2023. doi: 10.18178/ijiet.2023.13.2.1804

[12] J. Velander, M. A. Taiye, N. Otero, and M. Milrad, "Artificial intelligence in K-12 education: Eliciting and reflecting on Swedish teachers' understanding of AI and its implications for teaching and learning," *Education and Information Technologies*, vol. 29, no. 4, pp. 4085–4105, Jul. 2024. doi: 10.1007/s10639-023-11990-4

[13] M. G. Mohamed, P. Goktas, S. A. Khalaf, A. Kucukkuya, I. Al-Faouri, E. A. E. S. Seleem, A. Ibraheem, A. M. Abdelhafez, S. O. Abdullah, H. N. Zaki, and A. J. Nashwan, "Generative artificial intelligence acceptance, anxiety, and behavioral intention in the Middle East: A TAM-based structural equation modelling approach," *BMC Nursing*, vol. 24, no. 1, pp. 1–16, Jul. 2025. doi: 10.1186/s12912-025-03436-8

[14] C. S. R. Costa, J. G. Santos, and E. C. Aguiar, "Sustainability and tourist behavior: A discussion in the light of Environmental Psychology," *Revista de Administração da UFSM*, vol. 8, pp. 35–49, Aug. 2015. doi: 10.5902/1983465916393

[15] T. Huang, "Using SOR framework to explore the driving factors of older adults smartphone use behavior," *Humanities and Social Sciences Communications*, vol. 10, no. 1, pp. 1–16, Oct. 2023. doi: 10.1057/s41599-023-02221-9

[16] O. I. Bunea, R. A. Corboș, S. I. Mișu, M. Triculescu, and A. Trifu, "The next-generation shopper: A study of Generation-Z perceptions of AI in online shopping," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 19, no. 4, pp. 2605–2629, Sep. 2024. doi: 10.3390/jtaer19040125

[17] J. A. Sivasothey, S. F. Yeo, and C. L. Tan, "Assessing the applicability and reliability of the SOR theory in the healthcare sector: A comprehensive review of recent research," *Paper Asia*, vol. 40, no. 1, pp. 1–12, Feb. 2024. doi: 10.59953/paperasia.v40i1(b).55

[18] S. Dheepalakshmi and R. Geetha, "The antecedents of online purchase intention during Covid-19: A serial mediation approach," *Qubahan Academic Journal*, vol. 4, no. 1, pp. 201–209, Jan. 2024. doi: 10.48161/qaj.v4n1a359

[19] D. Chakraborty, H. B. Singu, A. K. Kar, and W. Biswas, "From fear to faith in the adoption of medicine delivery application: An integration of SOR framework and IRT theory," *Journal of Business Research*, vol. 166, Nov. 2023. doi: 10.1016/j.jbusres.2023.114140

[20] L. C. Haley, A. K. Boyd, N. B. Hebballi, E. W. Reynolds, K. G. Smith, P. T. Scully, T. L. Nguyen, E. V. Bernstam, and L. T. Li, "Attitudes on artificial intelligence use in pediatric care from parents of hospitalized children," *Journal of Surgical Research*, vol. 295, Mar. 2024. doi: 10.1016/j.jss.2023.10.027

[21] Kaharuddin, D. Ahmad, Mardiana, I. Latif, B. Arafah, and R. Suryadi, "Defining the role of artificial intelligence in improving English writing skills among Indonesian students," *Journal of Language Teaching and Research*, vol. 15, no. 2, pp. 568–578, Mar. 2024. doi: 10.17507/jltr.1502.25

[22] F. Kaya, F. Aydin, A. Schepman, P. Rodway, O. Yetişensoy, and M. Demir Kaya, "The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence," *International Journal of Human-Computer Interaction*, vol. 40, no. 2, pp. 497–514, Dec. 2024. doi: 10.1080/10447318.2022.2151730

[23] S. Safdar, M. Ren, and M. A. Z. Chudhery, "Cloud computing-based virtual learning environments: Factors that build trust and satisfaction leading to acceptance," *IEEE Transactions on Engineering Management*, vol. 71, pp. 4517–4529, 2022. doi: 10.1109/TEM.2022.3218707

[24] A. Al Adwan and R. Aladwan, "Use of artificial intelligence system to predict consumers' behaviors," *International Journal of Data and Network Science*, vol. 6, no. 4, pp. 1223–1232, 2022. doi: 10.5267/j.ijdns.2022.6.011

[25] S. Hlee, J. Park, H. Park, C. Koo, and Y. Chang, "Understanding customer's meaningful engagement with AI-powered service robots," *Information Technology and People*, vol. 36, no. 3, pp. 1020–1047, Apr. 2023. doi: 10.1108/ITP-10-2020-0740

[26] J. Yin and X. Qiu, "AI technology and online purchase intention: Structural equation model based on perceived value," *Sustainability*, vol. 13, no. 10, pp. 5671–5687, May 2021. doi: 10.3390/su13105671

[27] L. Yu and Y. Li, "Artificial intelligence decision-making transparency and employees' trust: The parallel multiple mediating effect of effectiveness and discomfort," *Behavioral Sciences*, vol. 12, no. 5, pp. 127–144, Apr. 2022. doi: 10.3390/bs12050127

[28] D. Cao, M. Meadows, and X. Ma, "Thinking fast and slow: A revised SOR model for an empirical examination of impulse buying at a luxury fashion outlet," *European Journal of Marketing*, vol. 58, no. 1, pp. 342–368, May 2024. doi: 10.1108/EJM-01-2022-0046

[29] S. Nieves-Pavón, N. López-Mosquera, and H. Jiménez-Naranjo, "The factors influencing STD through SOR theory," *Journal of Retailing and Consumer Services*, vol. 75, pp. 1–11, Nov. 2023. doi: 10.1016/j.jretconser.2023.103533

[30] C. Yang, S. Yan, J. Wang, and Y. Xue, "Flow experiences and virtual tourism: The role of technological acceptance and technological readiness," *Sustainability*, vol. 14, no. 9, pp. 5361–5378, Apr. 2022. doi: 10.3390/su14095361

[31] M. A. Camilleri, "Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework," *Technological Forecasting and Social Change*, vol. 201, pp. 1–13, Apr. 2024. doi: 10.1016/j.techfore.2024.123247

[32] E. Esiyok, S. Gokcearslan, and K. G. Kucukergin, "Acceptance of educational use of AI chatbots in the context of self-directed learning with technology and ICT self-efficacy of undergraduate students," *International Journal of Human-Computer Interaction*, vol. 41, no. 1, pp. 641–650, Jan. 2024. doi: 10.1080/10447318.2024.2303557

[33] G. Liu and C. Ma, "Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model," *Innovation in Language Learning and Teaching*, vol. 18, no. 2, pp. 125–138, Jul. 2023. doi: 10.1080/17501229.2023.2240316

[34] J. S. Roppelt, D. K. Kanbach, and S. Kraus, "Artificial intelligence in healthcare institutions: A systematic literature review on influencing factors," *Technology in Society*, vol. 76, pp. 1–12, Mar. 2024. doi: 10.1016/j.techsoc.2023.102443

[35] I. Albawwat and Y. Al Frijat, "An analysis of auditors' perceptions towards artificial intelligence and its contribution to audit quality," *Accounting*, vol. 7, no. 4, pp. 755–762, Jan. 2021. doi: 10.5267/j.ac.2021.2.009

[36] S. Kelly, S. A. Kaye, and O. Oviedo-Trespalacios, "What factors contribute to the acceptance of artificial intelligence? A systematic review," *Telematics and Informatics*, vol. 77, pp. 1–33, Feb. 2023. doi: 10.1016/j.tele.2022.101925.

[37] J. Kim, K. Merrill, and C. Collins, "AI as a friend or assistant: The mediating role of perceived usefulness in social AI vs. functional AI," *Telematics and Informatics*, vol. 64, Nov. 2021. doi: 10.1016/j.tele.2021.101694

[38] D. Teodorescu, K. A. Aivaz, D. P. C. Vancea, E. Condrea, C. Dragan, and A. C. Olteanu, "Consumer trust in AI algorithms used in e-commerce: A case study of college students at a Romanian public university," *Sustainability*, vol. 15, no. 15, pp. 1–15, Aug. 2023. doi: 10.3390/su151511925

[39] C. Zhou, X. Liu, C. Yu, Y. Tao, and Y. Shao, "Trust in AI-augmented design: Applying structural equation modelling to AI-augmented design acceptance," *Heliyon*, vol. 10, no. 1, pp. 1–13, Jan. 2024. doi: 10.1016/j.heliyon.2023.e23305

[40] K. A. Cho and Y. H. Seo, "Dual mediating effects of anxiety to use and acceptance attitude of artificial intelligence technology on the relationship between nursing students' perception of and intention to use them: A descriptive study," *BMC Nursing*, vol. 23, no. 1, pp. 1–8, Mar. 2024. doi: 10.1186/s12912-024-01887-z

[41] M. Li and A. Q. Noori, "Exploring the nexus of attitude, contextual factors, and AI utilization intentions: A PLS-SEM analysis among primary mathematics teachers in China," *Asian Journal for Mathematics Education*, vol. 3, no. 3, pp. 289–311, Aug. 2024. doi: 10.1177/27527263241269060

[42] Z. Osman, "Attitude as a catalyst: The role of perceived ease of use, perceived usefulness, and self-efficacy in shaping student intentions to use artificial intelligence in higher education," *International Journal of Academic Research in Accounting, Finance and Management Sciences*, vol. 15, no. 1, pp. 201–215, Mar. 2025. doi: 10.6007/ijarafms/v15-i1/24459

[43] C. B. Rathod, C. R. Patel, V. R. Mistri, B. M. Karnavat, and A. Vagadia, "AI and Generation Z: Exploring perceptions, attitudes, and usage intentions," *Journal of Information Systems Engineering and Management*, vol. 25, no. 2, pp. 155–168, Nov. 2025. doi: 10.55267/iadt

[44] V. Moravec, N. Hynek, M. Skare, B. Gavurova, and M. Kubak, "Human or machine? The perception of artificial intelligence in journalism, its socio-economic conditions, and technological developments toward the digital future," *Technological Forecasting and Social Change*, vol. 200, Mar. 2024. doi: 10.1016/j.techfore.2023.123162

[45] M. R. Allen, S. Webb, A. Mandvi, M. Frieden, M. Tai-Seale, and G. Kallenberg, "Navigating the doctor-patient-AI relationship – a mixed-methods study of physician attitudes toward artificial intelligence in primary care," *BMC Primary Care*, vol. 25, no. 1, Jan. 2024. doi: 10.1186/s12875-024-02282-y

[46] Ş. M. Kaya and V. Bayram, "Artificial intelligence awareness scale development study," *OPUS Journal of Society Research*, vol. 22, no. 4, pp. 657–672, 2025. doi: 10.26466/opusjsr.1680531

[47] E. M. R. Alamayreh, D. Almajali, L. A. Alsmadi, R. Masa'deh, A. S. Al-Sherideh, and S. Al Majali, "Antecedents of understanding the investors' acceptance of artificial intelligence: Perceptions from Jordanian context," *International Journal of Data and Network Science*, vol. 7, no. 4, pp. 1861–1874, Jan. 2023. doi: 10.5267/j.ijdns.2023.7.006

[48] G. Cao, Y. Duan, J. S. Edwards, and Y. K. Dwivedi, "Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making," *Technovation*, vol. 106, pp. 1–15, Aug. 2021. doi: 10.1016/j.technovation.2021.102312

[49] J. A. Kumar, B. Bervell, N. Annamalai, and S. Osman, "Behavioral intention to use mobile learning: Evaluating the role of self-efficacy, subjective norm, and WhatsApp use habit," *IEEE Access*, vol. 8, pp. 208058–208074, 2021. doi: 10.1109/ACCESS.2020.3037925

[50] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, 8th ed. Andover: Cengage Learning EMEA, 2019.

[51] P. Leekitchwatana, *Research Methods in Education*, 14th rev. ed. Bangkok: MEAN Service Supply Limited Partnership, 2025.

[52] K. Khontee and A. Poonputta, "Causal factors influencing the mathematical reasoning ability of grade 6 students," *Educational Process: International Journal*, vol. 17, e2025297, Jul. 2025. doi: 10.22521/edupij.2025.17.297

[53] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates, 1988.