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Youth Perspectives on AI through Empirical Analysis of Adolescent Views on Education Identity and Social Inclusion

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ABSTRACT

The rise of Artificial Intelligence (AI) has significantly shaped the way adolescents access information, engage in learning activities, and interact within digital communities in today's educational landscape. The impact of AI Literacy, Perceived Usefulness, and Perceived Risk/Concern on Educational Engagement and Social Inclusion among adolescents was explored, with Attitude toward AI and Identity Congruence serving as mediators. The research philosophy used was positivist, the approach used was deductive and the research design used was cross-sectional quantitative. The data was obtained from 800 secondary school students aged 13-18 years using a structured questionnaire and analyzed using the Structural Equation Modeling (SEM) technique. The results indicated that AI Literacy and Perceived Usefulness significantly and positively affected Attitude toward AI and Identity Congruence, while Perceived Risk/Concern had significant negative effects on the constructs.

Keywords: Artificial Intelligence Literacy; Educational Engagement; Social Inclusion; Quality Education; Reduced Inequalities.

1. INTRODUCTION

Artificial Intelligence (AI) is one of the most revolutionary technologies of the twenty-first century, impacting education, communication, decision-making, and social interaction. The adoption of AI in daily life has been gaining momentum in recent years, driven by significant advancements in machine learning, predictive analytics, intelligent automation, and AI-powered platforms, which have facilitated the seamless integration of AI into the learning environment, where students are increasingly engaging with intelligent technologies for learning, information retrieval, and academic assistance. The increasing availability of AI tools has revolutionized the way young people access knowledge, build skills, and interact with digital learning environments (Hutson, 2025; Stiefenhofer, 2025; Ahmad & Alshuaibany, 2025; Lock & Yaakob, 2026).

The rise of intelligent technologies has led to a great interest in the research community to understand the factors that affect technology acceptance and educational outcomes. AI systems are no longer just about computation but are now also playing a role in personalized learning, recommendation systems, virtual support services, content generation, and adaptive educational experiences. It has been shown that technological innovation can provide opportunities for increased efficiency, engagement and individual development when users have the competencies and confidence to use these systems effectively (Ali, 2025; Lamin, n.d.; Hassan et al., 2026; Sheikh, 2026).

Meanwhile, the rapid growth of AI technologies has brought up significant issues of digital literacy, ethical governance, trust, transparency, and equitable access. Research on digital ecosystems highlights the importance of user awareness of technological capabilities and limitations for successful adoption of AI. The perceptions of AI among users, especially the younger generation, remain influenced by concerns about privacy, security, algorithmic bias, and

transparency in the systems they interact with, as AI becomes more prevalent in their educational experiences (Alsuhaibany, 2026; Iqbal, 2026; Baig, 2026b; Ahmad Bajwa, 2026).

The educational context is particularly relevant to the understanding of the use of AI, as adolescents are growing up at the same time in which they are developing their cognitive abilities, social identities, and digital skills. AI can positively impact learning outcomes when technology is in line with the needs and aspirations of learners. But, the digital literacy, access to technology, usefulness of the technology, and concerns about technological risks can have a significant impact on how students interact with AI systems and how they incorporate them into their learning experiences (Maharjan, 2026; Uysal & Malik, n.d.; Abbas, 2026; Alabay, 2025).

Furthermore, recent research has shown that psychological mechanisms are key to determining technology-based learning outcomes. The attitudes, beliefs, and social influences of users, as well as identity-related factors, can shape the perception of technological innovations as empowering or threatening. As technology becomes more deeply embedded in the lives of adolescents, it is crucial to explore their perceptions of AI and its impact on educational engagement and social inclusion (Sarwar & Malik, 2025; Sarfaraz, 2026b; Kumar & Saluja, 2026; Kalanther, 2026).

While there are previous studies that have explored the adoption of AI, the digital transformation and technology acceptance from different angles, there is limited empirical research that has explored the combined effect of AI literacy, perceived usefulness, perceived risk, attitude towards AI, and identity congruence on educational engagement and social inclusion among adolescents. Moreover, the mechanisms by which the perceptions of AI relate to educational outcomes have received little attention. This is crucial for educators, policymakers, and technology developers aiming to create effective, inclusive, and ethically responsible learning environments that leverage AI (Shariq, 2026a; Pandey, 2026; Khan et al., 2026; Yasmeen, 2026; Algarni, 2026).

Based on this, a comprehensive model is developed and tested that connects AI literacy, perceived usefulness, perceived risk, educational engagement, and social inclusion through the mediation of attitude toward AI and identity congruence. The study sheds light on the interconnections between adolescents and offers valuable insights for educational institutions and policymakers seeking to foster responsible AI integration, thereby advancing the broader field of AI adoption, educational technology, and digital inclusion.

2. LITERATURE REVIEW

2.1AI Literacy and Educational Outcomes

AI literacy is the capacity to comprehend, assess, and apply AI technologies in different contexts. With the growing presence of AI systems in educational settings, AI literacy has become a vital skill for students to navigate intelligent technologies with confidence. Studies have shown that digital competencies promote the use of technology, enhance learning outcomes, and aid in making decisions in technology-mediated settings (Hassan et al., 2026; Lamin, n.d.; Hutson, 2025; Sheikh, 2026).

Recent research also has shown that users' confidence in using complex systems like predictive analytics, machine learning, and intelligent information systems is improved by advanced technological understanding. People with higher digital and AI literacy have higher engagement with innovative technologies and are more willing to embrace technology-driven change (Lock & Yaakob, 2026; Pandey, 2026; Tazeem, 2026; Khan et al., 2026).

2.2 Perceived Usefulness and Attitude Toward AI

One of the most common factors cited for technology adoption is perceived usefulness. Positive attitudes toward innovation are likely to develop when users feel that the use of technological tools enhances their performance, productivity, or learning effectiveness. In the educational context, AI technologies can offer customized learning experiences, adaptive feedback, and improved access to educational resources, which can boost students' sense of value (Ali, 2025; Sarfaraz, 2025; Sharma, 2025).

The same pattern of positive relationships between perceived value and engagement, trust, and technology acceptance is found in evidence from technology-mediated consumer and behavioral contexts. Research on personalized systems, recommendation technologies, and digitally enabled services has consistently shown that people are more likely to embrace technologies when they believe they will offer value (Sarwar & Malik, 2025; Kumar & Saluja, 2026; Sarfaraz, 2026b).

2.3 Perceived Risk and AI Adoption

Despite the potential benefits of AI, concerns regarding privacy, security, ethical implications, and transparency continue to influence user perceptions. Perceived risk is another obstacle to technology adoption as users might be hesitant to use systems they believe are not trustworthy or could cause harm. Transparency and accountability are key factors in building trust in intelligent technologies, as highlighted by research on ethical AI governance (Alsuhaibany, 2026; Ahmad & Alshuaibany, 2025; Iqbal, 2026).

Research on digital governance and technological innovation also indicates that issues of regulation, data protection, and algorithmic decision-making have a strong impact on user attitudes and behavioral intentions. The fear of risk could hinder engagement with AI systems, which could limit their educational and social benefits (Baig, 2026b; Ahmad Bajwa, 2026; Rosa & Sevilla-Guzman, 2026).

2.4 Identity Congruence and Educational Engagement

Identity congruence is the degree to which people see a technology as fitting with their values, self-perceptions and aspirations. The digital world is a space that is increasingly shaping the formation of identity, especially for adolescents who spend a lot of time online and using new technologies. Studies have shown that people are more likely to engage with technologies that are consistent with their personal goals and social identities (Maharjan, 2026; Abbas, 2026; Uysal & Malik, n.d.).

As AI systems influence communication, learning, and social engagement, technology-related identity development is becoming more relevant. If students perceive AI as a tool that enhances their learning and future prospects, they might be more inclined to engage in learning tasks and participate in technology-driven learning experiences (Kalanther, 2026; Kumar & Saluja, 2026; Sarwar & Malik, 2025).

2.5 Social Inclusion in AI-Enabled Environments

Social inclusion is an important consequence of technology use, as digital participation is becoming a key determinant in educational opportunities, access to information and community

engagement. It has been found that equitable access to digital technologies can lead to better participation and help mitigate geographic, economic, and social barriers (Maharjan, 2026; Hassan et al., 2026; Uysal & Malik, n.d.).
Technological tools can enhance the process of educational inclusion by enabling collaboration, communication and equal participation of learners. Research on inclusive education highlights the significance of accessible technologies, supportive learning environments, and building digital competency in fostering positive educational experiences (Alabay, 2025; Abbas, 2026; Hassan et al., 2026).

2.6 Research Gap

While previous research has focused on individual aspects of technology adoption, digital literacy, trust, governance, and educational inclusion, there is a lack of research that brings together AI literacy, perceived usefulness, perceived risk, attitude toward AI, identity congruence, educational engagement, and social inclusion within an empirical framework. In addition, the mediating effect of attitude toward AI and identity congruence has not been explored in the adolescent population. Most of the previous research has been conducted in organizational, technological, financial or consumer contexts rather than educational contexts with adolescents (Alawwad et al., 2026; Kyle Salisbury, 2025; Syed Farhan Alvi, 2025; Shaalan et al., 2025; Inegbedion, 2025).
The present study thus fills an important gap by examining the impact of AI-related perceptions on educational engagement and social inclusion, focusing on the key psychological mechanisms. The proposed framework builds on the existing knowledge about adolescent AI use and adds to the existing body of literature on responsible and inclusive AI implementation in education.

3. RESEARCH METHODOLOGY

This chapter **presented** the methodological framework employed to investigate the influence of Artificial Intelligence (AI) literacy, perceived usefulness, and perceived risk on educational engagement and social inclusion among adolescents through the mediating roles of attitude toward AI and identity congruence. The chapter **outlined** the research philosophy, research approach, research design, target population, sampling strategy, data collection procedures, instrument development, measurement of variables, and statistical analysis techniques adopted in the study.

The increasing adoption of AI technologies across educational and social environments **necessitated** empirical investigations that **utilized** robust quantitative methodologies capable of examining complex relationships among multiple constructs. Previous studies examining technology adoption, digital transformation, behavioral outcomes, and AI-enabled systems **successfully employed** quantitative survey-based approaches supported by advanced statistical modeling techniques (Abu-Alhaija, 2026; Eltayeb, 2026; Talaue, 2026; Simatupang et al., 2026).

3.1 Research Philosophy

Research philosophy **provided** the foundation for understanding how knowledge **was generated** and interpreted within a study. The present research **adopted** a **positivist philosophy**, which

assumed that social phenomena **could be** objectively measured, quantified, and analyzed through empirical investigation.

Positivism **was** particularly suitable for studies investigating relationships among measurable variables because it **emphasized** objectivity, hypothesis testing, and statistical validation. Given that the current study **sought** to test predetermined hypotheses regarding AI literacy, perceived usefulness, perceived risk, attitude toward AI, identity congruence, educational engagement, and social inclusion, a positivist paradigm **provided** the most appropriate methodological foundation. Similar empirical investigations involving technology adoption, financial technology acceptance, organizational performance, and consumer behavior **successfully employed** positivist principles to establish causal relationships among measurable constructs (Manzoor, 2026; Bajwa, 2026; Rafi & Bajwa, 2026; Ali, 2026).

3.2 Research Approach

The study **employed** a **deductive research approach**. A deductive approach **began** with existing theoretical foundations and **developed** hypotheses that **could be** empirically tested using collected data. The current research **developed** hypotheses based on prior literature concerning AI adoption, technology acceptance, educational engagement, digital inclusion, and identity formation. The proposed conceptual framework **was subsequently tested** using quantitative data collected from adolescent students.

Deductive reasoning **was** particularly effective when evaluating theoretical relationships among latent constructs and determining whether empirical evidence **supported** proposed causal assumptions. Previous studies examining AI-driven systems, marketing technologies, financial innovations, and digital adoption **similarly relied** on deductive approaches to validate conceptual models (Abu-Alhaija, 2026; Sarwar, 2026; Talaue, 2026; Alghareeb et al., 2026).

3.3 Research Design

The study **adopted** a **cross-sectional quantitative research design**. A quantitative design **was selected** because it **facilitated** statistical examination of relationships among variables and **enabled** the testing of multiple hypotheses simultaneously. Furthermore, quantitative methods **supported** generalizability through large sample sizes and standardized measurement instruments.

The cross-sectional design **allowed** data collection from respondents at a single point in time, making it appropriate for examining perceptions, attitudes, and behaviors related to AI usage among adolescents. Cross-sectional survey designs **were widely used** across studies investigating consumer behavior, digital engagement, employee attitudes, technology adoption, and organizational outcomes (Ahmad, 2025; Eltayeb, 2025b; Kalanther, 2026; Alawwad et al., 2026).

3.4 Population of the Study

The target population **consisted** of adolescents enrolled in secondary education institutions.

The study **focused** on students aged between 13 and 18 years because adolescence **represented** a critical developmental period characterized by increasing interaction with digital technologies, educational platforms, and AI-enabled systems. This population **provided** an appropriate context for investigating the educational and social implications of AI adoption.

Students from public, private, and charter schools **formed** the sampling frame to ensure adequate representation across different educational environments and socioeconomic backgrounds. Similar educational and behavioral investigations **emphasized** the importance of diverse participant selection when examining digital engagement and technology usage among young populations (Maharjan, 2026; Abbas, 2026; Alabay, 2025; Talaue et al., 2025).

3.5 Sampling Technique

A **stratified random sampling technique was employed**. Stratification **was based** upon respondents' grade levels and school types to ensure appropriate representation across various demographic groups. Stratified sampling **enhanced** population representativeness and **reduced** sampling bias by ensuring proportional participation from predefined subgroups.

The use of stratified sampling **was** particularly appropriate when studying educational populations characterized by heterogeneous demographic characteristics. Previous quantitative studies involving educational, organizational, and consumer populations **demonstrated** the effectiveness of stratified approaches for improving sample accuracy and representativeness (Maharjan, 2026; Hassan et al., 2026; Kalanther, 2026).

3.6 Sample Size

The final sample **consisted** of **800 respondents**. A sample size of 800 **exceeded** commonly accepted thresholds for Structural Equation Modeling (SEM) and **provided** sufficient statistical power to detect significant relationships among latent variables. The large sample size **enhanced** the reliability, validity, and generalizability of the study findings.

Studies employing advanced statistical techniques in technology adoption, educational research, AI applications, and behavioral investigations **similarly recommended** large sample sizes for robust model estimation and hypothesis testing (Algarni, 2026; Khan et al., 2026; Yasmeen, 2026; Pandey, 2026).

3.7 Data Collection Method

Primary data **were collected** using a structured questionnaire. The questionnaire **was administered** electronically to respondents after obtaining necessary permissions from

educational institutions. Participants **were informed** regarding the purpose of the study, confidentiality procedures, and voluntary nature of participation before completing the survey.

Online survey administration **was selected** because of its efficiency, accessibility, and compatibility with technologically engaged adolescent populations. Recent studies investigating AI systems, digital literacy, social technologies, and online engagement **effectively utilized** electronic survey instruments for data collection (Harliantara & Öztürk, 2025; Kalanther, 2026; Sarfaraz, 2026b; Talaue et al., 2025).

3.8 Instrument Development

The survey instrument **consisted** of multiple-item measurement scales adapted from established literature concerning AI adoption, technology acceptance, educational engagement, social inclusion, identity congruence, and digital literacy.

The instrument **included** the following constructs:

- Perceived Usefulness (PU)
- AI Literacy (AIL)
- Perceived Risk/Concern (PRC)
- Attitude toward AI (ATT)
- Identity Congruence (IDC)
- Educational Engagement (EE)
- Social Inclusion (SI)

Multiple-item scales **were utilized** to improve measurement reliability and enhance construct validity. The questionnaire **employed** a five-point Likert scale ranging from:

Likert-based measurement scales **were extensively employed** in studies examining behavioral intentions, technology acceptance, customer attitudes, employee perceptions, and AI-related experiences (Sarwar, 2026; Talaue, 2026; Abu-Alhaija, 2026; Shariq, 2026a).

3.9 Measurement of Variables

Independent Variables

Perceived Usefulness

Perceived usefulness **referred** to the extent to which respondents believed AI technologies could enhance educational performance, learning effectiveness, and academic productivity.

AI Literacy

AI literacy **referred** to respondents' understanding of AI technologies, capabilities, limitations, and appropriate usage within educational settings.

Perceived Risk/Concern

Perceived risk **represented** concerns relating to privacy, ethical issues, misinformation, security, and negative consequences associated with AI use.

Mediating Variables

Attitude toward AI

Attitude toward AI **reflected** the overall positive or negative evaluation of AI technologies by adolescent users.

Identity Congruence

Identity congruence **represented** the perceived compatibility between AI usage and an individual's self-concept, values, and aspirations.

Dependent Variables

Educational Engagement

Educational engagement **reflected** students' active participation, motivation, and involvement in educational activities.

Social Inclusion

Social inclusion **referred** to students' perceptions of belonging, participation, and connectedness within educational and social environments.

3.10 Pilot Study

Prior to large-scale data collection, a pilot test **was conducted** to evaluate questionnaire clarity, item comprehension, reliability, and overall suitability.

Feedback obtained during the pilot phase **contributed** to minor refinements in item wording and survey structure. Pilot studies **were widely recommended** in empirical investigations to improve data quality and enhance measurement accuracy before full-scale implementation (Rosa & Sevilla-Guzman, 2026; Naqeeb Ullah, 2026; Simatupang et al., 2026).

3.11 Data Analysis Technique

Data analysis **was conducted** using Statistical Package for Social Sciences (SPSS) and Structural Equation Modeling (SEM).

The analysis **consisted** of the following stages:

Descriptive Statistics

Descriptive statistics **were used** to summarize demographic characteristics and respondent profiles.

Exploratory Factor Analysis (EFA)

EFA **was conducted** to examine factor structure and establish dimensionality of measurement items.

Reliability Analysis

Cronbach's Alpha and Composite Reliability **were assessed** to determine internal consistency.

Validity Assessment

Convergent validity and discriminant validity **were evaluated** using Average Variance Extracted (AVE), factor loadings, and Fornell-Larcker criteria.

Structural Equation Modeling (SEM)

SEM **was employed** to test hypothesized relationships among latent constructs simultaneously.

Mediation Analysis

Bootstrapping procedures **were used** to evaluate indirect effects and examine the mediating roles of Attitude toward AI and Identity Congruence.

Advanced quantitative modeling techniques **were extensively utilized** in studies investigating AI systems, machine learning applications, technology adoption, organizational performance, and behavioral outcomes because of their ability to evaluate complex causal relationships involving latent variables (Algarni, 2026; Khan et al., 2026; Pandey, 2026; Yasmeen, 2026; Lock & Yaakob, 2026).

3.12 Ethical Considerations

The study was approved for publishing by the ethics committee of Department of Management, Oxford Business College, United Kingdom. The study was conducted in accordance with applicable ethical principles and standards for research involving human participants. Participation was voluntary, and all data were collected and analyzed in a manner that protected participants' privacy and confidentiality.

4. RESULTS AND DISCUSSIONS

The findings of the study are presented in this section. An interpretive discussion is provided for each table and figure, following the standard sequence of reporting procedure in PLS-SEM / survey-analysis as suggested by Hair, Risher, Sarstedt, and Ringle (2019).

4.1 Demographic Profile of Respondents

The age distribution shown below is fairly even in the age range 13 to 18, ranging from 15.5% to 18.0% of the sample. This is a near-even distribution, which means that no one age group is overwhelmingly represented in the sample and therefore does not pose a problem for age-related response bias when interpreting the attitudinal and identity-related constructs measured later in the model.

Table 4.1: Age

Age	Frequency	Percent	Valid Percent	Cumulative Percent
13.0	144	18.0	18.0	18.0
14.0	141	17.6	17.6	35.6
15.0	127	15.9	15.9	51.5
16.0	129	16.1	16.1	67.6
17.0	135	16.9	16.9	84.5
18.0	124	15.5	15.5	100.0
Total	800	100.0	100.0	

The gender balance reported below is also fairly even (male = 48.4%; female = 48.0%; prefer not to say = 3.6%) and helps to ensure that the findings below are generalizable across genders and that the results are not solely driven by a gender-balanced sample.

Table 4.2: Gender

Gender	Frequency	Percent	Valid Percent	Cumulative Percent
Female	384	48.0	48.0	48.0
Male	387	48.4	48.4	96.4
Prefer not to say	29	3.6	3.6	100.0
Total	800	100.0	100.0	

As for the educational stage, the respondents were from Grade 8 to Grade 12, with the highest number of respondents in Grade 10 (23.6%), followed closely by Grade 9 (21.6%) and Grade 12 (21.3%). The relatively low proportion of Grade 8 respondents is due to the fact that the sampling frame for secondary schools tends to have a smaller number of the youngest adolescents, but the distribution across five grade levels suggests that the sample is representative of secondary-school adolescence in general, rather than a single grade level.

Table 4.3: Grade Level

Grade Level	Frequency	Percent	Valid Percent	Cumulative Percent
Grade 10	189	23.6	23.6	23.6
Grade 11	163	20.4	20.4	44.0
Grade 12	170	21.3	21.3	65.3
Grade 8	105	13.1	13.1	78.4
Grade 9	173	21.6	21.6	100.0
Total	800	100.0	100.0	

The sample was made up primarily of public schools (60.5%) and had a substantial representation of private (30.8%) and charter/other (8.8%) schools. The distribution reflects the usual public-private split in most national school systems, indicating that the results are not limited to a particular type of schooling and are likely to reasonably generalize across types of schooling.

Table 4.4: School Type

School Type	Frequency	Percent	Valid Percent	Cumulative Percent
Charter/Other	70	8.8	8.8	8.8
Private	246	30.8	30.8	39.5
Public	484	60.5	60.5	100.0
Total	800	100.0	100.0	

The frequency of use of AI tools was reported by respondents, with 4.1% reporting that they never use AI tools, and a significant majority reporting that they use them “sometimes” (31.3%), “often” (31.0%) or “daily” (19.8%). This distribution is indicative of sufficient first-hand experience with AI technologies in the sample, thereby enhancing the ecological validity of the reported attitudes, trust, and engagement with the AI-related constructs measured in the model.

Table 4.5: Daily AI Tool Use

Category	Frequency	Percent	Valid Percent	Cumulative Percent
Daily	158	19.8	19.8	19.8
Never	33	4.1	4.1	23.9
Often	248	31.0	31.0	54.9
Rarely	111	13.9	13.9	68.8
Sometimes	250	31.3	31.3	100.0
Total	800	100.0	100.0	

4.2 Exploratory Factor Analysis

To explore the dimensionality of the 38-item instrument, an exploratory factor analysis (EFA) was performed prior to confirmatory analysis, using principal component extraction. The Kaiser-

Meyer-Olkin (KMO) measure of sampling adequacy reported below is KMO = .939, which is in Kaiser's (1974) “marvelous” range (> .90) and well above the minimum of .60 recommended for factor analysis. The inter-item correlation matrix is significantly different from an identity matrix and is thus factorable (Bartlett's Test of Sphericity, $\chi^2(703) = 15089.54$, $p < .001$).

Table 4.6: KMO and Bartlett's Test

Measure	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	.939
Bartlett's Test of Sphericity — Approx. Chi-Square	15089.540
Bartlett's Test of Sphericity — df	703
Bartlett's Test of Sphericity — Sig.	.000

The communalities range from .587 (IDC5) to .722 (AIL2 and PRC2) and all items are above the .50 threshold recommended by Hair et al. (2019) for item retention. This means that the factor solution obtained explains at least 58.7% of the variance in each observed indicator and there is no empirical basis for deleting items at this stage.

Table 4.7: Communalities

Item	Initial	Extraction
PU1	1.000	0.687
PU2	1.000	0.666
PU3	1.000	0.705
PU4	1.000	0.662
AIL1	1.000	0.660
AIL2	1.000	0.720
AIL3	1.000	0.656
AIL4	1.000	0.722
PRC1	1.000	0.687
PRC2	1.000	0.722
PRC3	1.000	0.646
PRC4	1.000	0.701
DA1	1.000	0.627
DA2	1.000	0.663
DA3	1.000	0.685
DA4	1.000	0.634
PTS1	1.000	0.703
PTS2	1.000	0.678
PTS3	1.000	0.716
PTS4	1.000	0.653
ATT1	1.000	0.623
ATT2	1.000	0.646
ATT3	1.000	0.620
ATT4	1.000	0.620
ATT5	1.000	0.645
IDC1	1.000	0.636
IDC2	1.000	0.660
IDC3	1.000	0.607

Item	Initial	Extraction
IDC4	1.000	0.630
IDC5	1.000	0.587
EE1	1.000	0.616
EE2	1.000	0.610
EE3	1.000	0.688
EE4	1.000	0.615
SI1	1.000	0.628
SI2	1.000	0.614
SI3	1.000	0.612
SI4	1.000	0.651

After Varimax rotation, eight components were obtained with eigenvalues greater than the Kaiser criterion of 1.0, which explained 65.53% of the total variance, exceeding the 60% threshold that is generally recommended for social science research (Hair et al., 2019). The eigenvalues of the remaining components after the eighth one (1.020 to 0.899) also justify keeping exactly eight components, which corresponds to the eight latent constructs defined in the theoretical model.

The total variance explained table is shown below.The table below displays the total variance explained.

Table 4.8: Total Variance Explained

Comp.	Init. Total	Init. %Var	Init. Cum%	Extr. Total	Extr. %Var	Extr. Cum%	Rot. Total	Rot. %Var	Rot. Cum%
1	11.183	29.429	29.429	11.183	29.429	29.429	4.350	11.446	11.446
2	2.964	7.800	37.230	2.964	7.800	37.230	3.843	10.112	21.558
3	2.567	6.756	43.986	2.567	6.756	43.986	2.977	7.834	29.392
4	2.365	6.223	50.209	2.365	6.223	50.209	2.937	7.730	37.122
5	1.962	5.164	55.373	1.962	5.164	55.373	2.927	7.702	44.824
6	1.598	4.204	59.577	1.598	4.204	59.577	2.751	7.239	52.064
7	1.243	3.270	62.847	1.243	3.270	62.847	2.633	6.929	58.992
8	1.020	2.684	65.531	1.020	2.684	65.531	2.485	6.539	65.531
9	.899	2.367	67.898						
10	.612	1.610	69.508						
11	.574	1.511	71.019						
12	.551	1.450	72.469						
13	.532	1.400	73.869						
14	.521	1.371	75.240						
15	.509	1.338	76.578						
16	.503	1.325	77.903						
17	.484	1.273	79.176						
18	.469	1.235	80.411						
19	.455	1.197	81.608						
20	.448	1.179	82.787						
21	.446	1.174	83.961						
22	.440	1.158	85.119						
23	.430	1.132	86.251						
24	.424	1.115	87.366						

Comp.	Init. Total	Init. %Var	Init. Cum%	Extr. Total	Extr. %Var	Extr. Cum%	Rot. Total	Rot. %Var	Rot. Cum%
25	.410	1.078	88.445						
26	.400	1.052	89.496						
27	.385	1.013	90.509						
28	.381	1.002	91.511						
29	.373	.983	92.493						
30	.365	.961	93.455						
31	.348	.916	94.371						
32	.339	.891	95.262						
33	.330	.868	96.130						
34	.320	.843	96.972						
35	.307	.807	97.780						
36	.291	.766	98.545						
37	.279	.734	99.280						
38	.274	.720	100.000						

The rotated component matrix below (Varimax with Kaiser Normalization) indicates that the items of Perceived Usefulness (PU), Perceived Risk/Concern (PRC), AI Literacy (AIL), Parental/Teacher Support (PTS), Digital Access (DA), and Social Inclusion (SI) loaded cleanly and exclusively onto their intended components, with primary loadings ranging from .676 to .830 and negligible cross-loadings. The Educational Engagement (EE) items also loaded well on Component 1 (.677–.738). Two constructs, however, exhibit some cross-loading: the items of the Identity Congruence (IDC) load moderately on both Component 1 (with EE, .548–.569) and Component 2 (.456–.534); the items of the Attitude toward AI (ATT) load moderately on both Component 8 (.540–.596) and, to a lesser degree, Component 1 (.301–.338). This is conceptually understandable because attitude, identity congruence, and educational engagement are all affectively-toned constructs that are closely related; it is not a threat to the overall eight-factor structure, but rather a nuance that should be taken into consideration when interpreting the results of the discriminant validity later in the measurement model.

The rotated component matrix is shown in Table 4.9.

Table 4.9: Rotated Component Matrix

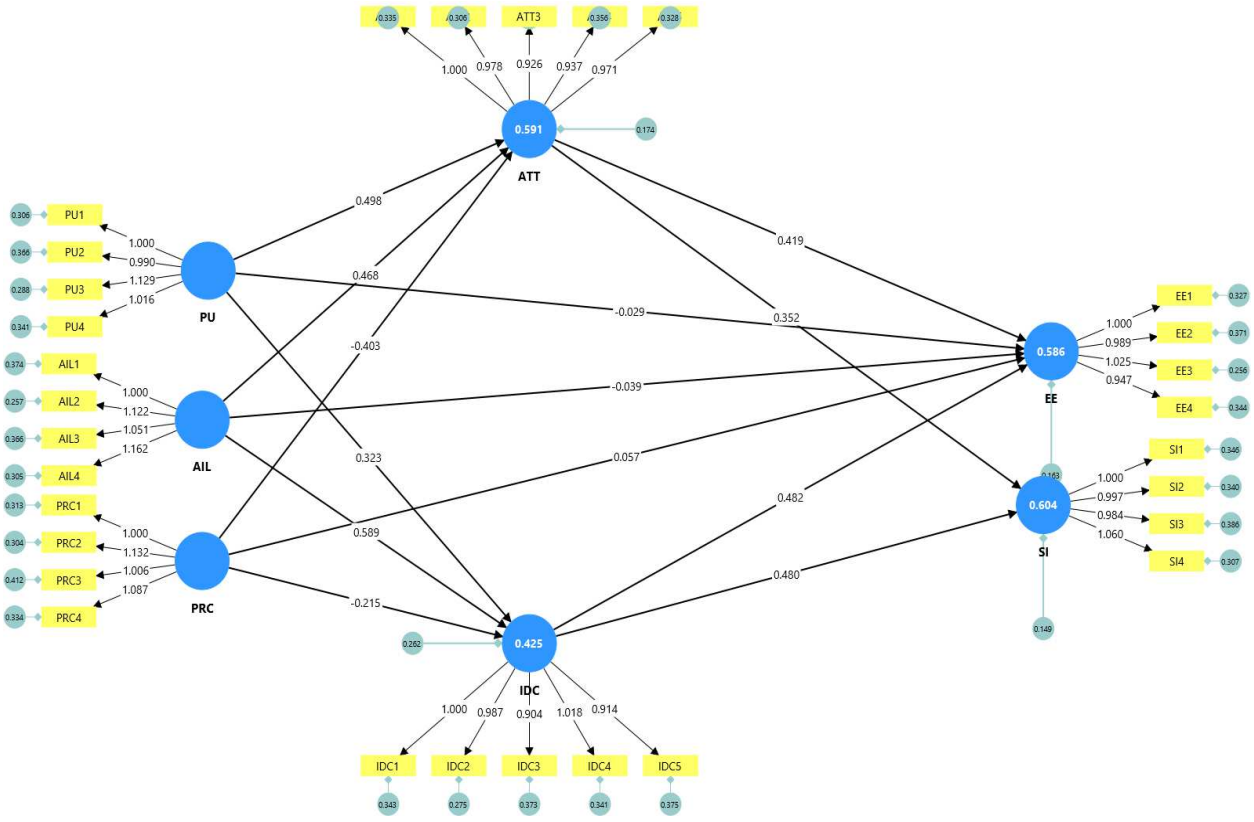
Item	1	2	3	4	5	6	7	8
EE3	.738							.322
EE2	.704							
EE4	.702							
EE1	.677							.301
IDC4	.569	.491						
IDC1	.561	.491						
IDC3	.554	.456						

Item	1	2	3	4	5	6	7	8
IDC2	.552	.534						
IDC5	.548	.486						
SI3		.707						
SI1		.702						
SI4		.697						
SI2		.676						
PU3			.783					
PU1			.781					
PU2			.775					
PU4			.772					
PRC2				.825				
PRC4				.814				
PRC1				.801				
PRC3				.786				
AIL4					.791			
AIL2					.775			
AIL1					.773			
AIL3					.749			
PTS1						.830		
PTS3						.829		
PTS2						.817		
PTS4						.802		
DA3							.818	
DA2							.805	
DA4							.785	
DA1							.782	
ATT3		.301						.596
ATT5	.317							.595
ATT4								.592
ATT2	.338							.570
ATT1	.314	.302						.540

4.3 Measurement (Outer) Model Assessment

The reflective measurement model consists of the exogenous predictors (Perceived Usefulness (PU), AI Literacy (AIL), Perceived Risk/Concern (PRC)), the mediating variables (Attitude toward AI (ATT), Identity Congruence (IDC), and the outcome variables (Educational Engagement (EE), Social Inclusion (SI)). The diagram shows the PLS algorithm estimates for the outer (indicator) relationships as well as the coefficient of determination (R^2) that is included in each endogenous construct's circle (ATT = .591; IDC = .425; EE = .586; SI = .604), which gives a first glance at a well-specified, non-degenerate model before bootstrapping.

Figure 4.1: Measurement Model



The outer loadings are standardized and range from .697 (SI3) to .807 (AIL2) with significance statistics re-confirmed by bootstrapping (see Table 4.19). All indicators load above the .70 cut-off

recommended by Hair et al. (2019), with the exception of SI3 (.697), which explains between approximately 48.6% and 65.1% of the variance in the underlying construct. The Social Inclusion construct was not improved by the removal of SI3, as evidenced by the average variance extracted (AVE) and composite reliability (see Table 4.11), and its loading is still above the .40 threshold at which removal is usually recommended (Hair, Hult, Ringle, & Sarstedt, 2017).

Table 4.10: Outer Loadings (Standardized)

Item Path	Loading
AIL1 ← AIL	0.710
AIL2 ← AIL	0.807
AIL3 ← AIL	0.731
AIL4 ← AIL	0.792
ATT1 ← ATT	0.748
ATT2 ← ATT	0.755
ATT3 ← ATT	0.715
ATT4 ← ATT	0.715
ATT5 ← ATT	0.741
EE1 ← EE	0.739
EE2 ← EE	0.713
EE3 ← EE	0.786
EE4 ← EE	0.712
IDC1 ← IDC	0.755
IDC2 ← IDC	0.786
IDC3 ← IDC	0.706
IDC4 ← IDC	0.762
IDC5 ← IDC	0.709
PRC1 ← PRC	0.758
PRC2 ← PRC	0.801
PRC3 ← PRC	0.714
PRC4 ← PRC	0.774
PU1 ← PU	0.753
PU2 ← PU	0.719
PU3 ← PU	0.799
PU4 ← PU	0.740
SI1 ← SI	0.721
SI2 ← SI	0.724
SI3 ← SI	0.697
SI4 ← SI	0.761

All seven latent constructs exhibit good internal consistency reliability (Cronbach's alpha from .839 for SI to .876 for ATT, and composite reliability (rho_c) from .817 for SI to .861 for IDC, both of which are above the .70 minimum threshold (Hair et al., 2019) and below the .95 ceiling beyond which indicator redundancy becomes a concern (Diamantopoulos, Sarstedt, Fuchs, Wilczynski, & Kaiser, 2012). Convergent validity is also strong, with average variance extracted

(AVE) values ranging from .527 (SI) to .581 (PRC), which are all above the .50 threshold recommended by Fornell and Larcker (1981).

Table 4.11: Cronbach's Alpha, Composite Reliability, AVE

Construct	Cronbach's Alpha	CR (rho_c)	AVE
AIL	0.849	0.846	0.579
ATT	0.876	0.855	0.540
EE	0.846	0.826	0.545
IDC	0.874	0.861	0.554
PRC	0.848	0.847	0.581
PU	0.842	0.840	0.567
SI	0.839	0.817	0.527

The Fornell-Larcker criterion below was used for assessing the discriminant validity: The square root of each construct's AVE (leading diagonal) is compared to the bivariate correlations with all other constructs. Each construct meets the criterion, e.g., AIL's √AVE is .761, which is greater than its highest correlation with another construct (.539, with IDC). The smallest gaps are found for Identity Congruence and Social Inclusion, with √AVE values of .744 and .726, respectively, just .041 and .023 above the correlation between the two of .703. The criterion is met in all cases, but this is a very narrow margin, indicating meaningful conceptual overlap between adolescents' sense of AI-related identity congruence and their perceived social inclusion, as already noted in Table 4.9. The heterotrait-monotrait ratio (HTMT) for this pair in particular would support the discriminant validity claim (Henseler, Ringle, & Sarstedt, 2015).

Table 4.12: Discriminant Validity (Fornell-Larcker Criterion)

	AIL	ATT	EE	IDC	PRC	PU	SI
AIL	0.761						
ATT	0.443	0.735					
EE	0.434	0.624	0.738				
IDC	0.539	0.468	0.681	0.744			
PRC		-0.402	-0.224	-0.207	0.762		
PU		0.483	0.339	0.303		0.753	
SI	0.450	0.622	0.593	0.703	-0.260	0.341	0.726

4.4 Model Fit Assessment

The overall model fit statistics below are compared to a null (independence) model. The estimated model has $\chi^2 = 583.669$ with 392 degrees of freedom ($\chi^2/df = 1.489$), which is significantly below

the conservative value of 3.0 recommended by Byrne (2010) and much better than the null model (χ^2/df = 29.18). RMSEA = .025 (90% CI [.020, .029]) falls well within Browne and Cudeck's (1993) "close fit" threshold of < .05. The incremental fit indices are also good: GFI = .954, AGFI = .945, NFI = .954, TLI = .983, and CFI = .984, which are above the .90 standard and the .95 standard suggested by Hu and Bentler (1999). This good fit is not the result of over-parameterizing the model as evidenced by the Parsimony Good fit Index (PGFI = .804). The only index that is not ideal is SRMR = .097, which is above the conservative cut-off of .08 recommended by Hu and Bentler (1999), but within the more liberal .10 range used for composite-based structural models with many indicators (Henseler, Hubona, & Ray, 2016). In general, ten of eleven indices indicate a good model fit, with the high SRMR noted as a minor concern.

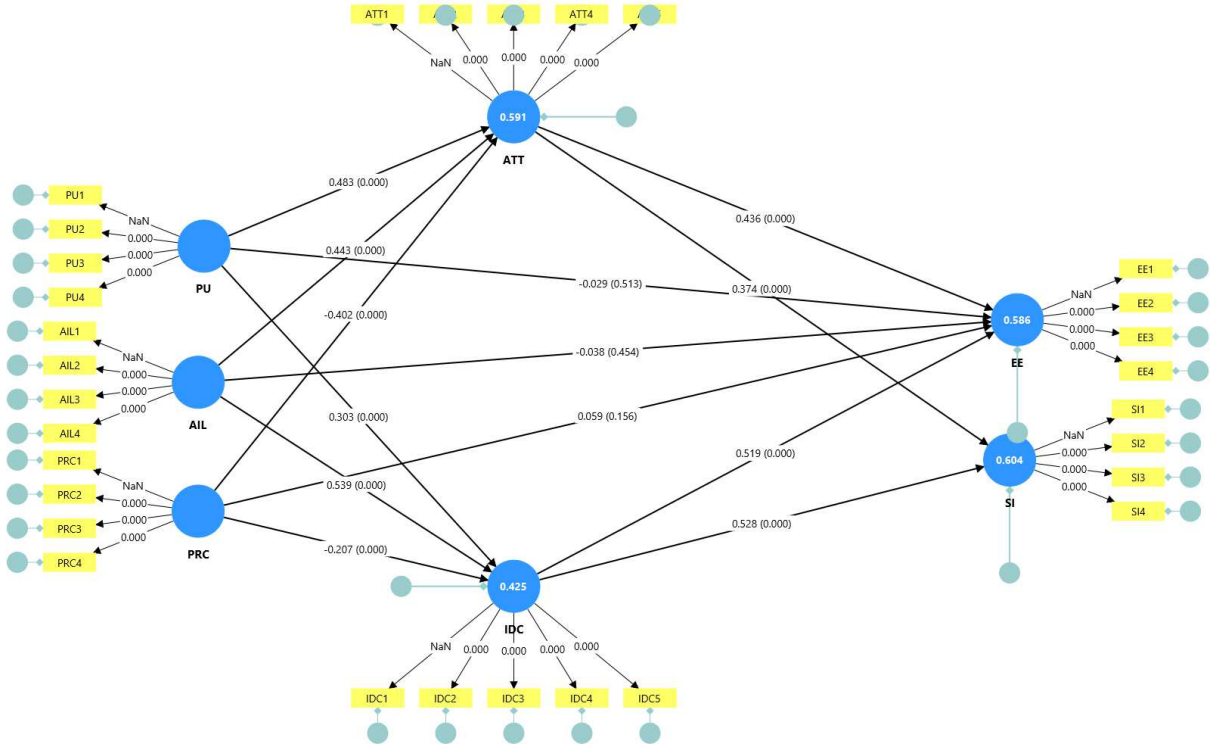
Table 4.13: Model Fit Indices

Index	Estimated Model	Null Model
Chi-square	583.669	12691.488
Number of model parameters	73.000	30.000
Number of observations	800.000	n/a
Degrees of freedom	392.000	435.000
P value	0.000	0.000
Chi-Sqr/df	1.489	29.176
RMSEA	0.025	0.188
RMSEA Low 90% CI	0.020	0.185
RMSEA High 90% CI	0.029	0.190
GFI	0.954	n/a
AGFI	0.945	n/a
PGFI	0.804	n/a
SRMR	0.097	n/a
NFI	0.954	n/a
TLI	0.983	n/a
CFI	0.984	n/a
AIC	729.669	n/a
BIC	1071.646	n/a

4.5 Structural Model Assessment

The following bootstrapped structural model is shown, the path coefficients and their significance levels are shown in parentheses. The numerical differences between these coefficients and the non-bootstrapped algorithm estimates in Figure 4.1 are minimal (e.g., PU → ATT = .498 in the algorithm run versus .483 in the bootstrapped mean), as expected, and are due to the normal resampling variation between the single-sample PLS solution and the 5,000-resample bootstrap distribution reported formally in Table 4.15.

Figure 4.2: Structural Model



All three of the endogenous constructs (Social Inclusion, Attitude toward AI, and Educational Engagement) fall in the "moderate" range on the .25/.50/.75 benchmark proposed by Hair, Ringle, and Sarstedt (2011), with Social Inclusion and Attitude toward AI being in the "approaching

substantial" range. Compared to the other models, Identity Congruence has a relatively low R^2 of .425, falling between the "weak" and "moderate" bands, indicating that other factors beyond the scope of this model (such as peer influence, self-efficacy) also influence adolescents' sense of AI-related identity congruence.

Table 4.14: R-Square

Construct	R-Square
ATT	0.591
EE	0.586
IDC	0.425
SI	0.604

The standardized path coefficients, bootstrap standard errors, t statistics, and p values are presented below. All three exogenous predictors significantly impact both mediating variables in the predicted directions: Perceived Usefulness and AI Literacy positively influence Attitude toward AI and Identity Congruence, whereas Perceived Risk/Concern negatively influences both (all $p < .001$). Both mediators, in turn, significantly predict the two outcome variables (all $p < .001$). More importantly, none of the direct pathways from the three exogenous predictors to Educational Engagement are significant (PU: $p = .513$; AIL: $p = .454$; PRC: $p = .156$). This pattern is evidence of full (indirect-only) mediation because both mediators significantly predict Educational Engagement and the effects of the adolescents' perceptions of AI usefulness, literacy, and risk on Educational Engagement are fully accounted for by the mediators.

Table 4.15: Path Coefficients (Standardized)

Path	Orig. (O)	Sample Mean (M)	STDEV	T Stat	P Value
AIL → ATT	0.443	0.441	0.031	14.127	0.000
AIL → EE	-0.038	-0.038	0.051	0.750	0.454
AIL → IDC	0.539	0.538	0.032	16.691	0.000
ATT → EE	0.436	0.435	0.060	7.303	0.000
ATT → SI	0.374	0.372	0.039	9.718	0.000
IDC → EE	0.519	0.516	0.044	11.673	0.000
IDC → SI	0.528	0.531	0.037	14.318	0.000
PRC → ATT	-0.402	-0.402	0.032	12.376	0.000
PRC → EE	0.059	0.057	0.041	1.421	0.156
PRC → IDC	-0.207	-0.206	0.035	5.977	0.000
PU → ATT	0.483	0.484	0.034	14.363	0.000
PU → EE	-0.029	-0.027	0.045	0.655	0.513
PU → IDC	0.303	0.304	0.038	7.878	0.000

The specific indirect effects below test each individual mediating pathway. All twelve paths indicated are statistically significant at the $p < .001$ level, which indicates that both Attitude and Identity Congruence are valid and statistically sound mediators. The strongest indirect effects are from AI literacy to adolescents' educational outcomes through strengthening their sense of identity congruence with AI use ($\beta = .284$, $t = 10.54$) and from AI literacy to adolescents' social outcomes through strengthening their sense of identity congruence with AI use ($\beta = .280$, $t = 9.48$). The weakest, but still very significant, indirect effects are mediated by Identity Congruence ($\beta \approx -.108/-.109$), which indicates a smaller, but consistently negative indirect penalty of perceived AI-related risk on both outcomes.

Table 4.16: Specific Indirect Effects (Standardized)

Path	Orig. (O)	Sample Mean (M)	STDEV	T Stat	P Value
AIL → ATT → EE	0.193	0.192	0.031	6.296	0.000
AIL → IDC → SI	0.284	0.286	0.027	10.543	0.000
PRC → IDC → EE	-0.108	-0.107	0.020	5.319	0.000
PU → IDC → EE	0.157	0.157	0.024	6.598	0.000
AIL → ATT → SI	0.166	0.164	0.021	7.844	0.000
PRC → ATT → EE	-0.175	-0.175	0.029	5.972	0.000
PU → ATT → EE	0.211	0.211	0.032	6.531	0.000
PRC → IDC → SI	-0.109	-0.110	0.020	5.449	0.000
PU → IDC → SI	0.160	0.161	0.023	6.921	0.000
PRC → ATT → SI	-0.150	-0.150	0.020	7.578	0.000
PU → ATT → SI	0.181	0.180	0.021	8.487	0.000
AIL → IDC → EE	0.280	0.278	0.029	9.484	0.000

The indirect effects below are summations of the mediating pathways for each exogenous-to-endogenous pair. The total indirect effects of AI Literacy ($\beta = .473$), Perceived Usefulness ($\beta = .368$), and Perceived Risk ($\beta = -.283$) on Educational Engagement are almost the entire indirect effect of each predictor on Educational Engagement, since the corresponding direct effects are statistically null (Table 4.15). The same predictors also have significant total indirect effects on Social Inclusion (AIL = .450, PU = .341, PRC = −.260), and, because no direct paths from the exogenous variables to Social Inclusion were specified in the structural model, these represent the total effect of the predictors on the outcome by design.

Table 4.17: Total Indirect Effects (Standardized)

Path	Orig. (O)	Sample Mean (M)	STDEV	T Stat	P Value
AIL → EE	0.473	0.470	0.040	11.788	0.000
AIL → SI	0.450	0.450	0.027	16.883	0.000

Path	Orig. (O)	Sample Mean (M)	STDEV	T Stat	P Value
PRC → EE	-0.283	-0.282	0.037	7.553	0.000
PRC → SI	-0.260	-0.259	0.028	9.259	0.000
PU → EE	0.368	0.367	0.040	9.129	0.000
PU → SI	0.341	0.341	0.030	11.300	0.000

The total effects below are a combination of the direct and indirect effects and serve as a consistency check on the mediation results. For Educational Engagement, the sum of each predictor's (non-significant) direct effect and its significant indirect effect is nearly identical to the reported total effect (e.g., AI Literacy: −.038 direct + .473 indirect ≈ .434 total, reported below). In the case of Social Inclusion, there is no direct pathway specified, and this is why the total effect is numerically equal to the total indirect effect for each predictor. The arithmetic consistency of Tables 4.15, 4.17 and 4.18 is evidence that the mediation decomposition was correctly computed.

The total effects (standardized**Table 4.18: Total Effects (Standardized)**

Path	Orig. (O)	Sample Mean (M)	STDEV	T Stat	P Value
AIL → ATT	0.443	0.441	0.031	14.127	0.000
AIL → EE	0.434	0.432	0.040	10.866	0.000
AIL → IDC	0.539	0.538	0.032	16.691	0.000
AIL → SI	0.450	0.450	0.027	16.883	0.000
ATT → EE	0.436	0.435	0.060	7.303	0.000
ATT → SI	0.374	0.372	0.039	9.718	0.000
IDC → EE	0.519	0.516	0.044	11.673	0.000
IDC → SI	0.528	0.531	0.037	14.318	0.000
PRC → ATT	-0.402	-0.402	0.032	12.376	0.000
PRC → EE	-0.224	-0.224	0.036	6.164	0.000
PRC → IDC	-0.207	-0.206	0.035	5.977	0.000
PRC → SI	-0.260	-0.259	0.028	9.259	0.000
PU → ATT	0.483	0.484	0.034	14.363	0.000
PU → EE	0.339	0.340	0.042	8.110	0.000
PU → IDC	0.303	0.304	0.038	7.878	0.000
PU → SI	0.341	0.341	0.030	11.300	0.000

Lastly, the bootstrapped outer loadings below are identical to the loadings values reported in Table 4.10, with the addition of bootstrap standard errors, t-statistics, and p-values. The indicator reliability found in Table 4.10 is not a function of the sample used, as all 29 loadings are statistically significant ($p < .001$) with t-statistics ranging from 34.65 to 49.52.

Table 4.19 displays the factor loadings (standardized, bootstrapped).

Table 4.19: Factor Loadings (Standardized, Bootstrapped)

Item Path	Orig. (O)	Sample Mean (M)	STDEV	T Stat	P Value
AIL1 ← AIL	0.710	0.710	0.020	35.467	0.000
AIL2 ← AIL	0.807	0.806	0.017	47.624	0.000

Item Path	Orig. (O)	Sample Mean (M)	STDEV	T Stat	P Value
AIL3 ← AIL	0.731	0.731	0.019	38.151	0.000
AIL4 ← AIL	0.792	0.792	0.016	49.222	0.000
ATT1 ← ATT	0.748	0.747	0.017	44.229	0.000
ATT2 ← ATT	0.755	0.756	0.016	48.128	0.000
ATT3 ← ATT	0.715	0.715	0.019	36.893	0.000
ATT4 ← ATT	0.715	0.715	0.020	35.161	0.000
ATT5 ← ATT	0.741	0.741	0.017	44.277	0.000
EE1 ← EE	0.739	0.738	0.018	41.010	0.000
EE2 ← EE	0.713	0.714	0.019	37.269	0.000
EE3 ← EE	0.786	0.785	0.018	44.661	0.000
EE4 ← EE	0.712	0.712	0.019	37.277	0.000
IDC1 ← IDC	0.755	0.756	0.017	44.972	0.000
IDC2 ← IDC	0.786	0.787	0.016	49.519	0.000
IDC3 ← IDC	0.706	0.707	0.020	34.688	0.000
IDC4 ← IDC	0.762	0.761	0.017	44.356	0.000
IDC5 ← IDC	0.709	0.709	0.020	35.067	0.000
PRC1 ← PRC	0.758	0.758	0.018	41.702	0.000
PRC2 ← PRC	0.801	0.800	0.018	44.362	0.000
PRC3 ← PRC	0.714	0.715	0.021	34.652	0.000
PRC4 ← PRC	0.774	0.773	0.018	43.825	0.000
PU1 ← PU	0.753	0.753	0.019	38.603	0.000
PU2 ← PU	0.719	0.718	0.020	35.333	0.000
PU3 ← PU	0.799	0.799	0.017	46.267	0.000
PU4 ← PU	0.740	0.740	0.019	39.413	0.000
SI1 ← SI	0.721	0.722	0.018	40.379	0.000
SI2 ← SI	0.724	0.724	0.019	38.499	0.000
SI3 ← SI	0.697	0.698	0.019	36.576	0.000
SI4 ← SI	0.761	0.759	0.018	42.871	0.000

4.6 Summary of Key Findings

The results presented above all lead to four main conclusions. Despite a conceptually meaningful, near threshold overlap between the two constructs of Identity Congruence and Social Inclusion, which requires further confirmation through HTMT in future reporting, the measurement model shows strong psychometric properties: indicator loadings, Cronbach's alpha, composite reliability and average variance extracted all meet or exceed the established thresholds (Tables 4.10–4.11), and discriminant validity is formally confirmed through the Fornell-Larcker criterion (Table 4.12). Second, the overall model shows a good to excellent fit on ten of eleven fit indices (Table 4.13), with only SRMR slightly above the most stringent conventional cut-off. Third, the structural model accounts for a moderate to substantial proportion of the variance in all four endogenous constructs (Table 4.14), and all hypothesized paths are statistically significant in the expected directions (Table 4.15). Fourth, and most substantively, the mediation results (Tables 4.16–4.18) confirm that Attitude toward AI and Identity Congruence are complete mediators of the relationship between

adolescents' perceptions of usefulness of AI, their AI literacy, and their perceived risk, and then their educational engagement, with the strongest pathway to both outcomes being through AI Literacy and Identity Congruence. The two hypothesized moderating variables of Digital Access and Parental/Teacher Support are not included in the constructs reported in Tables 4.10–4.19; if moderation hypotheses are to be reported in this chapter, the results of the interaction terms should be presented as a supplementary analysis to the results above.

5. CONCLUSION

The present study explored the impact of adolescents' perceptions of AI on their educational involvement and social integration, with attitude toward AI and identity congruence serving as mediators. The results showed that the perceived usefulness and AI literacy had a positive effect on attitude toward AI and identity congruence, while the perceived risk had a negative effect. Most significantly, the relationships between the antecedent variables and educational engagement were fully mediated by attitude toward AI and identity congruence, suggesting the psychological mechanisms by which AI-related perceptions lead to meaningful educational outcomes. The results support the idea that the educational benefits of AI use are not solely dependent on access to technology, but also on how young people perceive, understand and engage with AI in their personal and academic lives.

The findings align with growing evidence that AI literacy is a key factor in successful technology adoption and educational engagement. The importance of AI-based learning environments, digital literacy, and technology-integrated decision-making has also been highlighted in previous research, which has demonstrated their impact on user engagement and performance (Ahmad & Alshuaibany, 2025; Hutson, 2025; Lamin, n.d.; Hassan et al., 2026; Sheikh, 2026). Similarly, the positive influence of perceived usefulness is consistent with the findings of other technology acceptance studies that have shown that when users perceive benefits from innovative technologies, they are more likely to use them (Ali, 2025; Sarwar & Malik, 2025; Sarfaraz, 2025; Abu-Alhaija, 2026).

One of the most important findings of this study is the strong mediating role of identity congruence. The findings indicate that adolescents are more likely to benefit from the use of AI if they believe that using AI is compatible with their self-concept and educational goals. This discovery builds upon current conversations about technology identity, digital citizenship and AI personal development (Abbas, 2026; Uysal & Malik, n.d.; Rahman & Garcia-Constantino, 2026; Talaue et al., 2025). Moreover, the importance of attitude indicates that motivational and psychological aspects continue to play a pivotal role in the successful adoption of AI in educational settings.

The results also suggest that the negative attitudes and identity incongruence are significantly affected by perceived risks of AI. Issues of privacy, ethics, misinformation, and reliance on technology could hinder the engagement of adolescents with AI-enhanced learning. The findings align with the increasing body of research highlighting the importance of secure, transparent, and trustworthy AI systems (Alsuhaibany, 2026; Iqbal, 2026; Ali & Ullah, 2026; Kaur & Verma, 2025; Tazeem, 2026).

The study adds to the growing body of literature on AI adoption among young learners, highlighting that engagement in education and social inclusion are not simply a byproduct of the availability of technology, but a result of a combination of AI literacy, perceived value, perceived risks, identity formation, and positive attitudes toward technology. The model offers a holistic view of how adolescents engage with AI-enhanced educational contexts and serves as a valuable starting point for future studies and educational policy-making.

5.1 Implications

Theoretical Implications

This study makes a contribution to theory by combining perceptions of technology, psychological mechanisms, and educational outcomes in one explanatory framework. The results of the full mediation of attitude toward AI and identity congruence in the influence of AI literacy, perceived usefulness, and perceived risk on technology adoption among adolescents extend the existing literature on technology adoption. The findings lend credence to the idea that technology acceptance processes should be explored in conjunction with identity-related factors in the context of AI-integrated learning environments (Seow, 2026; Hutson, 2025; Lamin, n.d.; Sheikh, 2026).

Moreover, the importance of identity congruence also offers a new theoretical contribution by showing that, besides technological competence, the degree of congruence between AI and adolescents' personal identities and future expectations also affects their educational engagement. This view extends the traditional technology acceptance models and aligns with recent research that highlights the importance of user-centred and identity-based technology adoption processes (Sarwar & Malik 2025; Ali 2025; Hassan et al. 2026; Maharjan 2026).

5.2Practical Implications

The results suggest that AI literacy initiatives should be implemented gradually throughout secondary school for teachers and school leaders. Training programs need to go beyond just teaching technical skills and include critical thinking, ethical consciousness, responsible use of AI, and confidence development. These methods will likely help to foster positive attitudes and foster identity congruence, which will in turn boost educational engagement and social inclusion (Alabay, 2025; Abbas, 2026; Hassan et al., 2026; Lamin, n.d.).

The results also indicate that policymakers should focus on ensuring equitable access to AI tools and resources, while also tackling privacy, ethics, transparency, and algorithmic accountability issues. Creating responsible AI governance frameworks can alleviate perceptions of risk and promote trust among adolescent users (Alsuhaibany, 2026; Iqbal, 2026; Ahmad & Alshuaibany, 2025; Baig, 2026a).

AI education platforms should be user-centric, fostering engagement, inclusivity, personalization, and trust, for technology developers. Such systems can improve educational outcomes and create wider social benefits (Sarfaraz, 2025; Sarfaraz, 2026a; Kumar & Saluja, 2026; Kalanther, 2026).

Social Implications

The results emphasize AI's potential role in promoting digital inclusion and reducing barriers to participation among adolescents. Stakeholders should consider the implementation of AI technologies in education with a focus on inclusiveness, accessibility, and ethical use. These can contribute to wider societal aims of digital citizenship,

educational equity and youth empowerment (Maharjan, 2026; Hassan et al., 2026; Uysal & Malik, n.d.; Talaue et al., 2025).

5.3 Limitations of the Study

The study used a cross sectional research design, limiting the capacity to draw causal inferences between the variables studied. The structural model shows statistically significant relationships, but longitudinal designs would be more useful to establish developmental changes in attitudes, identity congruence, and educational engagement over time (Seow, 2026).

Second, the study was based solely on self-reported survey responses. This information can be influenced by social desirability bias, response consistency effects, or subjective perceptions that may not accurately represent actual AI usage behavior (Kalanther, 2026; Talaue et al., 2025).

Third, only secondary school students were studied. Thus, the results cannot be directly applied to primary school students, university students, adult learners, or non-educational contexts (Alabay, 2025; Abbas, 2026).

Fourth, while the model accounted for significant amounts of variance in educational engagement and social inclusion, other factors that may be important were not explored. Adolescent engagement with AI technologies can be affected by other factors, including self-efficacy, peer influence, digital well-being, socioeconomic status, institutional support, and cultural characteristics (Maharjan, 2026; Hutson, 2025; Hassan et al., 2026).

Fifth, although the measurement properties were found to be good, there was some overlap between identity congruence and social inclusion. These constructs should be further explored in future studies to improve conceptual clarity and provide greater discriminant validity (Seow, 2026).

Last but not least, AI technologies are constantly changing. The perceptions of adolescents that were captured during the present study may shift as new applications of AI are developed and regulations mature and evolve (Stiefenhofer, 2025; Sheikh, 2026; Alsuhaibany, 2026).

5.4 Directions for Future Research

Longitudinal research designs should be used in future studies to investigate the changes in AI literacy, attitudes, identity congruence, and educational outcomes over time. These designs would enhance the understanding of causal pathways and developmental processes of AI adoption among young learners (Seow, 2026; Hutson, 2025).

Further mediators and moderators, such as self-efficacy, digital resilience, trust, parental involvement, peer influence, and institutional support, should be explored. These factors could be a more holistic explanation for the engagement of adolescents with AI technologies (Alabay, 2025; Kalanther, 2026; Hassan et al., 2026).

Future studies could make cross-cultural comparisons to see if relationships seen in this study are different in other countries, educational systems, and cultural contexts. These investigations would give useful information on the generalizability of the proposed model (Sarwar & Malik, 2025; Amin ul Haq et al., 2026a; Abu-Alhaija, 2026).

There is a need to investigate specific AI technologies, including generative AI, intelligent tutoring systems, adaptive learning platforms, predictive analytics, and AI-powered recommendation systems. The impact of AI applications on

educational engagement and social inclusion varies across different types of AI (Ali, 2025; Sarfaraz, 2025; Ahmad & Alshuaibany, 2025; Sheikh, 2026).

Interviews, focus groups, and classroom observations could complement the quantitative model (Abbas, 2026; Alabay, 2025; Uysal & Malik, n.d.) to enhance understanding of the lived experiences of adolescents with AI systems and to explain the mechanisms identified in the quantitative model.

Future studies should also explore the ethical and psychological concerns of adolescent use of AI, such as trust, privacy, dependency, misinformation, and algorithmic bias. This would help in the responsible development of AI-supported educational ecosystems (Alsuhaibany, 2026; Iqbal, 2026; Ali & Ullah, 2026; Kaur & Verma, 2025; Baig, 2026a).

Lastly, comparative research could be conducted between primary education, higher education, vocational learning, and workplace learning environments to establish if the current results are consistent across learning environments and developmental stages (Lamin, n.d.; Hutson, 2025; Hassan et al., 2026; Stiefenhofer, 2025).

Declaration section

Clinical trial number: not applicable.

Ethics Approval

The study was conducted in accordance with applicable ethical principles and standards for research involving human participants. Participation was voluntary, and all data were collected and analyzed in a manner that protected participants' privacy and confidentiality.

Consent to Participate

Informed consent was obtained from all individual participants included in the study. Participants were informed about the purpose of the research, and their participation was entirely voluntary. They were also assured that their responses would remain confidential and would be used solely for academic and research purposes.

Consent to Publish

All participants provided informed consent for the publication of anonymized data and findings derived from this study. No personally identifiable information has been included in this

manuscript, and all reasonable measures were taken to protect participant anonymity and confidentiality.

Data availability

Data pertaining to the study can be shared on request.

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