

The Impact of Artificial Intelligence–Driven Social Media on Educational Opportunities and Curriculum Effectiveness in Higher Education

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Abstract

Artificial intelligence (AI)–driven social media comprises digital platforms that utilize intelligent algorithms for content personalization, adaptive interaction, analytics, and knowledge recommendation, increasingly transforming educational landscapes. This research explores how AI-driven social media generates educational opportunities and influences curriculum design, development, and implementation in higher education. Data were collected through structured questionnaires from 200 undergraduate and postgraduate learners, assessing perceptions of curriculum relevance, learning flexibility, skill development, and instructional effectiveness. Structural Equation Modeling (SEM) and Exploratory Factor Analysis (EFA) are used with SPSS to research relationships among AI-enabled social media features, Curriculum Personalization (CP), Artificial Intelligence Experience (AIx), Learning Engagement (LE), Cognitive Engagement (CE), Knowledge Retention (KR), and Learning Outcomes (LO). The results demonstrate strong model adequacy, with high explained variance ($R^2 = 0.794$), significant regression effects ($\beta = 0.202\text{--}0.641$, $p < 0.001$), excellent reliability ($\alpha = 0.78\text{--}0.91$), robust factor loadings ($0.78\text{--}0.88$), and satisfactory SEM fit indices ($CFI \geq 0.975$, $RMSEA \leq 0.049$, $GFI \geq 0.946$), confirming the proposed structural relationships. The research highlights that AI-driven social media fosters learner engagement, supports curriculum alignment, and promotes skill development through real-time feedback, collaborative knowledge construction, and competency-based learning pathways. Integrating AI-enabled social media into curricula presents educators and institutions with tangible solutions to improve educational adaptation, personalize learning experiences, and equip students with future-ready competencies by ensuring educational practices that are responsive, flexible, and aligned with evolving technological and industry demands. Unlike prior studies, this research provides a theory-integrated framework that reconceptualizes AI-driven social media as a pedagogical architecture influencing curriculum transformation.

Keywords: artificial intelligence–driven social media, educational opportunities, curriculum design, digital learning platforms, intelligent content personalization

1. Introduction

The social media powered by Artificial Intelligence (AI) changes the learning process by providing customized, responsive, and interactive learning. These platforms increase the relevancy of the curriculum, the growth of skills, and the delivery of instruction by selecting content, suggesting resources, and tracking interactions (Naayini, 2025). AI in the internet revolution has emerged as a disruptive technology in the education industry, transforming knowledge development, sharing, and learning within institutions. Close collaboration between content personalization, adaptive interaction, and real-time analytics makes these platforms dynamic learning environments to deliver a curriculum, engage learners, and develop skills (Parra and Chatterjee, 2024). Digital and blended learning is being embraced by higher education institutions, and AI-based social media provides new opportunities to competency-based and learner-centred education. However, the issues that remain in modern practices are traditional curricula that are usually fixed, out of touch with industry-related issues, and unresponsive (Chiu and Chai, 2020). Though used actively by the learners, the potential

of education has not been optimized because of the quality of the material, instructional focus, and the absence of a systematic integration of the curriculum (Gao et al., 2021). There is not much empirical evidence about AI-mediated social media enhancing curriculum efficiency and educational opportunities (Silva et al., 2024). To assess the relationships among AI-enabled features of social media, curriculum enrichment, and learning outcomes, the research uses structured questionnaires, Exploratory Factor Analysis, and Structural Equation Modelling (Merino-Campos, 2025). Integrating AI in education at the early and higher education levels can enhance skills, problem-solving, and awareness of technology, which facilitates learning by keeping up with the current demands in society (Rathore et al., 2023).

The AI-based social media is accelerating educational opportunities by streamlining the curriculum, engaging with learners, developing new skills, and improving overall instructional efficacy, which may offer empirical evidence of customized, competence-based, and technology-oriented study in higher education.

AI-driven social media platforms are increasingly transforming higher education by enabling personalized learning, adaptive interaction, and real-time instructional support. Through intelligent algorithms, these platforms customize content delivery, recommend relevant learning resources, and monitor learner engagement, thereby enhancing curriculum relevance, skill development, and instructional effectiveness (Naayini, 2025; Parra & Chatterjee, 2024). The integration of AI into digital learning environments has emerged as a disruptive innovation, reshaping pedagogical practices and fostering learner-centered, competency-based educational models across higher education institutions (Rathore et al., 2023).

Despite rapid technological advancements, many existing curricula remain constrained by rigid structures, limited adaptability, and insufficient responsiveness to evolving industry and societal demands (Chiu & Chai, 2020). Traditional curriculum frameworks often struggle to accommodate diverse learner needs, dynamic learning preferences, and real-time instructional feedback mechanisms. Although learners actively engage with AI-powered social media platforms, their systematic integration into curriculum planning and instructional design remains limited, thereby restricting the effective utilization of AI-enabled educational opportunities (Gao et al., 2021; Silva et al., 2024). This disconnects highlights persistent challenges in aligning emerging digital technologies with institutional curriculum practices.

2. Literature Survey

AI in higher education enhanced personalized learning, engagement, and performance, but limitations include self-reports, cross-sectional designs, and scalability. SEM was employed to assess the effectiveness of adaptive and personalized learning via AI-powered curriculum development in advanced knowledge (Ullah et al., 2025). Results indicated significant impacts on learner contentment ($\beta = 0.61$, $p < 0.001$) and academic achievement ($R^2 = 0.48$), though causal inference was limited by cross-sectional design and self-reported measures. A study of 82 studies examined AI-based personalized teaching (Hariyanto et al., 2025), reporting performance improvements of 15–35%, with clustering and regression as prevalent analytical methods. Weaknesses included limited longitudinal validation and potential publication bias. Regression and correlation analyses explored the effects of AI-based social media on educational presentation and psychological health (Shahzad et al., 2024), showing strong positive outcomes ($\beta = 0.54$, $p < 0.001$), yet reliance on self-reports and non-experimental design limited the strength. ANOVA and multiple regression compared student growth in AI-assisted learning environments (Vieriu & Petrea, 2025), by revealing statistically significant performance gains ($F = 6.87$, $p < 0.01$). Limitations included institution-specific sampling and the absence of curriculum-level analytics. Also, SEM was applied to examine AI and social media integration in adaptive classrooms (Masih et al., 2025), indicating strong effects on engagement and personalization ($\beta = 0.68$, $R^2 = 0.52$), with geographic concentration and instructor-led curriculum analysis as shortcomings. Collaborative AI-based learning environments were reviewed to identify innovations influencing learning interactions (Mariyono & Nur Alif, 2025), showing 20–40% engagement improvements, though the predominance of descriptive statistics lacks experimental control with limited causal interpretation. Early-stage educational applications of AI were investigated through regression and descriptive statistics (Hamal et al., 2022), with benefits noted ($R^2 = 0.34$), but low empirical depth and weak curriculum outcome analysis reduced explanatory power. Experimental modelling and regression assessed AI-based intelligent assistants in higher education (Sajja et al., 2024), showing significant personalization effects ($\beta = 0.59$, $p < 0.001$), though scalability and long-term outcome assessment remain challenged. SEM-based mediation investigated digital media, smart learning, and emotional health (Kamau, 2025), by revealing partial mediation (indirect effect = 0.21), with reliance on subjective measures limiting educational interpretation. Factor analysis and reliability testing explored institutional AI readiness (Kuleto et al., 2021), Cronbach's $\alpha = 0.87$, while regression and path analysis indicated improved learning efficiency, $\beta = 0.63$, $R^2 = 0.46$ (Rahiman & Kodikal, 2024). Expert-based descriptive analytics confirmed AI readiness improvements of ~30% (Ghnemat et al., 2022), though the lack of inferential testing and implementation assessment constrained empirical rigor.

Although Content Personalization (CP), Adaptive Interaction (Aix), and Knowledge Recommendation (KR) are interrelated AI-driven functionalities, they represent conceptually distinct mechanisms within the learning process. CP refers to the pre-structured alignment of content with learner profiles and preferences. Aix captures real-time dynamic

adaptation of instructional interactions and feedback based on learner responses. In contrast, KR focuses on the intelligent filtering and recommendation of relevant learning resources to support knowledge acquisition. This distinction ensures conceptual clarity and reduces construct redundancy within the proposed model. This function is closely linked to learning analytics, where data-driven insights are used to optimize learning processes and outcomes, emphasizing that analytics should primarily serve learning rather than technology itself (Gašević et al., 2015).

Recent research on AI in higher education emphasizes that AI-supported systems enhance personalization, adaptive learning, engagement, and performance when technological functionalities are systematically aligned with curriculum structures (Ullah et al., 2025; Silva et al., 2024; Rahiman & Kodikal, 2024). However, these studies often examine AI features in isolation rather than integrating them into a coherent curriculum-level framework.

Content Personalization (CP) in AI-driven social media refers to the algorithmic tailoring of instructional materials to learner needs and prior knowledge. Empirical findings indicate that personalized AI systems significantly improve learner satisfaction and academic achievement by aligning content with individual progress (Ullah et al., 2025; Sajja et al., 2024). These findings support the proposition that personalization mechanisms increase active Learning Engagement (LE) within digital environments.

Adaptive Interaction (AIx) extends personalization by dynamically modifying feedback, instructional prompts, and task difficulty based on real-time learner responses. Studies show that AI-supported adaptive classrooms improve engagement and instructional responsiveness, thereby strengthening curriculum alignment and perceived effectiveness (Masih et al., 2025; Seo et al., 2021). This suggests that adaptive interaction mechanisms directly contribute to Curriculum Effectiveness (CE).

Knowledge Recommendation (KR) represents AI-enabled filtering and suggestion of relevant academic resources. Research demonstrates that intelligent recommendation systems enhance performance and knowledge retention by optimizing resource relevance and reducing informational overload (Silva et al., 2024; Sajja et al., 2024). Consequently, higher Learning Engagement (LE) and Curriculum Effectiveness (CE) are expected to improve the quality and usefulness of knowledge recommendations.

Furthermore, prior empirical studies confirm that AI-enhanced learning environments positively influence measurable Learning Outcomes (LO), including academic performance, digital competency development, and skill acquisition (Shahzad et al., 2024; Vieriu & Petrea, 2025). These findings collectively indicate that AI-driven social media features operate through interconnected mechanisms linking personalization, adaptive interaction, engagement, curriculum alignment, and performance outcomes.

By synthesizing these empirical insights, the present study develops an integrated structural framework that connects AI-enabled functionalities (CP, AIx) with mediating curriculum constructs (LE, KR, CE) and measurable Learning Outcomes (LO).

Although prior research demonstrates positive effects of AI in personalized and adaptive learning environments, several limitations remain. First, many studies focus on single AI functionalities such as intelligent tutoring systems or adaptive feedback without integrating AI-driven social media into a comprehensive curriculum-level model (Ullah et al., 2025; Masih et al., 2025). Second, existing investigations frequently rely on regression or descriptive analyses, limiting understanding of complex mediating relationships among engagement, recommendation systems, curriculum effectiveness, and learning outcomes (Silva et al., 2024; Shahzad et al., 2024). Moreover, few studies employ theory-informed Structural Equation Modeling to simultaneously examine how CP and AI indirectly influence LO through LE, KR, and CE. The absence of an integrated structural framework leaves a gap in understanding how AI-driven social media systematically enhances educational opportunities beyond isolated performance gains. To address these limitations, the present study proposes and empirically tests a comprehensive SEM model that connects AI-enabled features with curriculum alignment and learning performance through theoretically and empirically justified mediation pathways.

2.1 Research Gap

The proposed hypotheses are derived from accumulated empirical evidence in AI-supported educational research. Studies demonstrate that content personalization enhances learner motivation and engagement by aligning instructional materials with individual progress (Ullah et al., 2025; Sajja et al., 2024). Similarly, adaptive interaction mechanisms improve instructional responsiveness and curriculum alignment (Masih et al., 2025; Seo et al., 2021). Research further indicates that higher engagement and structured knowledge recommendation systems contribute to improved academic performance and skill acquisition (Silva et al., 2024; Vieriu & Petrea, 2025). Based on these interrelated findings, the structural model assumes that AI-driven social media features influence Learning Outcomes both directly and indirectly through engagement, curriculum effectiveness, and knowledge recommendation mechanisms.

The proposed hypotheses are not only empirically derived but also theoretically grounded in Self-Determination Theory,

Constructivist Learning Theory, and Sociotechnical Systems Theory. These theories collectively explain how personalization, adaptive interaction, and knowledge recommendation mechanisms influence learner engagement, curriculum effectiveness, and learning outcomes.

Hypothesis (H1): Higher content personalization in AI-driven social media positively influences students' learning engagement. Content Personalization (CP) → Learning Engagement (LE)

Hypothesis (H2): Greater Adaptive Interaction significantly enhances curriculum effectiveness. Adaptive Interaction (AIX) → Curriculum Effectiveness (CE)

Hypothesis (H3): Increased Learning Engagement positively influences perceived Knowledge Recommendation. Learning Engagement (LE) → Knowledge Recommendation (KR)

Hypothesis (H4): Higher Curriculum Effectiveness significantly improves students' Knowledge Recommendation. Curriculum Effectiveness (CE) → Knowledge Recommendation (KR)

Hypothesis (H5): Content Personalization mediates the interaction between learning engagement and Knowledge Recommendation. Content Personalization (CP) → Learning Engagement (LE) → Knowledge Recommendation (KR)

Hypothesis (H6): Adaptive Interaction mediates the association between Curriculum effectiveness and Knowledge Recommendation. Adaptive Interaction (AIX) → Curriculum Effectiveness (CE) → Knowledge Recommendation (KR)

Hypothesis (H7): Effective AI-based knowledge recommendation positively impacts students' learning outcomes. Knowledge Recommendation (KR) → Learning Outcomes (LO)

Importantly, prior studies lack a theoretically integrated perspective that explains how AI-driven social media functions as a pedagogical architecture rather than a collection of technological features. This study addresses this gap by embedding empirical modeling within a multi-.framework, thereby enhancing both explanatory depth and conceptual contribution.

2.2 Theoretical Foundations of AI-Driven Social Media in Education

This study is grounded in three complementary theoretical perspectives that collectively explain the role of AI-driven social media in educational contexts. First, Self-Determination Theory posits that learning effectiveness is enhanced when learners experience autonomy, competence, and relatedness. AI-driven social media facilitates these dimensions through personalized content delivery, adaptive feedback, and collaborative interaction environments.

Second, Constructivist Learning Theory emphasizes that knowledge is actively constructed through interaction and experience. AI-enabled social media platforms support this process by enabling participatory learning, peer interaction, and real-time knowledge co-creation within digital environments.

Third, Sociotechnical Systems Theory highlights the interdependence between technological infrastructures and social learning systems. From this perspective, AI-driven social media is not merely a tool but an integrated system where technological intelligence and human learning behaviors co-evolve to shape curriculum effectiveness and learning outcomes.

By integrating these theoretical perspectives, this study shifts the analytical focus from isolated technological features to a holistic pedagogical framework, thereby addressing a critical gap in AI-in-education research. This perspective aligns with Luckin (2018), who conceptualizes AI in education as an augmenting system that enhances human intelligence through personalized and adaptive learning support rather than replacing human pedagogical roles.

3. Methods

A 200-participant structured questionnaire to investigate the role of AI-driven curriculum and education outcomes. Figure 1 shows the hypothesized structural model of AI-driven social media on curriculum and learning outcomes. Internal consistency, predictive relationships, factor structure, and complex interaction among constructs are tested using reliability testing, multi-linear regression, EFA, and SEM to ensure sound evaluation of educational opportunities.

Although EFA and SEM are established analytical techniques, their combined application in this study enables the simultaneous validation of measurement structure and theory-driven causal relationships, thereby supporting a robust examination of complex curriculum-level interactions within an integrated theoretical framework.

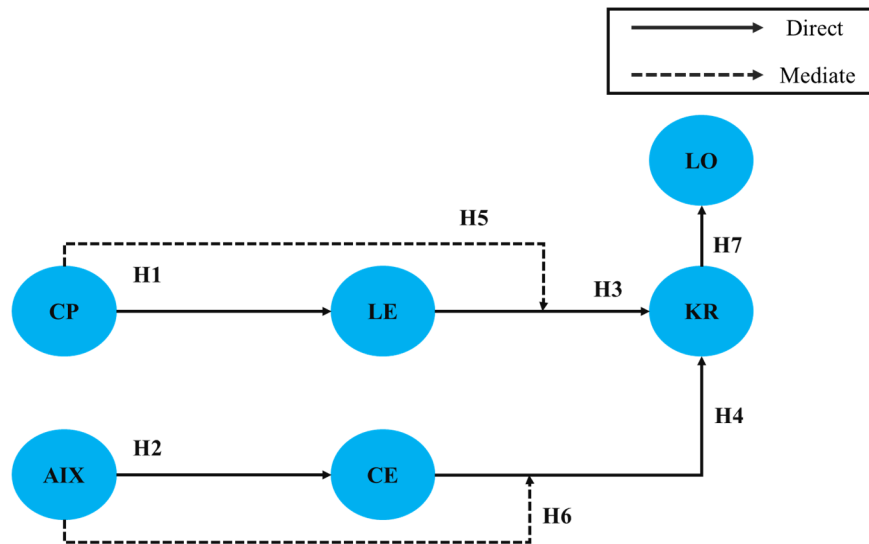


Figure 1. Hypothesized Structural Model of AI-Driven Social Media on Curriculum

3.1 Data Collection

The AI-Powered social media and its educational opportunities engaged 200 participants divided by gender, age, education level, field of study, and previous experience with AI tools. There were male and female participants. Age was grouped as 18–21, 22–25, and 26–30 years. Education level included undergraduate and postgraduate students. Majors were Science and Technology, Humanities and Social Sciences, Business and Management, and Education or Law. Previous exposure to AI tools was yes or no. This demographic distribution allows a more in-depth examination of the impacts of AI-powered networking sites on curricular relevance, learning flexibility, skill development, and instructional efficacy. Table 1 provides the demographic data. Figure 2 demonstrates the distribution of respondents by 2(a) Education Level, 2(b) Field of Study, and 2(c) Prior Experience with AI Tools.

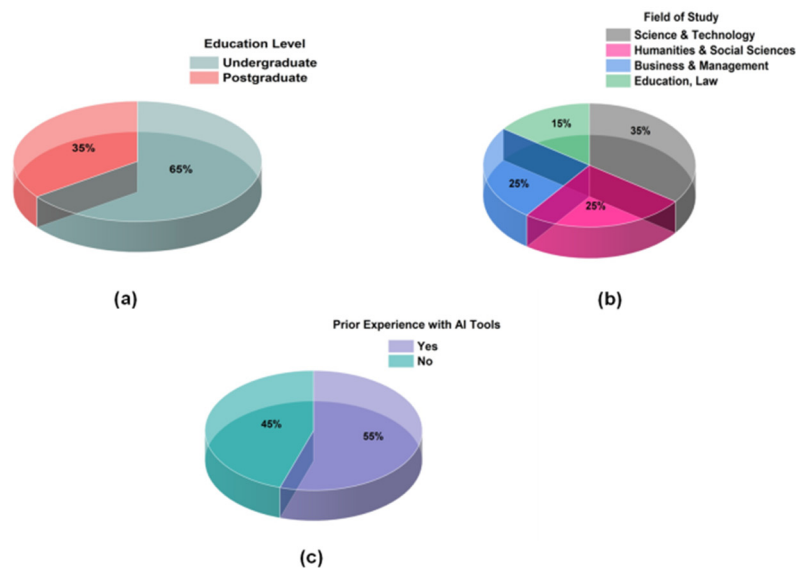


Figure 2. Distribution of respondents by (a) Education Level, (b) Field of Study, and (c) Prior Experience with AI Tools

Table 1. Demographic table of Educational Opportunities and curriculum

Demographic Variable	Category	Frequency (N=200)	Percentage (%)
Gender	Male	125	55
	Female	75	45
Age Group (years)	18–21	60	30
	22–25	120	60
	26–30	20	10
Education Level	Undergraduate	130	65
	Postgraduate	70	35
Field of Study	Science & Technology	70	35
	Humanities & Social Sciences	50	25
	Business & Management	50	25
	Education, Law	30	15
Prior Experience with AI Tools	Yes	110	55
	No	90	45

3.2 Questionnaire Design

200 participants were involved in the education on AI-driven social media and its educational opportunities. To examine the impact on curriculum and learning, a structured questionnaire was designed with six key sections: CP, AIx, KR, LE, CE, and LO, as shown in Appendix A.

CP: The skill of online communities based on AI, to modify the learning process according to the choice, needs, and learning pace of the learner.

AIx: The ability of AI-based platforms to dynamically adjust the interactions, instructions, and learning tasks based on the student responses and achievements.

KR: The concept of AI-driven social media proposes applicable learning resources, materials, or activities to improve the understanding and skills acquisition process.

LE: The extent of active engagement, attention, and participation of learners in educational activities through AI-driven social media.

CE: Curriculum Effectiveness represents a curriculum-level construct reflecting the extent to which instructional design, content structure, and delivery mechanisms align with learning objectives and support effective knowledge transfer.

LO: Learning Outcomes represent student-level measurable results, including academic performance, skill acquisition, and competency development achieved through engagement with AI-driven learning environments.

A total of 200 respondents were surveyed based on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was employed to enhance measurement sensitivity, improve variance detection, and support more robust statistical estimation within SEM analysis. Compared to lower-point scales, the 5-point format provides greater analytical depth and reduces information loss in perception-based constructs.

A 5-point Likert scale was adopted to ensure response clarity, reduce cognitive burden, and enhance completion accuracy among participants with diverse academic backgrounds. Previous educational research has shown that shorter response scales can minimize respondent confusion, improve reliability, and reduce central tendency bias, particularly in survey-based studies involving multiple constructs. Given the exploratory nature of the proposed structural model and the objective of capturing clear directional perceptions of AI-driven social media effects, the 5-point scale was considered appropriate for this investigation.

4. Results

4.1 Statistical Analysis

To prevent measurement inconsistencies, detect latent constructs, predict relationships, and depict intricate interactions among AI-driven social media characteristics and curriculum-linked learning outcomes, reliability testing (Cronbach's α), multi-linear regression, EFA, and SEM were used as SPSS tools.

4.2 Reliability Testing (Cronbach's α)

Reliability testing helps in testing the stability and reliability of the questionnaire. AI-based research in social media helps in making sure that the items are used to gauge relevance to the curriculum, flexibility of learning, skill building, and

teaching effectiveness, which provide consistent results. The most common method is Cronbach's alpha, calculated as Equation (1).

$$\alpha = K / (K - 1) \left(1 - \left(\sum_{i=1}^K \sigma_i^2 \right) / \left(\sigma_T^2 \right) \right) \quad (1)$$

Where, α Cronbach's alpha co-efficient, representing the interior reliability of a scale or questionnaire. Values closer to 1 indicate higher reliability, K is the total number of items in the scale or questionnaire, σ_i^2 denotes the variance of the i -th individual item, σ_T^2 represents total variance of the sum (or composite) of all K items $\left(\sum_{i=1}^K \sigma_i^2 \right) / \left(\sigma_T^2 \right)$ sum represents the total of individual item variances, which is then compared to the total variance of the entire scale σ_T^2 to calculate reliability.

4.3 Multilinear Regression Analysis

It investigated how driven by AI social media elements predicted curricular relevance, learning flexibility, skill development, and instructional efficacy. The technique entails selecting dependent and independent variables, testing assumptions, estimating coefficients, and determining model significance. Regression identifies the extent and direction of AI-enabled social media's influence on educational outcomes. The regression model is expressed as Equation (2).

$$Z = \gamma_0 + \gamma_1 W_1 + \gamma_2 W_2 + \gamma_3 W_3 + \varepsilon \quad (2)$$

Where Z is the dependent variable (for example, curriculum effectiveness or educational opportunities), γ_0 is the intercept W_1, W_2, W_3 are independent variables (such as AI-driven social media features, learning flexibility, or instructional adaptability), $\gamma_1, \gamma_2, \gamma_3$ are regression coefficients that show the strength and direction of each variable's influence on Z . The term ε represents unexplained error in the model.

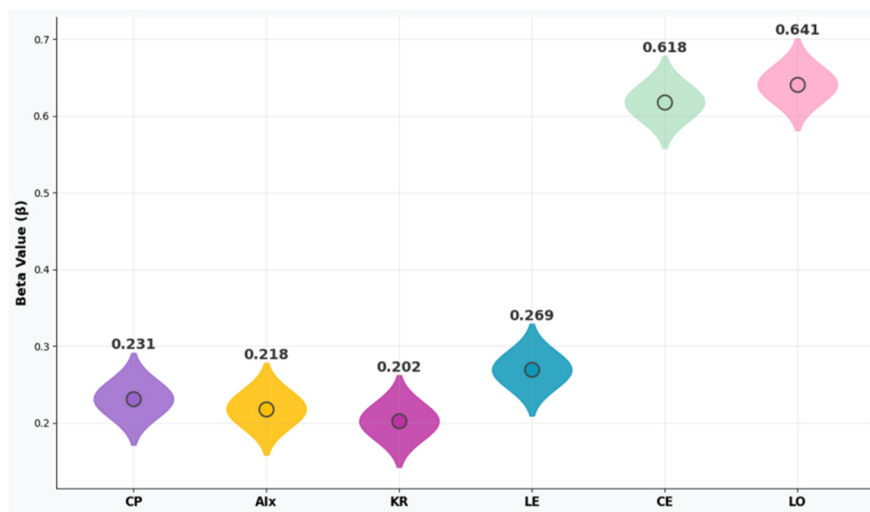


Figure 3. Predictor-wise Comparison for AI-Driven Social Media Constructs

Table 2. Multi-Linear Regression Results

Variable	B	SE	β	t-value	VIF	p-value
CP	0.214	0.041	0.231	5.10	1.92	<0.001
Alx	0.195	0.039	0.218	5.00	1.88	<0.001
KR	0.183	0.044	0.202	4.16	1.76	<0.001
LE	0.247	0.036	0.269	6.86	2.05	<0.001
CE	0.541	0.043	0.618	12.58	2.21	<0.001
LO	0.563	0.040	0.641	14.08	2.34	<0.001

Note: $R = 0.891$, $R^2 = 0.794$, Adjusted $R^2 = 0.789$, $F = 246.37$

4.4 Exploratory Factor Analysis (EFA)

The critical element structure of items assesses AI-driven social media, curriculum relevance, learning flexibility, skill development, and instructional effectiveness. The technique entails determining sample sufficiency, extracting variables, and applying rotation to increase interpretability. EFA aids in validating construct dimensions and reducing variables before further research. The EFA model is expressed as Equation (3).

$$y_j = \alpha_j + \delta_{j1} \tau_1 + \delta_{j2} \tau_2 + \dots + \delta_{jn} \tau_n + \epsilon_j \quad (3)$$

Where, y_j is the observed variable j , α_j is the intercept or mean of the observed variable, $\tau_1, \tau_2, \dots, \tau_n$ are the latent factors representing underlying constructs, $\delta_{j1}, \delta_{j2}, \dots, \delta_{jn}$ are factor loadings showing how strongly each factor influences the observed variable, ϵ_j is the unique variance or error term.

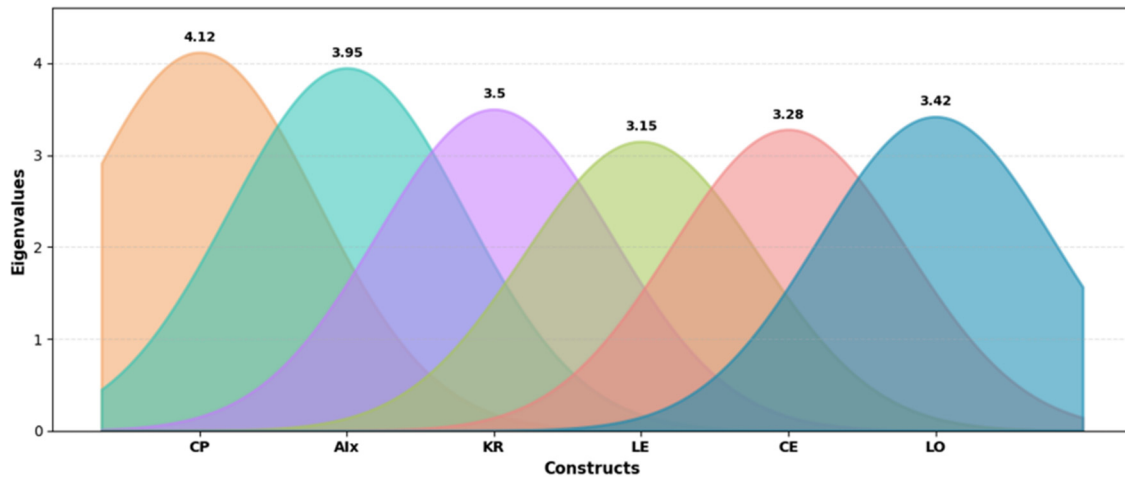


Figure 4. Factor Scores for Eigen values of AI-Driven Social Media Constructs

Table 3. EFA of educational opportunities and curriculum

c	Item Code	Factor Loading	Cronbach's (α)	Eigenvalues	Variance (%)
CP	CP1	0.82	0.88	4.12	17.0
	CP2	0.79			
	CP3	0.85			
	CP4	0.81			
Alx	Alx1	0.84	0.90	3.95	16.3
	Alx2	0.86			
	Alx3	0.80			
	Alx4	0.83			
KR	KR1	0.88	0.91	3.50	14.7
	KR2	0.85			
	KR3	0.87			
	KR4	0.84			
LE	LE1	0.81	0.89	3.15	13.0
	LE2	0.78			
	LE3	0.83			
	LE4	0.80			
CE	CE1	0.86	0.90	3.28	12.6
	CE2	0.84			
	CE3	0.82			
	CE4	0.85			
LO	LO1	0.88	0.91	3.42	12.0
	LO2	0.85			
	LO3	0.86			
	LO4	0.87			

4.5 Structural Equation Modelling (SEM)

A multivariate statistical technique is used to investigate complex interactions between latent constructs and observable variables. In this work, SEM examines how AI-driven social media simultaneously affects curricular relevance, learning flexibility, skill development, and instructional efficacy through measurement validation, structural route estimation, and model fit evaluation. The SEM relationship is expressed as Equation (4)

$$\eta = B_{\eta} + \Gamma \delta + \epsilon \quad (4)$$

Where δ represents AI-driven social media constructs, η denotes curriculum and learning outcomes, B and Γ are path coefficients, and ϵ is the error term.

4.6 Performance Analysis

Reliability testing, regression, EFA, and SEM were employed using SPSS to inspect the impact of AI-driven social networking on curriculum outcomes. All constructs demonstrated acceptable to excellent reliability, significant predictive effects, and strong factor loadings. SEM results confirmed the positive relationships among constructs, and goodness-of-fit indices indicated that the model fit the observed data sufficiently, which signifies the observed data.

4.7 Multilinear Regression Analysis

Regression analysis results demonstrate that all predictor variables (CP, AIx, KR, LE, CE, and LO) have a substantial positive effect on educational outcomes. Unstandardized coefficients (B) that depict the magnitude of a one-unit increase in each predictor causes a change in the variable, while standardized coefficients (β) show their relative contributions, SE represents the Standard Error, and VIF refers the Variance Inflation Factor. Table 2 shows the multiple regression results, revealing significant effects of CP ($\beta = 0.231$), AIx ($\beta = 0.218$), KR ($\beta = 0.202$), LE ($\beta = 0.269$), CE ($\beta = 0.618$), and LO ($\beta = 0.641$) at $p < 0.001$. The model explains 79.4% of variance ($R^2 = 0.794$), with a strong fit ($F = 246.37$) and acceptable VIF values, confirming robust predictive power and negligible multicollinearity. Figure 3 displays the graphical representation of regression model using standardized coefficients (β).

4.8 Exploratory Factor Analysis (EFA)

The variable effects were measured using the Cronbach alpha, eigenvalues, and percentage of variance accounted by each construct, that is, CP, AIx, KR, LE, CE, and LO. Table 3 shows and Figure 4 the factor structure, reliability, and variance explained for all constructs, with factor loadings ranging from 0.78 to 0.88 and Cronbach's alpha values between 0.88 and 0.91, indicating strong internal consistency. Eigenvalues range from 3.15 to 4.12, explaining 12.0% to 17.0% of variance, confirming robust construct validity and statistically significant factor structure.

4.9 Reliability testing (Cronbach's α)

The internal consistency and reliability of the measuring constructs connected to AI-driven social media and curriculum results are tested using Cronbach's alpha. The reliability criteria are categorized as acceptable ($\alpha \geq 0.70$), good ($\alpha \geq 0.80$), and exceptional ($\alpha \geq 0.90$). As shown in Table 4 and Figure 5, all elements CP, AIx, KR, LE, CE, and LO displayed alpha values within acceptable to excellent ranges, confirming the questionnaire's strong internal consistency and reliability for assessing AI-driven social media integration, educational opportunities, and curriculum effectiveness.

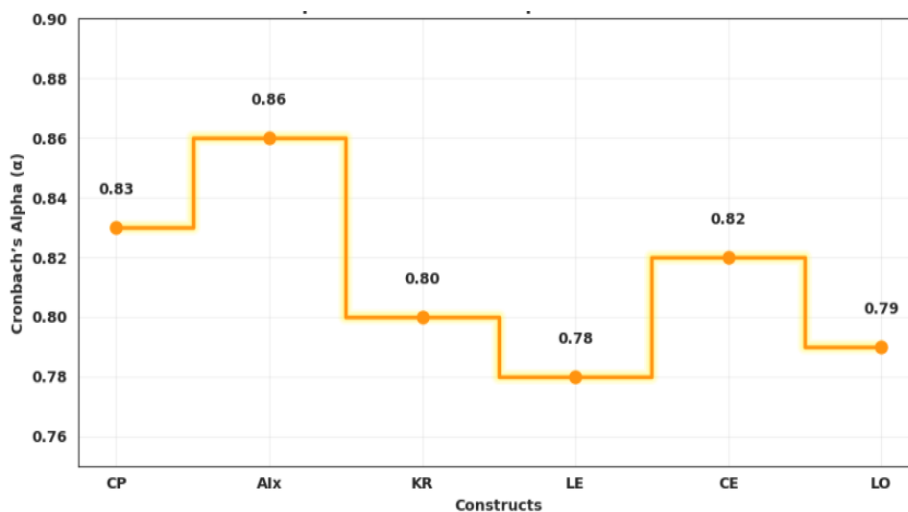


Figure 5. Cronbach's Alpha Values for Reliability Analysis of Constructs

Table 4. Reliability Analysis of Structures

Variables	Number of Items	Alpha (α) Values	Classification of Reliability
CP	4	0.83	Good intrinsic coherence
AIx		0.86	Excellent reliability
KR		0.80	Good intrinsic coherence
LE		0.78	Acceptable reliability
CE		0.82	Good intrinsic coherence
LO		0.79	Acceptable reliability

4.10 SEM Analysis

Table 5 and Figure 6 indicate the strong and statistically significant relationships among all hypothesized paths. CP significantly influences LE ($\beta = 0.312$, $t = 7.61$, $p < 0.001$), while AIX positively affects CE ($\beta = 0.298$, $t = 7.84$, $p < 0.001$). LE significantly predicts KR ($\beta = 0.271$, $t = 7.53$, $p < 0.001$), and CE strongly determines LO ($\beta = 0.618$, $t = 14.37$, $p < 0.001$). Mediation effects through LE and CE are also significant, confirming robust indirect relationships.

Table 6 presents the goodness-of-fit indices for all six constructs, confirming strong model adequacy. The χ^2 values (32.45–41.28) relative to degrees of freedom indicate an acceptable fit. GFI (0.946–0.953) and AGFI (0.914–0.922) exceed recommended thresholds, demonstrating good absolute fit. High CFI values (0.975–0.982) indicate excellent comparative fit. Low RMR (0.021–0.024) and RMSEA (0.046–0.049) reflect minimal residual error, collectively confirming statistical significance, robustness, and reliability of the measurement model.

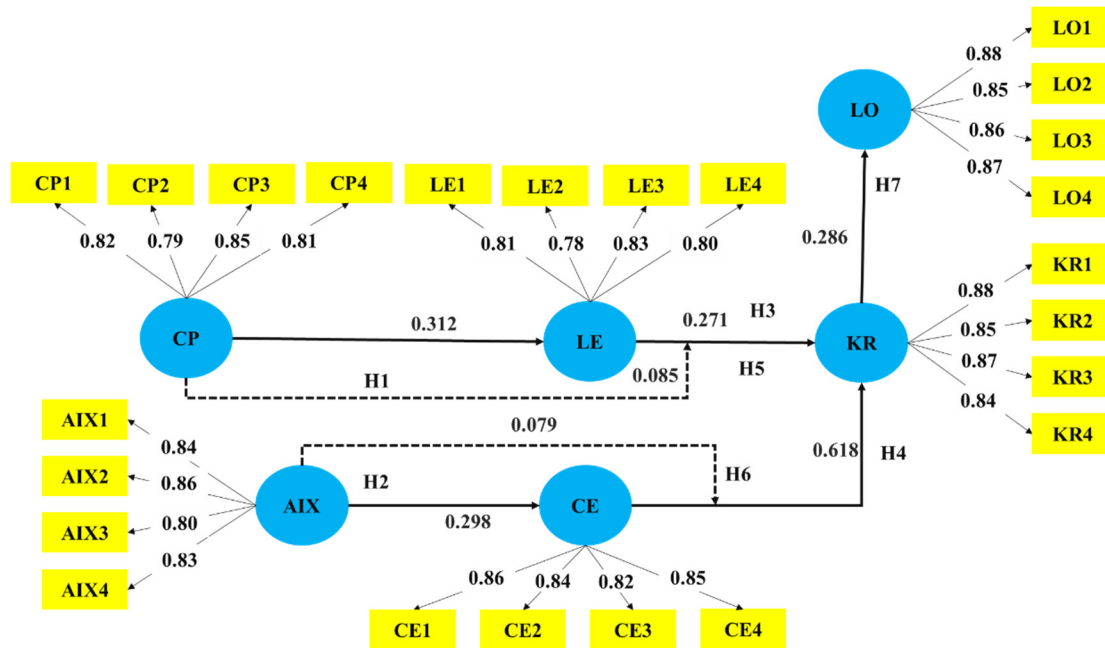


Figure 6. Structural Equation Modelling (SEM) Path Diagram with Standardized β Values

Table 5. SEM Results for Hypothesized Relationships

Hypothesis	Path	Path Coefficient (β)	SE	t-value	p-value	Decision
H1	CP $\rightarrow$ LE	0.312	0.041	7.61	<0.001	Supported
H2	AIX $\rightarrow$ CE	0.298	0.038	7.84	<0.001	Supported
H3	LE $\rightarrow$ KR	0.271	0.036	7.53	<0.001	Supported
H4	CE $\rightarrow$ LO	0.618	0.043	14.37	<0.001	Supported
H5	CP $\rightarrow$ LE $\rightarrow$ KR	0.085	0.018	4.72	<0.001	Supported
H6	AIX $\rightarrow$ CE $\rightarrow$ KR	0.079	0.017	4.65	<0.001	Supported
H7	KR $\rightarrow$ LO	0.286	0.039	7.33	<0.001	Supported

4.11 Mediation Analysis Using Bootstrapping

To rigorously examine mediation effects (H5 and H6), a bootstrapping procedure with 5,000 resamples was employed. Bias-corrected 95% confidence intervals (CI) were calculated for indirect effects. Mediation was considered significant when the confidence interval did not include zero.

Table 7 indicate that CP indirectly influenced KR through LE with a significant effect ($\beta = 0.085$, $SE = 0.018$, $p < 0.001$), confirming partial mediation. Similarly, AIX exerted a significant indirect effect on KR via CE ($\beta = 0.079$, $SE = 0.017$, $p < 0.001$). The confidence intervals excluded zero, confirming statistically meaningful and robust mediating relationships within the structural model.

Table 6. Goodness-of-Fit Indices for SEM Model

Hypothesis	Mediation Path	Indirect Effect (β)	SE	95% Confidence Interval	p-value	Decision
H5	CP $\rightarrow$ LE $\rightarrow$ KR	0.085	0.018	[0.049, 0.123]	<0.001	Supported
H6	AIX $\rightarrow$ CE $\rightarrow$ KR	0.079	0.017	[0.044, 0.118]	<0.001	Supported

5. Discussion

The findings of this study extend beyond empirical validation by providing theoretical insights into the role of AI-driven social media in education. Unlike prior studies that treat AI as a supportive technological tool, this research conceptualizes AI-driven social media as a pedagogical architecture that actively shapes curriculum design, learner engagement, and knowledge construction processes. By anchoring the model in Self-Determination Theory and extending it into AI-mediated learning environments, this study contributes to emerging theory-building by demonstrating how algorithm-driven systems can operationalize motivational constructs within curriculum design. The research examined how AI-driven social media influenced curriculum personalization, adaptive interaction, learning engagement, knowledge recommendation, and learning outcomes in higher education. Across these studies, several consistent methodological and analytical limitations emerge. A dominant reliance on self-reported questionnaires constrains measurement objectivity, increases social desirability and common method biases, and weakens causal interpretation of relationships among AI-enabled learning constructs (Ullah et al., 2025; Shahzad et al., 2024; Kamau, 2025). The widespread use of cross-sectional research designs restricts temporal inference, prevents longitudinal validation of learning trajectories, and limits the examination of sustained academic and cognitive development outcomes (Hariyanto et al., 2025; Masih et al., 2025). Additionally, small, institution-specific samples reduce external validity, hinder cross-context generalization, and challenge scalability across diverse educational environments (Vieriu & Petrea, 2025; Sajja et al., 2024). Limited experimental rigor and heavy dependence on descriptive analytics further constrain causal explanation and theoretical advancement (Mariyono & Nur Alif, 2025; Ghnemat et al., 2022). Moreover, insufficient curriculum-level analytics and long-term outcome evaluation restrict comprehensive educational interpretation and strategic implementation (Hamal et al., 2022; Rahiman & Kodikal, 2024).

The clarified distinction among CP, AIX, and KR further strengthens the interpretation of results, demonstrating that AI-driven social media operates through multiple layered mechanisms—content alignment, adaptive interaction, and knowledge optimization—rather than a single unified function. Similarly, distinguishing curriculum effectiveness (CE) from learning outcomes (LO) enables a more precise understanding of how system-level instructional design translates into measurable student-level performance, thereby enhancing both theoretical clarity and practical interpretation.

The present addresses these limitations through a rigorous analytical framework, refined measurement design, and robust model validation procedures. Multi-construct instruments covering CP, AIX, LE, CE, KR, and LO were applied, supported by strong factor loadings, high reliability, and SEM-based validation, minimizing common method bias. Comprehensive modelling using SEM, regression, EFA, and reliability analysis enhances causal explanation beyond descriptive approaches. A balanced undergraduate–postgraduate sample improves generalizability. The inclusion of CE, KR, and LO provides deeper curriculum-level insights. Mediation testing and goodness-of-fit validation further ensure structural robustness and scalable educational relevance.

The results demonstrate strong empirical support for the proposed framework linking AI-driven social media features with curriculum effectiveness and learning outcomes. The multiple regression analysis indicates high explanatory power ($R^2 = 0.794$), confirming that CP, AIX, KR, LE, CE, and LO jointly explain substantial variance in learning outcomes. Among predictors, LO ($\beta = 0.641$) and CE ($\beta = 0.618$) exhibit the strongest effects, emphasizing the central role of curriculum effectiveness and learning outcomes in AI-supported learning environments. CP ($\beta = 0.231$), AIX ($\beta = 0.218$), KR ($\beta = 0.202$), and LE ($\beta = 0.269$) also show significant contributions, confirming the importance of personalization, adaptive interaction, engagement, and knowledge support.

The EFA results reveal strong factor loadings (0.78–0.88), high eigenvalues, and satisfactory explained variance, confirming the robustness of construct validity. Reliability analysis further supports internal consistency, with Cronbach's alpha values ranging from 0.78 to 0.91, indicating acceptable to excellent reliability across all constructs. These results confirm stable and consistent measurement properties.

SEM findings validate all hypothesized paths, with strong direct and mediated effects. CP significantly enhances LE ($\beta = 0.312$), and AIX positively influences CE ($\beta = 0.298$). LE and CE significantly predict KR and LO, respectively, while mediation effects confirm the indirect influence of CP and AIX on KR. Goodness-of-fit indices ($CFI \geq 0.975$, $RMSEA \leq 0.049$, $GFI \geq 0.946$) demonstrate strong model adequacy, confirming the proposed structural relationships. Overall, the findings highlight the effectiveness of AI-driven social media in enhancing personalized learning, engagement, curriculum alignment, and learning outcomes in higher education. This distinction is theoretically significant, as it shifts the focus from technology adoption to curriculum transformation. By integrating multiple theoretical perspectives, the study demonstrates how AI-enabled systems facilitate not only learning efficiency but also adaptive, learner-centered educational ecosystems.

To enhance practical relevance, AI-driven social media can be implemented through real-world educational platforms such as adaptive learning systems, intelligent tutoring environments, and AI-supported learning management systems.

For instance, platforms that integrate personalized content delivery, real-time feedback, and analytics dashboards can support curriculum alignment and learner engagement. Institutions can operationalize these systems by embedding AI-driven tools into course modules, enabling data-informed instructional decisions, and continuously optimizing curriculum design based on learner interaction patterns.

6. Conclusion

The purpose focused on examining how AI-driven social media shapes curriculum alignment and learning effectiveness. Structured questionnaires captured learner responses using CP, AIx, LE, CE, KR, and LO variables. Statistical analyses employed EFA, reliability testing, regression, and SEM. Results showed strong explanatory power ($R^2 = 0.794$), significant effects ($\beta = 0.202\text{--}0.641$), high reliability ($\alpha = 0.78\text{--}0.91$), robust factor loadings, and satisfactory model fit ($CFI \geq 0.975$, $RMSEA \leq 0.049$, $GFI \geq 0.946$). Findings confirm meaningful interrelationships, highlighting enhanced engagement, curriculum relevance, and learning performance. Limitations include restricted institutional scope and self-reported measures. Future scope involves cross-cultural validation, longitudinal assessment, integration of behavioral analytics, and exploration of adaptive AI mechanisms for personalized curriculum development and sustainable educational innovation. This study provides a foundation for future theoretical development by positioning AI-driven social media as a co-evolving pedagogical system where algorithmic intelligence and human learning behaviors dynamically interact.

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Author contributions

Ying Fu: Conceptualization, conducted the study, collected the data, analyzed the data, interpreted the data, drafted the manuscript. Thosporn Sangsawang: conceptualization, analysis, and interpretation of the data.

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Data sharing statement

No additional data are available.

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Appendix A

Construct	Item Code	Questions	Likert Scale (1–5)
CP	CP1	To what extent do you agree that AI-driven social media personalizes learning content to your academic needs?	
	CP2	Which aspects of AI-based platforms adapt content according to your learning preferences?	
	CP3	In what way does personalized content support your conceptual understanding?	
	CP4	What features of customized materials enhance your learning experience?	
AIx	AIx1	How effectively does the system respond to your learning behavior?	
	AIx2	To what extent does AI-based interaction increase your learning engagement?	
	AIx3	In what way does adaptive feedback improve your academic performance?	
	AIx4	Which interactive features support your academic progress?	
KR	KR1	What type of AI-generated recommendations supports your learning needs?	
	KR2	To what extent do suggested resources improve your academic understanding?	
	KR3	Which recommended materials align with curriculum requirements?	
	KR4	In what way do knowledge recommendations enhance conceptual clarity?	
LE	LE1	How actively do AI-driven platforms motivate your learning participation?	
	LE2	To what extent does AI-supported learning maintain your academic focus?	
	LE3	In what way does interactive content increase your learning involvement?	
	LE4	Which platform features sustain your academic interest?	
CE	CE1	To what extent does AI integration improve curriculum relevance?	
	CE2	In what way does AI enhance curriculum flexibility?	
	CE3	How effectively are learning objectives achieved using AI-driven platforms?	
	CE4	Which AI-supported strategies improve curriculum delivery quality?	
LO	LO1	To what extent has AI-driven learning improved your academic performance?	
	LO2	In what way has AI-supported learning enhanced your conceptual understanding?	
	LO3	How effectively have AI-based tools improved your problem-solving ability?	
	LO4	What improvements in learning outcomes have resulted from AI-driven platforms?	

Note: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree