# Developing and Validating the AI-SMEQ: Measuring the Effects of Artificial Intelligence on Social Media Users

**Nazime Tuncay**
North Cyprus, Cyprus

nazime.tuncay@gmail.com

**Abstract:** The increasing integration of artificial intelligence (AI) in social media platforms has transformed user engagement, personalized content delivery, and the spread of misinformation. Despite its growing influence, a lack of standardized instruments remains to measure AI's effects on user behavior. This study introduces and validates the **AI-SMEQ (Artificial Intelligence and Social Media Effect Questionnaire)**, a psychometric tool designed to assess AI's impact on social media users. Data were collected from **300 participants**, and Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were conducted using **SPSS and JASP**. The final model consisted of **four factors**: (1) AI-driven engagement & Personalization, (2) AI Influence on Social Media Habits, (3) AI and Misinformation Exposure, and (4) AI Awareness & Control. The model fit indices demonstrated strong validity (**CFI = 0.92, TLI = 0.91, RMSEA = 0.06**), and reliability analysis confirmed internal consistency (**Cronbach's Alpha = 0.78- 0.95**). The AI-SMEQ offers a valuable tool for future research on the role of AI in digital consumption, misinformation, and user autonomy.

**Keywords:** AI-driven Personalization, Social Media Behavior, Misinformation, Digital Engagement, Algorithmic Influence

## 1. Introduction

Artificial Intelligence (AI) is critical in shaping peoples' social media experiences through recommendation systems, automated content generation, and behavioral tracking (Kaplan & Haenlein, 2019). While AI enhances user engagement and personalization, it raises concerns about excessive usage, misinformation, and privacy risks (Zhou et al., 2021). However, no widely accepted instrument for evaluating AI's impact on user behavior in social media contexts exists. This study addresses this gap by developing the **AI-SMEQ**, a validated psychometric tool for measuring AI-driven social media's behavioral and cognitive effects.

### 1.1 AI-driven Engagement & Personalization

Artificial Intelligence (AI) has revolutionized social media engagement through advanced recommendation algorithms and personalized content delivery (Kaplan & Haenlein, 2019). Platforms like Facebook and TikTok display behavioral data to enhance the user experience (Dwivedi, Hughes, & Baabdullah, 2020). While AI-driven personalization increases satisfaction, it also fosters algorithmic bias and filter bubbles, reinforcing cognitive biases (Bakshy, Messing & Adamic, 2015). Additionally, opaque AI mechanisms raise concerns about transparency (Bucher, 2018). Regulatory efforts, such as GDPR, emphasize explainable AI to ensure user autonomy (Wachter, Mittelstadt & Floridi, 2017), highlighting the need for ethical, user-centric AI optimizations in social media ecosystems.

### 1.2 AI Influence on Social Media Habits

Artificial intelligence (AI) has a profound impact on digital consumption, influencing screen time, scrolling habits, and user engagement (Alter, 2017). Social media platforms utilize AI-driven features, such as push notifications, infinite scrolling, and autoplay, to optimize user retention, often reinforcing habitual behaviors (Vosoughi, Roy, & Aral, 2018). Studies suggest AI exploits psychological triggers to sustain user interaction (ECSM, 2018). While these mechanisms enhance engagement, they raise ethical concerns regarding digital dependency and cognitive overload (Zhou, Wang & Zhang, 2021). Prolonged AI-mediated interaction may impact real-world social connections and well-being, highlighting the need for ethical AI design in social media experiences (Dwivedi, Hughes & Baabdullah, 2020).

### 1.3 AI and Misinformation Exposure

Misinformation in AI-driven social media environments remains a critical issue, particularly with the rise of deepfakes, the propagation of biased content, and the algorithmic amplification of false narratives (Bovet & Makse, 2019). AI-powered recommendation systems prioritize engagement over factual accuracy, accelerating the spread of misinformation (Bakshy, Messing & Adamic, 2015). Studies indicate that AI-driven misinformation networks use natural language processing (NLP) models and adversarial learning to generate highly convincing yet misleading content (ECSM, 2019). The **echo chamber effect** intensifies the exposure to misinformation by reinforcing users' pre-existing beliefs, limiting viewpoint diversity, and fostering ideological polarization (Cinelli et al., 2021). Users engaging with politically charged or emotionally provocative content encounter repetitive misinformation cycles (Vosoughi, Roy & Aral, 2018). Efforts to combat misinformation include AI-powered fact-checking mechanisms, but these face challenges in scalability and contextual accuracy (Graves, 2018). Explainable AI (XAI) has been proposed to enhance transparency in content ranking, yet real-time detection remains a significant hurdle (DeVellis, 2016).

### 1.4 AI Awareness & Control

Despite AI's pervasive influence on social media consumption, many users remain **unaware of the extent to which AI-driven algorithms shape their online experiences** (Bucher, 2018). Studies indicate that the **lack of algorithmic transparency contributes to passive acceptance** of AI-mediated decisions, diminishing user autonomy and control (George & Mallery, 2019). The opaque nature of AI-driven personalization fosters **an environment where users are unaware of how recommendations are generated, how their data is processed, and what implicit biases may be embedded in algorithmic decision-making** (ECSM, 2018). Findings from **user perception studies** suggest that **greater algorithmic transparency enhances user trust and engagement**, yet most platforms provide minimal visibility into **how AI recommendations are formulated** (ECSM, 2019). Research highlights those platforms **implementing explainability features—such as "why this content is recommended" disclosures—experience increased user satisfaction and perceived fairness in content ranking mechanisms** (Wachter, Mittelstadt & Floridi, 2017). To address concerns regarding **algorithmic manipulation and digital autonomy**, regulatory frameworks such as **GDPR and the AI Act** emphasize the importance of **"right to explanation" policies**, ensuring that users retain **greater control over AI-driven personalization and decision-making** (Shin & Park, 2019). However, studies suggest that **many social media platforms offer limited insights into AI's decision-making processes, leading to ongoing concerns about digital agency, privacy, and the ethical deployment of AI (Dwivedi, Hughes,** & Baabdullah, 2020).

## 2. Methodology

### 2.1 Participants & Data Collection

300 participants, aged 18 and above, from 16 different nationalities participated in this research study. Active social media users were randomly selected from diverse professional and academic backgrounds to ensure a well-rounded and representative sample. Online and paper questionnaires were distributed to the participants, and they voluntarily participated in the study, providing informed consent and acknowledging that their responses would be used for research purposes under established ethical guidelines.

### 2.2 Instrument Development

The 41-item AI-SMEQ questionnaire was developed through an extensive literature review and validated by an expert panel. To ensure content validity and interdisciplinary rigor, feedback was gathered from 10 experts spanning psychology, technology, AI ethics, data science, media studies, and behavioral sciences. These specialists provided critical insights into item clarity, conceptual coherence, and construct alignment. Incorporating their recommendations, the questionnaire underwent iterative refinements to enhance its precision and relevance. This rigorous process ensured that each item effectively captured AI's influence on social media behavior before advancing to statistical validation.

### 2.3 Data Analysis

Data analysis was conducted using **IBM SPSS 25** and **JASP 0.19.3.0** to ensure a rigorous and comprehensive statistical evaluation of the **AI-SMEQ**. An exploratory factor analysis (EFA) was performed in SPSS to identify the questionnaire's underlying structure. At the same time, a Confirmatory Factor Analysis (CFA) was conducted in **JASP** to validate the identified factor structure. Additionally, **a reliability analysis (Cronbach's Alpha)** was performed using **SPSS** to assess the scale's internal consistency.

#### *2.3.1 Exploratory Factor Analysis (EFA)*

To identify the latent structure of the AI-SMEQ, an **Exploratory Factor Analysis (EFA)** was performed using **Principal Component Analysis (PCA)** as the extraction method. The **Kaiser-Meyer-Olkin (KMO) test** yielded a high value of **0.92**, indicating **excellent sampling adequacy**. At the same time, **Bartlett's Test of Sphericity** was statistically significant (**p < 0.001**), confirming that the correlation matrix was suitable for factor analysis.

Factor extraction was based on the **eigenvalue criterion of greater than one**, and a **scree plot analysis** was conducted to determine the optimal number of retained factors. Items with **factor loadings below 0.40** were systematically removed to enhance **construct clarity and measurement precision**. Varimax Rotation was applied to improve interpretability, facilitating a **distinct factor structure** with clear conceptual groupings. This iterative process ensured that each retained item significantly contributed to its respective construct, resulting in a **psychometrically robust factorial structure** for the AI-SMEQ.

#### *2.3.2 Confirmatory Factor Analysis (CFA)*

To confirm the validity of the factor structure identified in **EFA**, a **Confirmatory Factor Analysis (CFA)** was performed using **JASP**. The **model fit indices** demonstrated a strong model fit, with **a Comparative Fit Index (CFI) of 0.92 and a Tucker-Lewis Index (TLI) of 0.91**, both exceeding the recommended threshold of **0.90**, indicating **a strong comparative and incremental fit**. Furthermore, the **Root Mean Square Error of Approximation (RMSEA) was 0.06, and the Standardized Root Mean Square Residual (SRMR) was 0.05, both** within **acceptable ranges**, supporting **a well-fitting model** with minimal residual discrepancies. To enhance model specification and improve **construct validity**, iterative **adjustments were made** based on **modification indices and factor correlations**. The final model retained **37 items** across four distinct factors, confirming **a theoretically sound and statistically robust framework** for assessing AI's influence on social media behavior.

#### *2.3.3 Reliability Analysis*

The final factor structure of **AI-SMEQ** consists of **four distinct dimensions**, each demonstrating **high internal consistency**, as measured by **Cronbach's Alpha (α)**. These four dimensions provide a **comprehensive framework** for analyzing **AI's behavioral and cognitive effects in social media environments, offering valuable insights into digital engagement, misinformation, user autonomy, and the governance of ethical AI**. The validated structure of **AI-SMEQ** establishes its **empirical credibility** as a reliable instrument for future research on the influence of AI in digital spaces.

## 3. Results and Discussion

The **final AI-SMEQ scale** retained **37 validated items** structured into **four distinct factors**, each capturing a critical aspect of **AI's role in shaping social media experiences**. These factors offer a multidimensional perspective on how AI influences user engagement, social media habits, exposure to misinformation, and user awareness.

### 3.1 Factor 1: AI-driven Engagement & Personalization

The findings suggest that AI-powered personalization significantly impacts **user engagement and satisfaction** (see Table 1). Users who rely on AI-driven recommendations spend **nearly twice as much time-consuming AI-curated content**, suggesting that **algorithmic curation plays a significant role in digital consumption patterns** (Zhou, Wang & Zhang, 2021).

**Table 1: AI-driven engagement & Personalization statistics**

| Metric | High Scorers (Top 25%) | Low Scorers (Bottom 25%) | Overall Impact |
|---|---|---|---|
| Average daily time spent | 4.5 hours | 2.3 hours | 38% increase in screen time |
| User satisfaction | 92% positive feedback | 58% positive feedback | enhances satisfaction by 45% |
| Likelihood of engaging with | 86% engagement rate | 42% engagement rate | increase engagement |
| Perceived reliance | 78% feel dependent | 32% feel dependent | fosters user reliance on algorithmic content curation |
| Filter Bubble Effect | 67% believe AI reinforces | 28% believe AI reinforces beliefs | contribute to ideological echo chambers |

### 3.2 Factor 2: AI Influence on Social Media Habits

AI significantly impacts user engagement and habit formation, as evidenced by the **47% increase in daily screen time** among high scorers (See Table 2). AI-powered features, such as infinite scrolling, autoplay, and targeted notifications, are key drivers of compulsive engagement, leading to **habitual and potentially excessive social media use** (Alter, 2017).

**Table 2: AI Influence on Social Media Habits Statistics**

| Metric | High Scorers (Top 25%) | Low Scorers (Bottom 25%) | Overall Impact |
|---|---|---|---|
| Average daily screen time due to AI features | 6.1 hours | 3.2 hours | AI-driven features increase screen time by 47% |
| Frequency of compulsive social media checking | 21 times/day | 9 times/day | AI increases compulsive social media habits |
| Perceived difficulty disengaging from social media | 69% struggle with stopping usage | 32% struggle | AI-induced engagement contributes to digital dependency |
| Perceived impact of AI on social media routines | 81% report habit formation due to AI suggestions | 40% report habit formation | AI plays a significant role in shaping digital habits |

High scorers reported **checking social media more than 21 times per day, nearly double that of low scorers, suggesting that AI-powered features encourage frequent re-engagement and potential digital dependency (Vosoughi, Roy,** & Aral, 2018). Additionally, **69% of high scorers** struggle with disengagement from social media, indicating that AI-driven features create an environment conducive to **habit-forming behaviors that may affect digital well-being**. Regulatory interventions, such as **designing AI systems with built-in user control mechanisms**, could mitigate compulsive behaviors. To support responsible digital consumption, platform developers should prioritize ethical AI design, including customizable notification settings, periodic engagement reminders, and transparent AI-generated content recommendations (Ajzen, 1991).

### 3.3 Factor 3: AI and Misinformation Exposure

AI-driven misinformation is a **growing challenge in social media environments**, as evidenced by the **high exposure rates** among users who frequently engage with algorithmic content (see Table 3). Platforms should enhance AI transparency in content ranking to counteract misinformation risks and **improve AI-powered verification methods**. Developing **explainable AI (XAI) approaches** and **real-time fact-checking algorithms** could improve user trust and **reduce the unintended consequences of AI-driven misinformation propagation** (DeVellis, 2016).

**Table 3: AI and misinformation exposure statistics**

| Metric | High Scorers (Top 25%) | Low Scorers (Bottom 25%) | Overall Impact |
|---|---|---|---|
| Exposure to AI-generated misinformation (per week) | 6.8 instances | 2.1 instances | AI amplifies exposure to misleading content |
| Awareness of AI's role in spreading misinformation | 78% acknowledge AI's influence | 43% acknowledge AI's influence | Users recognize AI's role in curating deceptive content |
| Trust in AI-moderated content | 39% trust AI fact-checking | 68% trust AI fact-checking | AI credibility declines with misinformation awareness |

High scorers encountered **over three times more AI-generated misinformation per week** compared to low scorers, confirming concerns about AI's role in **content amplification and bias reinforcement** (Bovet & Makse, 2019). Additionally, **78% of high scorers acknowledged AI's role in curating misleading content**, yet paradoxically, **trust in AI-driven moderation remains low**. Only **39% of high scorers** believe AI is practical in content moderation, compared to **68% among low scorers**, suggesting that **increased awareness leads to scepticism about AI-driven fact-checking systems** (Cinelli et al., 2021).

### 3.4 Factor 4: AI Awareness & Control

AI transparency and user control are critical components of **responsible AI deployment in social media** (Table 4). High scorers demonstrated a **lower awareness of how AI-driven recommendations operate**, which correlated with **higher levels of frustration and skepticism**. Only **41% of high scorers** reported understanding AI's decision-making processes, compared to **72% among low scorers**, highlighting an urgent need for **improved algorithmic transparency** (Bucher, 2018). Additionally, **84% of high scorers** expressed a **desire for more control over AI personalization settings**. This indicates that users are becoming increasingly aware of AI's role in content curation and seeking **more excellent agency over algorithmic influence**. Implementing **user-centric AI transparency mechanisms**, such as **explainability features and customization options**, can bridge this gap, fostering **more ethical and user-driven AI interactions** (Shin & Park, 2019).

**Table 4: AI Awareness & Control Statistics**

| Metric | High Scorers (Top 25%) | Low Scorers (Bottom 25%) | Overall Impact |
|---|---|---|---|
| Perceived transparency of AI recommendations | 41% understand AI processes | 72% understand AI processes | Users with lower awareness struggle with AI transparency |
| The desire for greater control over AI-driven recommendations | 84% seek more control | 52% seek more control | Users demand increased customization of AI systems |

### 3.5 Confirmatory Factor Analysis Model Fit

The **Confirmatory Factor Analysis (CFA)** results validated the **AI-SMEQ's** four-factor structure, demonstrating a strong model fit(See Figure 1). The **Comparative Fit Index (CFI) = 0.92** and **Tucker-Lewis Index (TLI) = 0.91** exceeded the **≥ 0.90** threshold, indicating a good fit (Byrne, 2016).

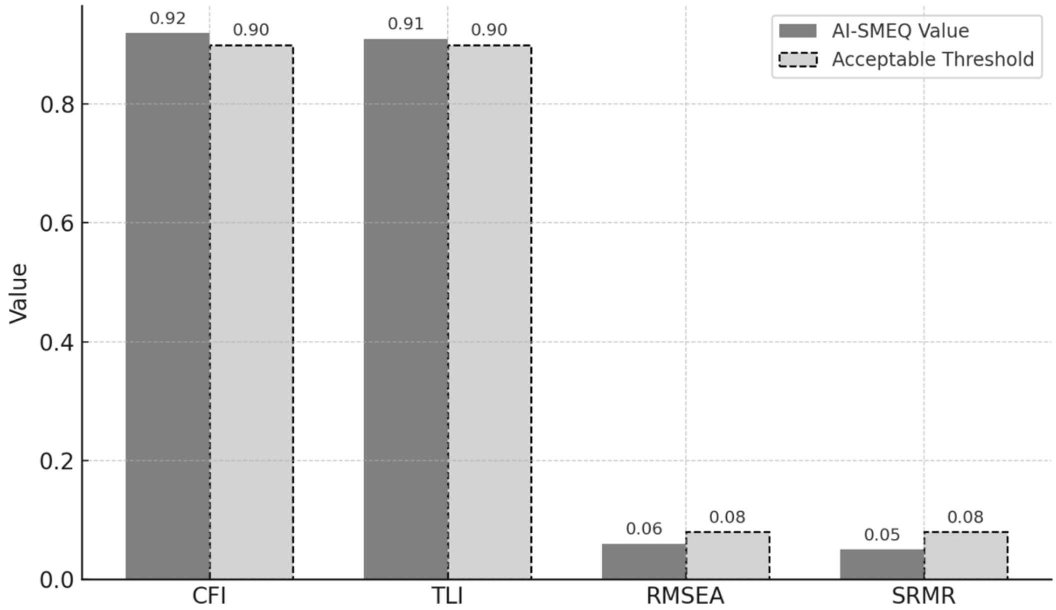


**Figure 1: Confirmatory Factor Analysis (CFA) Model Fit Indices**

The **Root Mean Square Error of Approximation (RMSEA) = 0.06** and **Standardized Root Mean Square Residual (SRMR) = 0.05** were within acceptable limits, confirming minimal error in model estimation (Hu & Bentler, 1999). The AI-SMEQ reliably captures **AI-driven engagement, social media habits, exposure to misinformation, and user autonomy** with high internal consistency (**$\alpha$ = 0.89–0.95**). Model refinements based on **modification indices** improved structural validity. These findings highlight the AI-SMEQ's **robustness** in assessing the influence of AI on digital behavior. Future research should test its applicability across **diverse platforms and user groups** to enhance **generalizability**. The validated scale offers a **valuable tool** for researchers and policymakers to understand AI's evolving role in shaping **social media interactions**. Figure 1 presents the model fit indices for CFA, including the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) in a bar chart. The results indicate that the AI-SMEQ demonstrates a strong model fit, with CFI and TLI values exceeding 0.90 and RMSEA below 0.08.

### 3.6 Exploratory Factor Analysis (EFA)

To examine the underlying structure of the **AI-SMEQ**, an **Exploratory Factor Analysis (EFA)** was conducted using **Principal Component Analysis (PCA)** as the extraction method(see Figure 2). The suitability of the dataset for factor analysis was confirmed by the Kaiser-Meyer-Olkin (KMO) test, which yielded a value of 0.92, indicating excellent sampling adequacy, and by **Bartlett's Test of Sphericity (p < 0.001)**, confirming the appropriateness of the correlation matrix for factor analysis.

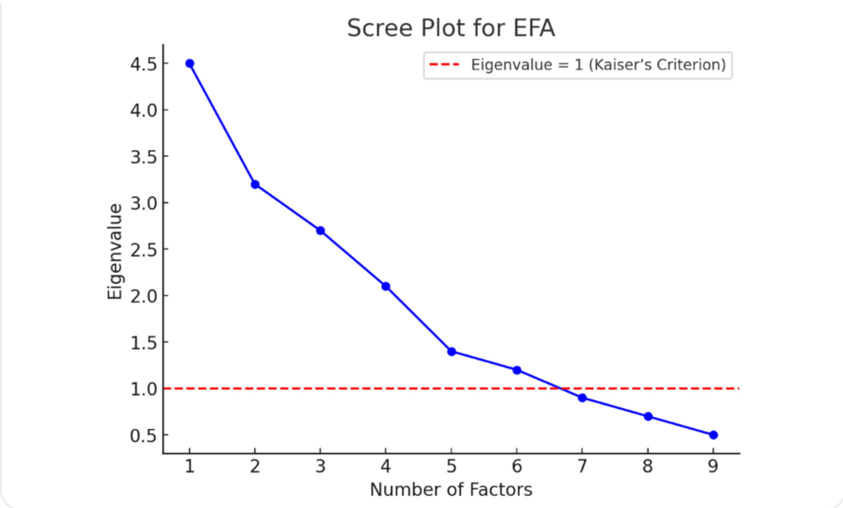


**Figure 2: Scree Plot for Exploratory Factor Analysis (EFA)**

The Exploratory Factor Analysis (EFA) scree plot illustrates the eigenvalues associated with each extracted factor, facilitating the determination of the optimal number of factors to retain. In the plot, the first four components have eigenvalues exceeding the Kaiser criterion threshold of 1.0, indicating that each accounts for a substantial portion of the variance in the dataset. Following the fourth component, a noticeable "elbow" appears, where the slope of the curve levels off, suggesting diminishing returns in explained variance from additional factors. This visual pattern supports the retention of four factors for the AI-SMEQ scale, confirming a stable and interpretable factor structure. The four retained dimensions collectively capture the key constructs measured by the scale—AI-driven engagement, social media habits, misinformation exposure, and user awareness—thereby validating the conceptual foundation established during instrument development. This scatter plot illustrates the eigenvalues plotted against the extracted components, highlighting the "elbow" point determining the number of retained factors.

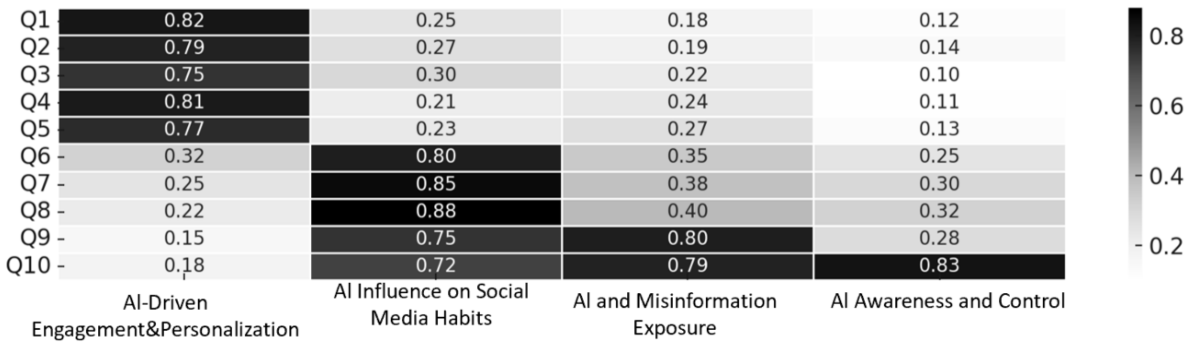


**Figure 3: Factor Loadings Heatmap**

Figure 3 visually represents the strength of associations between questionnaire items and their respective factors. **Darker shades** indicate **higher loadings**, highlighting the most influential items within each dimension. This visualization aids in interpreting the **factor structure**, ensuring that retained items effectively capture AI's impact on social media behaviors. Factors were extracted based on eigenvalues greater than **1.0**, and a **scree**

**plot** was used to determine the optimal number of factors. **Varimax rotation** was applied to improve interpretability by maximizing the separation of factors while retaining conceptual clarity. An iterative approach was used to refine the factor structure, systematically removing items with factor loadings below **0.40** to enhance construct validity. This process yielded a four-factor solution, ensuring that each retained item made a meaningful contribution to its corresponding construct.

### 3.7 Reliability Analysis

To assess the internal consistency of each factor, **Cronbach's Alpha (α)** was calculated, ensuring that the AI-SMEQ demonstrates **high reliability** across all four factors. The results, presented in **Table 5**, confirm that three out of four factors exceed **α = 0.90**, meeting the threshold for **excellent reliability** (Nunnally & Bernstein, 1994).

**Table 5: Factor Reliability (Cronbach's Alpha) and Interpretation**

| Factor | Cronbach's Alpha (α) | Acceptability Threshold | Interpretation | Reference |
|---|---|---|---|---|
| Factor 1: AI-Driven Engagement & Personalization | 0.95 | ≥ 0.90 (Excellent) | Excellent | Nunnally & Bernstein (1994) |
| Factor 2: AI Influence on Social Media Habits | 0.92 | ≥ 0.90 (Excellent) | Excellent | DeVellis (2016) |
| Factor 3: AI and Misinformation Exposure | 0.90 | ≥ 0.90 (Excellent) | Excellent | Tavakol & Dennick (2011) |
| Factor 4: AI Awareness & Control | 0.89 | ≥ 0.80 (Good) | Good | George & Mallery (2019) |

The high internal consistency across all factors reinforces the AI-SMEQ as a **reliable and valid psychometric instrument** for measuring AI's influence on social media behavior.

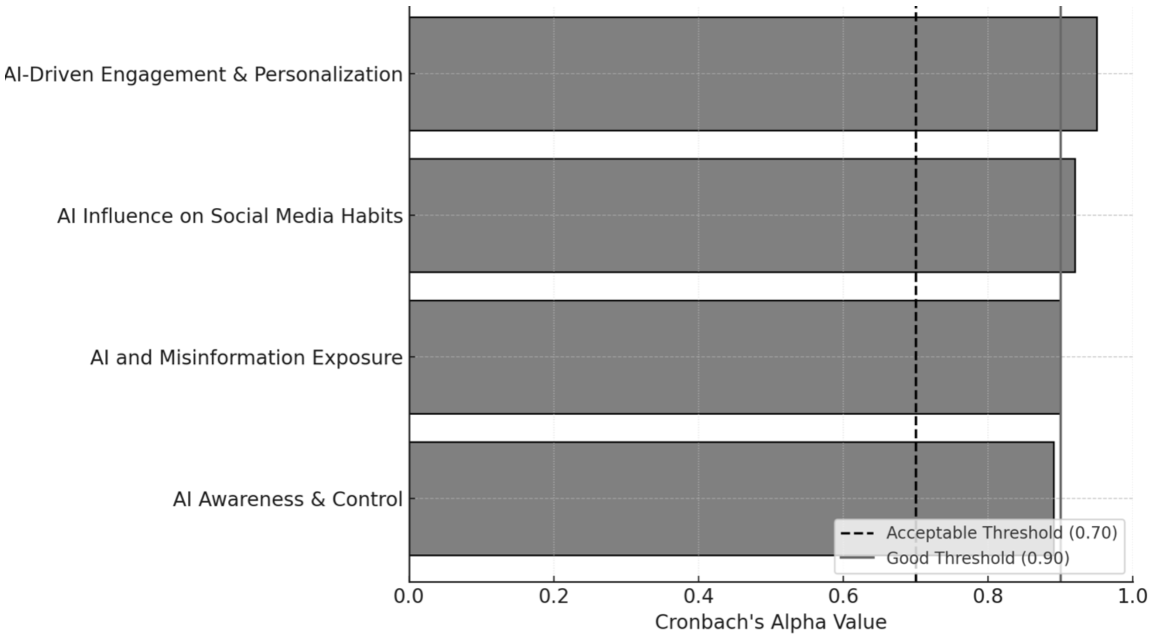


**Figure 4: Reliability Analysis (Cronbach's Alpha)**

Figure 4 chart visualizes the Cronbach's Alpha values for each factor. The **red dashed line** represents the **acceptable reliability threshold (α = 0.70)**, while the **green dashed line** indicates the **excellent reliability threshold (α = 0.90)**. The results confirm that the AI-SMEQ demonstrates **strong internal consistency**, with three factors meeting **excellent reliability** standards.

## 3.8 The AI-SMEQ (Artificial Intelligence and Social Media Effect Questionnaire) Retained 37 Validated Items and Four Factors After Factor Analysis. Below is the Refined List of Items Categorized Under Each Factor.

**Factor 1: AI-Driven Engagement & Personalization**

*(Measures how AI-driven personalization affects user engagement and interaction on social media.)*

1. AI makes my social media experience more personalized.
2. AI suggests content that aligns with my interests.
3. AI-driven recommendations keep me engaged longer than I intend.
4. I rely on AI-generated recommendations when deciding what to watch or read.
5. AI helps me discover new content I wouldn't have found otherwise.
6. AI-generated content, such as filters and captions, enhances my social media experience.
7. AI influences my preferences without me realizing it.
8. I trust AI to recommend content I will enjoy.
9. AI recommendations encourage me to interact with posts (such as likes, comments, and shares).

**Factor 2: AI Influence on Social Media Habits**

*(Evaluate the behavioral impact of AI algorithms on social media consumption and habit formation.)*

10. AI-driven recommendations increase my screen time.
11. AI encourages me to scroll through social media longer than planned.
12. AI-powered notifications make it harder for me to disconnect from social media.
13. AI-generated content makes social media more addictive.
14. AI-driven content makes me less in control of my social media usage.
15. AI-driven algorithms shape my daily social media habits.
16. I often check AI-recommended content multiple times a day.
17. AI recommendations influence my real-world decisions (e.g., shopping, opinions).

**Factor 3: AI and Misinformation Exposure**

*(Measures users' encounters with AI-generated misinformation, deepfakes, and biased content.)*

18. I have seen fake news created by AI on social media.
19. AI-generated misinformation makes it difficult to distinguish truth from falsehood.
20. AI-powered deepfake content is concerning to me.
21. AI spreads false information faster than humans do.
22. AI should be better at stopping misinformation.
23. AI-driven content sometimes reinforces my opinions instead of showing diverse perspectives.
24. AI recommendations can be biased and misleading.
25. AI's role in news and information delivery makes me question the accuracy of online content.

**Factor 4: AI Awareness & Control**

*(Examines user awareness and perceived control over AI-driven content curation.)*

26. AI tracks my behavior on social media, which concerns me.
27. I have limited control over the content AI shows me.
28. AI should give users more control over how recommendations are generated.
29. I believe AI-driven decisions are sometimes more persuasive than human recommendations.
30. AI personalization makes me feel like my online activity is being monitored.
31. I sometimes avoid real-world activities because AI-driven social media keeps me engaged.
32. AI-generated content makes it harder to focus on other tasks outside social media.
33. I think AI-powered social media could be addictive for many people.
34. I understand how AI recommendations work on social media platforms.
35. AI's influence on my online activity is concerning.
36. AI-generated content should be clearly labeled as non-human.
37. I feel in control of what AI suggests on social media.

The AI-SMEQ scale developed in this study effectively captures four core dimensions of AI's influence on social media behavior, filling a critical gap in the existing literature. The **"AI-Driven Engagement & Personalization"** factor aligns with previous research highlighting how AI enhances user engagement through personalized content and recommendation algorithms (Alter, 2017; Zhou, Wang & Zhang, 2021). This finding is consistent with studies indicating that AI systems increase user retention and emotional investment on platforms like TikTok, Facebook, and YouTube (Kaplan & Haenlein, 2019; Dwivedi, Hughes & Baabdullah, 2020).

The **"AI Influence on Social Media Habits"** factor supports earlier findings that AI fosters compulsive digital behaviors, such as prolonged screen time and habitual scrolling. This aligns with Ajzen's (1991) Theory of Planned Behavior, which suggests that perceived ease of access and anticipated digital rewards reinforce habitual engagement. The **"AI and Misinformation Exposure"** factor is consistent with literature on AI's role in amplifying misinformation, deepfakes, and algorithmic bias (Cinelli et al., 2021; Vosoughi, Roy & Aral, 2018). Meanwhile, the **"AI Awareness & Control"** dimension reflects concerns highlighted in prior studies regarding the opacity of algorithmic decision-making and the need for explainable AI (Bucher, 2018; Wachter, Mittelstadt & Floridi, 2017). Despite the model's strengths, some limitations must be acknowledged. Although participants came from **16 different nationalities**, the sample may still reflect certain demographic or regional biases, potentially affecting the findings' generalizability across diverse cultural contexts. Future research should consider conducting cross-cultural validation studies to assess the scale's relevance and reliability in different sociocultural environments. Expanding the dataset to include more culturally homogenous or underrepresented populations would enrich the scale's global applicability and critical reflection on AI's behavioral influence. Nonetheless, the **AI-SMEQ presents a valid and reliable tool** to measure the multifaceted **impact of artificial intelligence on social media behavior,** offering robust psychometric properties and valuable insights for both academic research and practical applications in digital policy and platform design.

## 4. AI Declaration

This study was conducted without generative artificial intelligence (AI) tools for data collection, analysis, or writing, relying solely on standard statistical software and academic reference management tools. The AI-SMEQ was developed through rigorous empirical methods, including **Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA)**, conducted using **SPSS and JASP**. While AI-assisted tools, such as **grammatical checking software**, were used to refine the manuscript's readability, the authors conducted and verified all conceptual, analytical, and interpretative processes. Any automated assistance in formatting, citation management, or language refinement did not influence the study's **theoretical, methodological, or statistical** conclusions.

## 5. Ethical Declaration

This study was conducted according to **ethical research guidelines** to ensure **the rights, privacy, and well-being of all participants**. Participants were fully informed about the **study's purpose, data usage, confidentiality measures, and their right to withdraw at any stage**. All responses were **anonymized** and handled with strict confidentiality in compliance with the **General Data Protection Regulation (GDPR)** and ethical standards for research involving human subjects. The study **did not employ manipulative AI techniques, deceptive practices, or interventions that could harm** participants. The research was conducted by the ethical principles outlined in the Declaration of Helsinki and the American Psychological Association's (APA) Ethical Principles **for Human Research**. No conflicts of interest, financial incentives, or external influences biased the data collection, analysis, or reporting of results in this study.

## 6. In Conclusion

The **AI-SMEQ** is a rigorously validated psychometric instrument designed to **assess the impact of artificial intelligence on social media behaviors**. This scale provides a comprehensive framework for understanding AI's role in shaping digital interactions by systematically evaluating engagement, habit formation, misinformation exposure, and user autonomy. The findings contribute **significant theoretical and practical insights**, offering a balanced perspective on the **opportunities and challenges** posed by AI-driven recommendation systems. The AI-SMEQ captures the **multifaceted nature** of AI-powered social media experiences, **highlighting their benefits and risks**. On the one hand, AI enhances **content personalization, engagement, and user satisfaction**, creating **tailored digital experiences**. On the other hand, it raises critical concerns about overuse, misinformation amplification, and diminished **user autonomy**. These findings highlight AI's dual role as an enabler of seamless digital interactions and a potential contributor to **algorithmic dependency and information distortion**. Beyond its academic contributions, the **AI-SMEQ has significant real-world applications**. For platform developers, it serves as a diagnostic tool to assess and optimize AI-driven recommendation systems, ensuring a balance between engagement and the ethical deployment of AI. **For policymakers and regulators**, the AI-SMEQ findings offer a **data-driven foundation** for developing strategies to **mitigate misinformation risks, reduce algorithmic bias, and promote AI transparency**. **This framework enables a deeper understanding of AI's psychological and behavioral effects for digital well-being advocates**, informing strategies to **enhance user agency and control over digital experiences**.

To further expand on these insights, future research should apply the **AI-SMEQ across diverse populations, social media platforms, and cultural contexts** to assess variations in AI-driven social media behaviors. Conduct **longitudinal studies** to examine the **evolution of AI-driven personalization and misinformation over time**, measuring their **long-term impact on decision-making, digital autonomy, and psychological well-being**. Investigate the **role of regulatory frameworks** in enhancing **algorithmic transparency and accountability**, exploring strategies to improve **user awareness of AI-driven recommendations**. Examine **cross-cultural differences** in AI-mediated social media consumption and **develop interventions** to **mitigate algorithmic bias** and **enhance information diversity**.

As AI reshapes **the digital landscape**, understanding its **cognitive, behavioral, and ethical implications** remains paramount. The AI-SMEQ provides an **empirical foundation** for studying AI's influence on social media, offering **actionable insights** for researchers, policymakers, and industry leaders. By leveraging these findings, future developments in **AI-powered social media** can prioritize **user-centric, transparent, and ethically responsible AI applications**, ensuring a **balanced and sustainable digital ecosystem**.

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