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Social Media Marketing and Young Consumers' Online Purchase Intention in Addis Ababa, Ethiopia

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Abstract

This study examines how five SMM dimensions, namely, social media content, consumer engagement, brand–consumer interaction, brand awareness and perception, and influencer marketing relate to purchase intentions among young consumers in Addis Ababa. The Elaboration Likelihood Model (ELM) provides the theoretical foundation. A quantitative cross-sectional design was used, with structured questionnaires administered to 230 respondents aged 18–55 (the working-age bracket as defined by the United Nations and World Bank), recruited through purposive sampling. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM); Confirmatory Tetrad Analysis (CTA-PLS) confirmed a reflective measurement structure for all constructs. Reliability and validity were satisfactory throughout: Cronbach's α exceeded 0.70, composite reliability (ρc) surpassed 0.70, and average variance extracted (AVE) cleared the 0.50 threshold for every construct. The model explains 48.6% of variance in online purchase intention ($R^2 = 0.486$) and shows strong predictive relevance ($Q^2 = 0.455$) and acceptable model fit (SRMR = 0.015). With 10,000 bootstrap subsamples, influencer marketing was the only statistically significant predictor of purchase intention ($\beta = 0.688$, $t = 18.145$, $p < .001$, $f^2 = 0.691$), a large positive effect. Social media content, engagement, interaction, and brand awareness each had directionally positive but non-significant effects. The findings contribute empirical evidence from a sub-Saharan African context, where such data remain scarce, and point to influencer credibility as the main driver of young Addis Ababa consumers' online purchase decisions.

Keywords: *brand awareness, Ethiopia, influencer marketing, purchase intention, social media marketing*

1. Introduction

Social media, once considered private communication channels, have transformed into powerful marketing platforms impacting buying behavior (Kaplan and Haenlein, 2010). Among emerging economies, SMM efforts including content generation, influencer marketing, and personal communications now appear among the most consistent determinants of online purchasing intention of the young consumers (Deepika and Massand, 2025; Ismael et al., 2025; Wang et al.,

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2025). This is particularly true for millennials using social media as well as e-commerce platforms concurrently.

The experience of Ethiopia may be used for research purposes. The country has adopted its national strategy, namely Digital Ethiopia 2030, which led to an accelerated adoption of digital technologies: by 2030 ethio telecom recorded about 46.6 million mobile internet users, corresponding to the 25% penetration level (Kemp, 2025). It was projected that e-commerce purchases would total around US$6 billion in 2025 (Statista, 2025), and a considerable number of those would belong to the urban young people. Young population constitutes 40% of the entire Ethiopian population and is characterized by the 19-year-old median age (UNDESA, 2025; World Bank, 2025). Moreover, such social media channels as YouTube, TikTok, Instagram, and Telegram are now part of their everyday lives.

Despite having highly engaged consumers on social media platforms, the young consumer population in Addis Ababa is often known to drop off at the final stage of their online purchase journey. This has been attributed to issues of trust towards the platform, secure payment, reliable delivery, and issues regarding the authenticity of the products (Iceaddis, 2024). However, the academic field seems not to have kept up since there are very few studies conducted on social media marketing among young consumers that are based in Africa or even Asia. In other words, there are no studies conducted on young consumers in the context of sub-Saharan Africa or even Ethiopia (Dangaiso, 2024; Nurhadi et al., 2025; Xia et al., 2024).

This study aims to bridge the above research gap. In the present study, five constructs of social media marketing namely social media content, engagement, interaction, brand awareness and perception, and influencer marketing are studied to determine their relationship with the purchase intentions of young consumers in Addis Ababa, employing Elaboration Likelihood Model (Petty and Cacioppo, 1986) as the conceptual model for analysis.

The study has the following specific objectives:

- To determine the relationship between social media content and the purchase intention of young consumers in Addis Ababa.
- To determine the relationship between consumer engagement and the purchase intention of young consumers in Addis Ababa.
- To investigate the relationship between brand–consumer interaction and the purchase intention of young consumers in Addis Ababa.
- To examine the relationship between brand awareness and perception and the purchase intention of young consumers in Addis Ababa.
- To determine the relationship between influencer marketing and the purchase intention of young consumers in Addis Ababa.

2. Literature Review

Theoretical Foundation: The Elaboration Likelihood Model

The Elaboration Likelihood Model (ELM), created by Petty and Cacioppo (1986) and further elaborated by Kitchen et al. (2014), is one of the most commonly used theories in persuasion research. It suggests that there are two possible routes through which attitude change takes place. If the individual is motivated and has sufficient cognitive ability, he/she uses the central route and evaluates carefully the persuasive arguments based on their quality and applicability. The attitudes that are formed under this mechanism are stable, resistant to counter-arguments, and have high predictive power. If the level of motivation or cognitive ability is low, the individual resorts to the peripheral route, which relies on heuristic cues (such as source attractiveness, followers, emotions, or visual appeal) (Petty and Cacioppo, 1986).

Elaboration likelihood exists on a continuum rather than in either-or terms. There are two factors that define the degree of elaboration that an individual has: motivation (which is dependent on personal relevance of the message) and ability (cognitive resources). According to Kitchen et al. (2014), this is one of the disadvantages of ELM because many marketing studies make references to ELM without measuring the level of elaboration properly or distinguishing between the routes.

ELM gives a comprehensive explanation in the context of SMM of why certain marketing factors might have varying effects on consumers' attitudes. The informative and personal nature of the message stimulates the central route of processing and careful evaluation of the product messages prior to making purchasing decisions. Peripheral factors, such as an influencer's credibility, an aesthetically pleasing post, and high levels of engagement, stimulate the peripheral route of persuasion which operates fast but not necessarily is long-lasting (Kitchen et al., 2014; Ismael et al., 2025). Unlike other theories, ELM does not force people to choose between two factors – both can be activated at the same time through a single message due to differences in digital literacy of consumers and their familiarity with the product/platform.

Social Media Marketing: Conceptual Overview

Social Media Marketing (SMM) is the application of social media platforms in communicating with customers, information dissemination and consumers' involvement (Ismael et al., 2025). SMM differs from traditional advertisement in that it provides immediate two-way communication where consumers not only receive branded message but participate in its creation via user-generated content, peers' reviews and social endorsements (Kaplan and Haenlein, 2010). The impact of social media on consumption behavior has significantly increased over the last ten years (Park et al., 2021) as consumers frequently turn to social media before consulting traditional resources while looking for information about products (Kar and Kushwaha, 2021).

The number of theoretical approaches to SMM has risen recently. According to Kim and Ko (2012), as cited in Ismael et al. (2025), the basic elements of SMM are: entertainment, interaction, trendiness, customization, and word-of-mouth. Four constructs related to youth consumers were outlined by Ismael et al. (2025): social media content, engagement and interaction, brand awareness and perception, and influencer marketing. The current research follows this conceptualization but distinguishes engagement and interaction in separate constructs resulting in five independent variables.

Social Media Content and Purchase Intention

Social media content should be relevant, useful, informative, credible, and attractive (Shien et al., 2023). As per ELM theory, good content is that which consists of substantial arguments which help in making decisions through the central route process. These include the description of products, reviews, demonstration videos and informative images which eliminate information asymmetry and help consumers evaluate the quality of products and purchase risks (Alalwan et al., 2022). Shien et al. (2023) indicate that utilitarian as well as hedonic elements in contents increase purchase intentions of young consumers while Alalwan et al. (2022) observe that the content makes brands more cognitively and emotionally relevant.

For young people, short videos, branded stories and user-generated content become peripheral cues which make evaluation easier for them and help in processing central arguments. Young consumers of Addis Ababa who live in a developing social media landscape prefer creative and culturally relevant content rather than promotional contents. This results in hypothesis number one:

H_1: There is a positive association between social media content and purchase intention of young consumers in Addis Ababa.

Engagement and Purchase Intention

In the SMM scenario, consumer engagement involves participation in activities related to the brand – liking the post, sharing content, writing comments, and creating user-generated content (Emini and Zeqiri, 2021). Engagement through the ELM approach is related to both processing routes – clicking 'like' on a post represents the peripheral route cue in the form of social proof, whereas leaving a review can be viewed as the central route of processing (Algharabat et al., 2023).

Active consumer engagement was identified by Algharabat et al. (2023) as a factor promoting customer satisfaction and loyalty, especially when brands react quickly. Rahman et al. (2022) proved that engagement mediates the influence of brand experience on brand loyalty. It means that the impact of engagement on purchase intention is achieved through the mediation of trust and emotional attachment. For young Ethiopian consumers, spending much time on social media platforms, peer validation of likes and shares will diminish purchase hesitation:

H_2: There is a positive association between engagement and purchase intention of young consumers in Addis Ababa.

Interaction and Purchase Intention

Whereas engagement consists of actions such as likes and shares, interaction represents a two-way dialogue between a consumer and a brand through responding to messages, taking part in branded campaigns, and direct conversations (Emini and Zeqiri, 2021). According to Othman and Rahim (2019), interactive tools, such as direct brand responses and user-generated campaigns, create relational ties that are impossible to achieve in conventional advertising. In the case of online shopping, when physical inspection is impossible, two-way communication mitigates risk perceptions through providing a channel of personal information exchange. Two-way communication also has a social identity component. Young consumers' affiliation with brands having similar values results in **a** stronger affiliative attitude and **a** higher intention to make purchases (Wijayaa et al., 2021). In the case of the developing market of e-commerce in Ethiopia, when suspicion towards online retailing is widespread, two-way brand communication might be used as a sign of trust**.**

H_3: There is a positive association between interaction and purchase intention of young consumers in Addis Ababa.

Brand Awareness, Perception, and Purchase Intention

BAP involves consumer recognition and perception of the brand after being exposed to it on social media (Ismael et al., 2025). Brands that are familiar with consumers do not need much effort to evaluate, are less risky, and get into consumer considerations (Fajri et al., 2021). Social media makes it possible for brands to create awareness of themselves through constant communication at a low cost.

According to Heidari et al. (2023), consistency in SMM efforts leads to brand equity and positive perception, which is related to higher purchase intentions on the part of young consumers. As noted by Emini and Zeqiri (2021), brand perception can be influenced not just by brand messages, but also by the overall sentiment on social media: peer reviews, user-generated content, and how brands react to criticism make their social identity. When there is not much differentiation between products in the market, brand perception becomes the critical point in moving from awareness to purchase intentions:

H4: There is a positive association between brand awareness perception and purchase intention of young consumers in Addis Ababa.

Influencer Marketing and Purchase Intention

Influencer marketing involves the use of the persuasive power of social media personalities who have different levels of audience ranging from niche micro-influencers to celebrities whose product recommendations are often more credible and more relevant to individual users compared to any kind of marketing message created by brands (Ismael et al., 2025). In terms of ELM, influencer marketing uses both routes. The expertise of influencers and the high quality of their content can trigger the central route of processing, while the personal characteristics of influencers and the development of parasocial relationships with them serve as peripheral persuasive cues (Kitchen et al., 2014).

There is empirical evidence that backs up this idea. Thus, Aji et al. (2020) discovered that influencer marketing increased brand equity, word-of-mouth and purchase intentions of consumers. Chen and Yang (2023) proved that influencer-led live-streaming increases purchase intentions through trust and affective relationships. Sesar et al. (2022) identified the components of a credible endorsement as credibility, trustworthiness, expertise, and authenticity. Finally, Karunasingha and Abeysekera (2022) established that parasocial relationships intensify the persuasive effect of endorsements.

Ethiopian culture tends to emphasize interpersonal trust and social networks for word of mouth that affect consumers' purchase behavior, which means that social media influencers could potentially play a similar role to that of trusted advisers online. Consumers who relate to the values and lifestyle of an influencer are more likely to form purchase intentions (Wang et al., 2025). However, the match between an influencer and a brand is significant because:

H5: There is a positive association between influencer marketing and purchase intention of young consumers in Addis Ababa.

Conceptual Framework

In light of the theory behind the Elaboration Likelihood Model (Petty & Cacioppo, 1986) and the literature review described above, the following conceptual framework has been developed based on five dimensions of social media marketing and their link to young consumers' online purchase intention in Addis Ababa. According to the framework, the independent variables are the five aforementioned dimensions of social media marketing, each of which is believed to have a direct effect on purchase intention (the dependent variable). Following the dual process model of ELM, five constructs are proposed to be considered as equal predictors instead of sequential or hierarchical models. In particular, content, engagement, and brand awareness are the constructs which are linked to the central route of persuasion and therefore require more cognitive processing, whereas interaction and especially influencer marketing work through peripheral cues. Figure 1 presents the conceptual model where all five hypotheses (H_1-H_5) about the direct influence of one dimension of social media marketing on online purchase intention are illustrated.

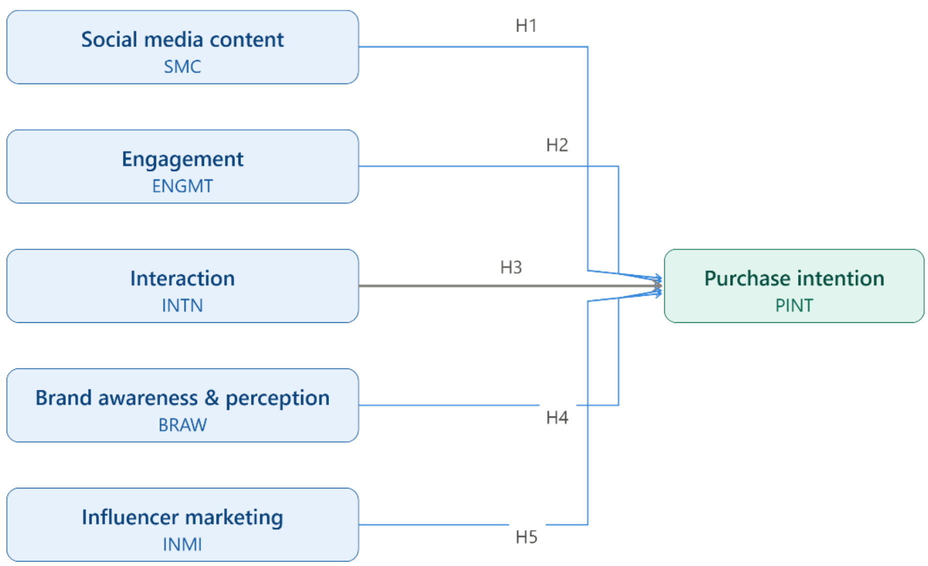

Figure 1 Conceptual framework of the study
Source: Adapted from Petty and Cacioppo (1986) and Ismael et al. (2025)

3. Materials And Methods

Research Design and Approach

An explanatory research design using the deductive and quantitative paradigm is adopted for this study. The study utilized a cross-sectional survey research design where the data on consumer perceptions were taken as a snapshot during the 2025/2026 data gathering stage. Hypotheses grounded on the theoretical framework (ELM and previous literature) were tested against empirical survey data using inferential analysis. For analysis, SmartPLS 4 software using PLS-

SEM method was employed. PLS-SEM is suited for predictive-oriented studies, can handle complex multi-construct models, can deal with non-normal data and evaluate reflective and formative measurement models at once (Hair et al., 2022).

Population, Sampling, and Sample Size

The target population consisted of young people from Addis Ababa in the age group of 18-55 years (working-age group as classified by the United Nations and World Bank) who had used online or social commerce before to make purchases. Purposive (non-probability) sampling was employed to select only those people who satisfied these requirements. The number of sample size was estimated via G*Power software (Faul et al., 2009) for a medium effect size ($f^2 = 0.15$), 80% power, and alpha level of 0.05. In line with Malhotra and Dash (2017) who suggested having at least 200 respondents in SEM researches, 250 questionnaires were administered. Out of them, 236 were retrieved back, and 230 (92%) were found valid.

Data Collection and Measurement

The data collection process involved the use of structured questionnaires based on a five-point Likert Scale (1=Strongly disagree to 5=Strongly agree). All the measurement variables used in the questionnaire have been borrowed from previous research work. Questionnaires were completed using the face-to-face method to ensure that the questions were answered well. Table 1 below shows the complete model specification.

Model Specification

In the structural model, Purchase Intention (PINT) is taken as the dependent variable, while Social Media Content (SMC), Engagement (ENGMT), Interaction (INTN), Brand Awareness & Perception (BRAW), and Influencer Marketing Impact (INMI) are considered independent latent variables. The Inner Model is:

$$PINT = \beta_1(SMC) + \beta_2(ENGMT) + \beta_3(INTN) + \beta_4(BRAW) + \beta_5(INMI) + \varepsilon$$

Here, β_1–β_5 represent path coefficients (expected to be positive) and ε is the error term. All constructs were considered reflective variables, a categorization validated through Confirmatory Tetrad Analysis (CTA-PLS, Gudergan et al., 2008). For details on the measurement model, please refer to Table 1.

Table 1 Model specification: constructs, measurement items, and sources

Construct (Role)	Items Used	Sample Measurement Indicators	Scale Source
Social Media Content – SMC (IV)	4*	SMC1: Social media content about products is informative and helpful. SMC2: Brand content is visually appealing. SMC3: Content helps me evaluate products effectively. SMC4: Content influences how I perceive product quality.	Shien et al. (2023)
Engagement – ENGMT (IV)	2	ENGMT1: I frequently like, share, or comment on brand posts.	Emini and Zeqiri (2021)

		ENGMT2: I enjoy engaging with brands through social media.	
Interaction – INTN (IV)	2*	INTN2: Interacting with brand content makes me feel connected. INTN3: I participate in brand-related discussions or campaigns.	Emini and Zeqiri (2021)
Brand Awareness & Perception – BRAW (IV)	3*	BRAW2: Social media marketing helps me remember brand names. BRAW3: I have a favorable perception of active social media brands. BRAW4: I trust brands with consistent social media communication.	Emini and Zeqiri (2021)
Influencer Marketing – INMI (IV)	5	INMI1: Influencer recommendations affect my product choices. INMI2: I trust product reviews by influencers I follow. INMI3: I try products endorsed by influencers I like. INMI4: Influencers help me discover new brands. INMI5: Influencer-promoted products seem more reliable.	Bilgin (2018)
Purchase Intention – PINT (DV)	4	PINT1: I am likely to purchase products promoted on social media. PINT2: I intend to buy products from brands I follow. PINT3: SMM increases my intention to purchase online. PINT4: I recommend products discovered through social media.	Shien et al. (2023)

*Note: * Items deleted after iterative purification process. IV = independent variable; DV = dependent variable. BRAW1, INTN1, SMC5 removed due to low factor loadings. Sources: Shien et al. (2023); Emini and Zeqiri (2021); Bilgin (2018); Ismael et al. (2025).*

Analytical Procedure and Validity Assessment

The analysis was done based on the two-step procedure proposed by Hair et al. (2022). The first step consisted of the evaluation of the outer model (i.e., measurement model), including indicator reliability, internal consistency, convergent validity, and discriminant validity. The second step comprised the analysis of the inner model (i.e., structural model) that included the evaluation of R-squared, f-squared, Q-squared, model fit, and hypothesis testing through bootstrapping. Multicollinearity was determined using Variance Inflation Factor (VIF < 5.0 for outer and inner models) and SRMR < 0.08 (Henseler et al., 2015).

Ethical Considerations

This study adhered to established ethical principles for research involving human participants. Prior to data collection, informed consent was obtained from all respondents; participants were briefed on the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any stage without penalty. No incentives were offered that could have unduly influenced participation.

Anonymity and confidentiality were maintained throughout the research process. No personally identifying information (name, phone number, or address) was collected on the questionnaire, and responses were coded and analyzed in aggregate form only, ensuring that no individual respondent could be identified in the reported findings. Completed questionnaires and the resulting dataset were stored securely and accessed only by the research team for the purposes of this study.

Participation was limited to individuals who met the eligibility criteria (residents of Addis Ababa aged 18 years and above with prior online or social commerce purchasing experience), and no vulnerable populations (e.g., minors) were targeted or included. Given the face-to-face administration method, enumerators were instructed to avoid any coercive framing and to allow respondents adequate time and privacy to complete the instrument honestly.

The study also observed academic integrity standards in the use of secondary sources, ensuring that all borrowed measurement scales (Shien et al., 2023; Emini and Zeqiri, 2021; Bilgin, 2018) were properly cited and used with appropriate acknowledgment. The research did not involve deception, and there was no known physical, psychological, or reputational risks to participants beyond those encountered in everyday life.

4. Results

Respondent Profile

Table 2 shows the demographic profile of the 230 respondents. Women were a slight majority (57.0% vs. 43.0% male). The 31–45 age group was the largest (38.3%), followed by those aged 41–55 (33.9%) and 18–30 (26.1%). Educational attainment ranged from high school (20.4%) to postgraduate (15.3%), with bachelor's degree holders the largest single group (32.6%). Most respondents reported shopping online rarely (43.5%) or monthly (37.8%). YouTube was the most-used platform (40.4%), followed by X/Twitter (30.9%), TikTok (14.3%), Instagram (11.3%), and Facebook (3.0%).

Table 2 Demographic profile of respondents (n = 230)

Category	Subcategory	Frequency (N)	Percent (%)
Gender	Male	99	43.0
	Female	131	57.0
Age	18–30 years	60	26.1
	31–45 years	88	38.3
	41–55 years	78	33.9
	Above 55 years	4	1.7
Education Level	High School	47	20.4
	Diploma	73	31.7
	Bachelor's	75	32.6
	Master's or above	35	15.3
Online Shopping Frequency	Never	17	7.4
	Rarely	100	43.5
	Monthly	87	37.8
	Weekly	26	11.3
Primary Platform	Facebook	7	3.0
	Instagram	26	11.3
	TikTok	33	14.3
	YouTube	93	40.4

	X (Twitter)	71	30.9

Source: Survey data, 2026

Descriptive Statistics

Table 3 presents descriptive statistics for all latent constructs. Every construct scored above the scale midpoint of 3.0 (range: 3.71–3.85), reflecting generally favorable perceptions of SMM activities. Standard deviations ranged from 0.53 to 0.72, indicating moderate response consistency. Skewness was negative across all constructs (range: −0.58 to −1.12), pointing toward higher ratings. Kurtosis was highest for influencer marketing impact (2.377) and social media content (1.988), indicating more peaked response distributions for these constructs.

Table 3 Descriptive statistics (n = 230)

Construct	Mean	Std Dev	Skewness	Std Error	Kurtosis	Std Error
Social Media Content	3.792	0.528	−0.783	0.160	1.988	0.320
Engagement	3.713	0.600	−0.860	0.160	0.725	0.320
Interaction	3.851	0.600	−0.581	0.160	0.040	0.320
Brand Awareness & Perception	3.838	0.722	−0.712	0.160	1.124	0.320
Influencer Marketing Impact	3.832	0.641	−1.122	0.160	2.377	0.320
Online Purchase Intention	3.814	0.656	−1.063	0.160	1.352	0.320

Source: Survey data, 2026

Multicollinearity Test

Multicollinearity among the five independent variables was assessed using SPSS with purchase intention as the criterion variable. The standard threshold is VIF > 5.0 or tolerance < 0.10 (Hair et al., 2019). As shown in Table 4, all VIF values fell between 1.281 (Interaction) and 2.176 (Influencer Marketing Impact), well within acceptable bounds. Tolerance values ranged from 0.460 to 0.781, confirming that no predictor approximates a linear combination of the others. Multicollinearity is not a concern in the structural model.

Table 4 Outer model multicollinearity

Independent Variable	Tolerance	VIF
Social Media Content (SMC)	0.608	1.645
Engagement (ENGMT)	0.738	1.355
Interaction (INTN)	0.781	1.281
Brand Awareness & Perception (BRAW)	0.618	1.619
Influencer Marketing Impact (INMI)	0.460	2.176

Note: Threshold: VIF < 5.0; Tolerance > 0.10

Source: SPSS v.27, Survey data, 2026

Confirmatory Tetrad Analysis (CTA-PLS)

The reflective or formative nature of each construct was established empirically through Confirmatory Tetrad Analysis (CTA-PLS) with 5,000 bootstrap subsamples (Gudergan et al., 2008; Hair et al., 2024). A construct is classified as reflective when model-implied tetrads are non-significant ($p > 0.05$) and the 95% bias-corrected confidence intervals span zero with mixed positive and negative bounds (Ringle, 2024). Significant tetrads with confidence intervals that exclude zero indicate formative measurement.

Table 5 shows that 80% of tetrads across constructs were non-significant, with zero-spanning confidence intervals and mixed signs, supporting a reflective specification for all first-order latent variables. One tetrad for INMI ($p = 0.021$) approaches significance, but with a lower CI bound at 0.000 and a positive upper bound, the case for formative measurement is weak. All constructs are therefore treated as reflective in subsequent analyses.

Table 5 Confirmatory Tetrad Analysis (CTA-PLS) results (bootstrap subsamples = 5,000)

Construct	Tetrad	p-value	CI Low (adj.)	CI Up (adj.)	Model Type
Social Media Content (SMC)	T1	0.129	−0.067	0.014	Reflective
	T2	0.113	−0.012	0.067	Reflective
Engagement (ENGMT)	T1	0.088	−0.077	0.012	Reflective
Interaction (INTN)	T1	0.030	−0.082	0.003	Reflective
Influencer Marketing (INMI)	T1	0.021	0.000	0.163	Reflective†
Brand Awareness (BRAW)	T1	0.081	−0.045	0.019	Reflective
Purchase Intention (PINT)	T1	0.096	−0.058	0.027	Reflective

Note: Reflective classification when p > 0.05 and CI spans zero with mixed signs (Gudergan et al., 2008). † Marginal case retained as reflective; see text.

Source: SmartPLS 4 Survey data, 2026

Measurement Model: Factor Loadings, Reliability, and Convergent Validity

Indicator reliability was assessed by examining outer factor loadings against their designated latent constructs. The recommended minimum is FL ≥ 0.70 (Hair et al., 2022), though items loading above 0.50 may be retained if the construct's AVE exceeds 0.50 and composite reliability exceeds 0.70 (Schumacker and Lomax, 2015). Three items were removed through iterative purification—BRAW1, INTN1, and SMC5—as each reduced AVE. Their removal raised SMC's AVE from 0.430 to 0.526, Cronbach's α for Interaction from 0.52 to 0.851, and Cronbach's α for SMC from 0.66 to 0.719.

Table 6 reports item-level factor loadings alongside construct reliability and convergent validity statistics. All retained items load at or above 0.564 on their intended construct. Two SMC items (SMC3 = 0.564; SMC4 = 0.578) fall below 0.70 but were kept because the SMC construct satisfies both AVE > 0.50 and $\rho c > 0.70$. All constructs except SMC achieve Cronbach's $\alpha > 0.80$, with SMC meeting the minimum 0.70 standard. Composite reliability (ρc) exceeds 0.70 for every construct, and AVE exceeds 0.50 for all, confirming convergent validity throughout the measurement model.

Table 6 Item-level factor loadings, reliability, and convergent validity

Construct / Item	Factor Loading	Cronbach's α	ρc	AVE	Status
Brand Awareness (BRAW)		0.902	0.923	0.803	
BRAW2	0.970				Retained
BRAW3	0.962				Retained
BRAW4	0.736				Retained
BRAW1 (deleted)	< 0.70				Removed
Engagement (ENGMT)		0.944	0.970	0.942	
ENGMT1	0.988				Retained
ENGMT2	0.953				Retained
Influencer Marketing (INMI)		0.915	0.923	0.706	
INMI1	0.856				Retained
INMI2	0.886				Retained
INMI3	0.801				Retained
INMI4	0.882				Retained
INMI5	0.770				Retained
Interaction (INTN)		0.851	0.920	0.852	
INTN2	0.866				Retained
INTN3	0.977				Retained
INTN1 (deleted)	< 0.70				Removed
Social Media Content (SMC)		0.719	0.810	0.526	
SMC1	0.795				Retained
SMC2	0.907				Retained
SMC3	0.564a				Retained (AVE > 0.50)
SMC4	0.578a				Retained (AVE > 0.50)
SMC5 (deleted)	< 0.70				Removed
Purchase Intention (PINT)		0.923	0.945	0.812	
PINT1	0.884				Retained
PINT2	0.916				Retained
PINT3	0.916				Retained
PINT4	0.887				Retained

Note: a Items retained despite loading < 0.70 because construct AVE > 0.50 and ρc > 0.70 (Hair et al., 2022; Schumacker and Lomax, 2015). BRAW = Brand Awareness; ENGMT = Engagement; INMI = Influencer Marketing Impact; INTN = Interaction; SMC = Social Media Content; PINT = Purchase Intention.

Source: SmartPLS 4, Survey data, 2026

Discriminant Validity: Fornell-Larcker Criterion

Discriminant validity was first evaluated using the Fornell-Larcker criterion (Fornell and Larcker, 1981), which requires the square root of each construct's AVE (bold diagonal values in Table 7) to exceed that construct's highest correlation with any other construct. Table 7 confirms this condition throughout. For example, BRAW's AVE root of 0.896 exceeds its largest inter-construct correlation of 0.596 (with INTN). ENGMT (0.971), INMI (0.840), INTN (0.923), PINT (0.901), and SMC (0.725) all similarly exceed their respective maximum off-diagonal correlations, confirming that each construct shares more variance with its own indicators than with any other.

Table 7 Fornell-Larcker criterion for discriminant validity (square root of AVE on diagonal)

Construct	BRAW	ENGMT	INMI	INTN	PINT	SMC
BRAW	0.896					
ENGMT	−0.125	0.971				
INMI	0.377	0.129	0.840			
INTN	0.596	−0.033	0.435	0.923		
PINT	0.280	0.083	0.694	0.287	0.901	
SMC	0.464	−0.340	0.311	0.594	0.253	0.725

Note: Diagonal values in bold represent the square root of AVE. Off-diagonal values are inter-construct correlations. Discriminant validity is established when diagonal > row/column maximum.

Source: SmartPLS 4, Survey data, 2026.

Discriminant Validity: Cross-Loadings

Cross-loading analysis served as a supplementary check. Each indicator must load more strongly on its intended construct than on any other (Hair et al., 2022). Table 8 presents the full cross-loading matrix. Across all 20 retained items, primary loadings exceed all cross-loadings by at least 0.10, the standard rule of thumb in PLS-SEM. BRAW2, for instance, loads 0.970 on BRAW against a maximum cross-loading of 0.595 on INTN; INMI3 loads 0.801 on INMI against a maximum of 0.460 on INTN. These results reinforce the Fornell-Larcker findings.

Table 8 Cross-loadings of all retained measurement items

Item	BRAW	ENGMT	INMI	INTN	PINT	SMC
BRAW2	0.970*	−0.118	0.414	0.595	0.317	0.443
BRAW3	0.962*	−0.137	0.298	0.567	0.234	0.465
BRAW4	0.736*	−0.010	0.272	0.342	0.037	0.293
ENGMT1	−0.104	0.988*	0.131	−0.011	0.097	−0.316
ENGMT2	−0.156	0.953*	0.118	−0.074	0.049	−0.364
INMI1	0.229	0.121	0.856*	0.353	0.311	0.201
INMI2	0.291	0.126	0.886*	0.399	0.355	0.254
INMI3	0.351	0.100	0.801*	0.460	0.307	0.251
INMI4	0.466	−0.051	0.882*	0.452	0.458	0.360
INMI5	0.254	0.176	0.770*	0.263	0.898	0.227
INTN2	0.379	0.051	0.283	0.866*	0.139	0.550
INTN3	0.641	−0.066	0.464	0.977*	0.327	0.566
PINT1	0.222	0.126	0.580	0.268	0.884*	0.215
PINT2	0.368	0.088	0.670	0.380	0.916*	0.281
PINT3	0.259	0.013	0.635	0.244	0.916*	0.258
PINT4	0.147	0.075	0.611	0.132	0.887*	0.150
SMC1	0.211	−0.352	0.157	0.254	0.259	0.795*
SMC2	0.404	−0.408	0.164	0.503	0.177	0.907*
SMC3	0.379	−0.069	0.350	0.559	0.102	0.564*
SMC4	0.506	−0.001	0.378	0.642	0.134	0.578*

*Note: * Indicates the item's intended construct. Bold entries mark primary loadings.*

Source: SmartPLS 4, Survey data, 2026

Inner Model Multicollinearity (VIF)

In addition to this, inner model VIF scores have also been analyzed using SmartPLS to check whether the structural paths' coefficients have any bias due to redundancy among the predictors. The acceptable VIF score according to Hair et al., (2022) is VIF < 5.0. Table 9 presents VIF scores for the inner model which lie well within this limit (1.258 – 2.122).

Table 9 Inner model multicollinearity assessment (SmartPLS VIF values)

Path (Predictor → PINT)	VIF
Brand Awareness (BRAW → PINT)	1.654
Engagement (ENGMT → PINT)	1.258
Influencer Marketing (INMI → PINT)	1.334
Interaction (INTN → PINT)	2.122
Social Media Content (SMC → PINT)	1.904

Note: Threshold: VIF < 5.0 (Hair et al., 2022). PINT = Purchase Intention

Source: SmartPLS 4, Survey data, 2026

Structural Model: Coefficient of Determination (R^2) and Effect Size (f^2)

R-Square (coefficient of determination) measures the proportion of variance in PINT explained by all five variables collectively. According to Table 10, $R^2 = 0.486$, which means that 48.6% of variance in PINT is explained by the regression model. According to Hair et al., (2022), R^2 equal to or higher than 0.26 is considered substantial in social science PLS-SEM research.

Effect size (f^2) is the measure of the increase in R^2 caused by adding a predictor to the model as compared with removing it (Cohen, 1988). Benchmarks are: $f^2 < 0.02$ = negligible; 0.02–0.15 = small; 0.15–0.35 = medium; > 0.35 = large. One finding stands out sharply: influencer marketing (INMI) produced an exceptionally large f^2 of 0.691, confirming its dominant role in the model. All other predictors—SMC ($f^2 = 0.006$), ENGMT ($f^2 = 0.001$), INTN ($f^2 = 0.005$), and BRAW ($f^2 = 0.001$)—registered negligible individual contributions, consistent with their non-significant path coefficients.

Table 10 Coefficient of determination (R^2) and effect sizes (f^2)

Index	Construct / Path	Value	Benchmark
R-square (R^2)	Purchase Intention (PINT)	0.486	0.26 = substantial (Hair et al., 2022)
Adjusted R^2	Purchase Intention (PINT)	≤0.486	Accounts for predictor count
Effect Size (f^2) – BRAW → PINT	BRAW	0.001	< 0.02 = negligible
Effect Size (f^2) – ENGMT → PINT	ENGMT	0.001	< 0.02 = negligible
Effect Size (f^2) – INMI → PINT	INMI	0.691	> 0.35 = large
Effect Size (f^2) – INTN → PINT	INTN	0.005	< 0.02 = negligible
Effect Size (f^2) – SMC → PINT	SMC	0.006	< 0.02 = negligible

Note: f^2 benchmarks: < 0.02 = negligible; 0.02–0.15 = small; 0.15–0.35 = medium; > 0.35 = large (Cohen, 1988)

Source: SmartPLS 4, Survey data, 2026

Predictive Relevance (Q^2) and Model Fit

The Q^2 statistic of Stone-Geisser that is calculated by blindfolding evaluates the ability of the model to predict the value of the excluded cases. According to Hair et al. (2013), the threshold of $Q^2 > 0.35$ means good predictive relevance. The Q^2 of purchase intention is calculated in Table 11, and it equals to 0.455, exceeding the mentioned threshold. The indicators of RMSE (0.751) and MAE (0.545) demonstrate an appropriate level of prediction.

Table 11 Predictive relevance (Q^2), RMSE, and MAE

Construct	Q^2 Predict	RMSE	MAE	Benchmark
Purchase Intention (PINT)	0.455	0.751	0.545	$Q^2 > 0.35$ = strong

Note: Q^2 threshold > 0.35 = strong predictive relevance (Hair et al., 2013).
Source: SmartPLS 4, Survey data, 2026

Table 12 Overall model fit indices

Fit Index	Saturated Model	Estimated Model	Threshold
SRMR	0.0150	0.0150	< 0.08 (acceptable)
d_ULS	4.697	4.697	Lower = better
d_G	5.236	5.236	Lower = better
Chi-square	3802.425	3802.425	Sensitive to sample size
NFI	0.440	0.440	> 0.90 (noted as low)

Note: SRMR < 0.08 = acceptable model fit (Henseler et al., 2015). NFI > 0.90 = good fit.
Source: SmartPLS 4, Survey data, 2026

Table 12 above reports overall model fit. The SRMR of 0.015 is well below the 0.08 threshold, indicating good fit and minimal discrepancy between observed and model-implied covariance matrices. The NFI of 0.440 falls below the conventional 0.90 benchmark, likely due to model complexity, and should be interpreted with caution. The d_ULS (4.697), d_G (5.236), and Chi-square (3802.425) values are sensitive to sample size and model complexity and are provided for reference.

Bootstrapping and Hypothesis Testing

Hypothesis testing used bootstrapping with 10,000 subsamples (Streukens and Leroi-Werelds, 2016; Hair et al., 2022). Bootstrapping is a non-parametric resampling procedure that produces an empirical sampling distribution for path coefficients, t-statistics, and 95% bias-corrected confidence intervals without requiring parametric distributional assumptions. This is especially applicable in PLS-SEM since it does not have an assumption of multivariate normality. Bias correction improves inference compared to percentile intervals, particularly for complicated models with moderate sample sizes (Lamberti and La Rocca, 2025).

The bootstrapping results are provided in Table 13 below. A path is said to be statistically significant when $t > 1.96$ (two-tailed test; $\alpha = 0.05$), and the 95% CI does not include zero. Only Hypothesis H5—influencer marketing to purchase intention—achieves significance ($\beta = 0.688$, t

= 18.145, $p < .001$, 95% CI [0.614, 0.763]). All other paths resulted in values for t-statistics less than 1.96, higher p-values than 0.05, and confidence intervals crossing 0, resulting in the rejection of hypotheses H1, H2, H3, and H4.

Table 13 Bootstrapping results and hypothesis testing (subsamples = 10,000)

Hypothesis	Path	β	STDEV	t-stat	p-value	f²	Decision
H1	SMC → PINT	0.076	0.084	0.902	0.184	0.006	Partially Supported
H2	ENGMT → PINT	0.021	0.061	0.344	0.365	0.001	Partially Supported
H3	INTN → PINT	−0.077	0.080	0.964	0.168	0.005	Not Supported
H4	BRAW → PINT	0.034	0.073	0.463	0.322	0.001	Partially Supported
H5	INMI → PINT	0.688	0.038	18.145	0.000***	0.691	Supported

*Note: *** $p < .001$. t-threshold for significance: > 1.96 (two-tailed, α = 0.05). 95% bias-corrected confidence intervals. f^2 benchmarks per Cohen (1988).*

Source: SmartPLS 4, Survey data, 2026

Figure 2 presents the estimated PLS-SEM model as generated in SmartPLS 4, displaying the outer (measurement) model together with the inner (structural) model. The figure reports standardized path coefficients (β) for each of the five hypothesized relationships (H1–H5), the corresponding t-values derived from the 10,000-subsample bootstrapping procedure, and the coefficient of determination ($R^2 = 0.486$) for the endogenous construct, Online Purchase Intention (PINT). As shown in the figure *2*, the path from Influencer Marketing (INMI) to Purchase Intention (β = 0.688, t = 18.145) is the only relationship exceeding the critical t-value of 1.96, visually corroborating the statistical significance reported in Table 13, while the paths from Social Media Content, Engagement, Interaction, and Brand Awareness & & Perception to Purchase Intention remain comparatively weak and non-significant.

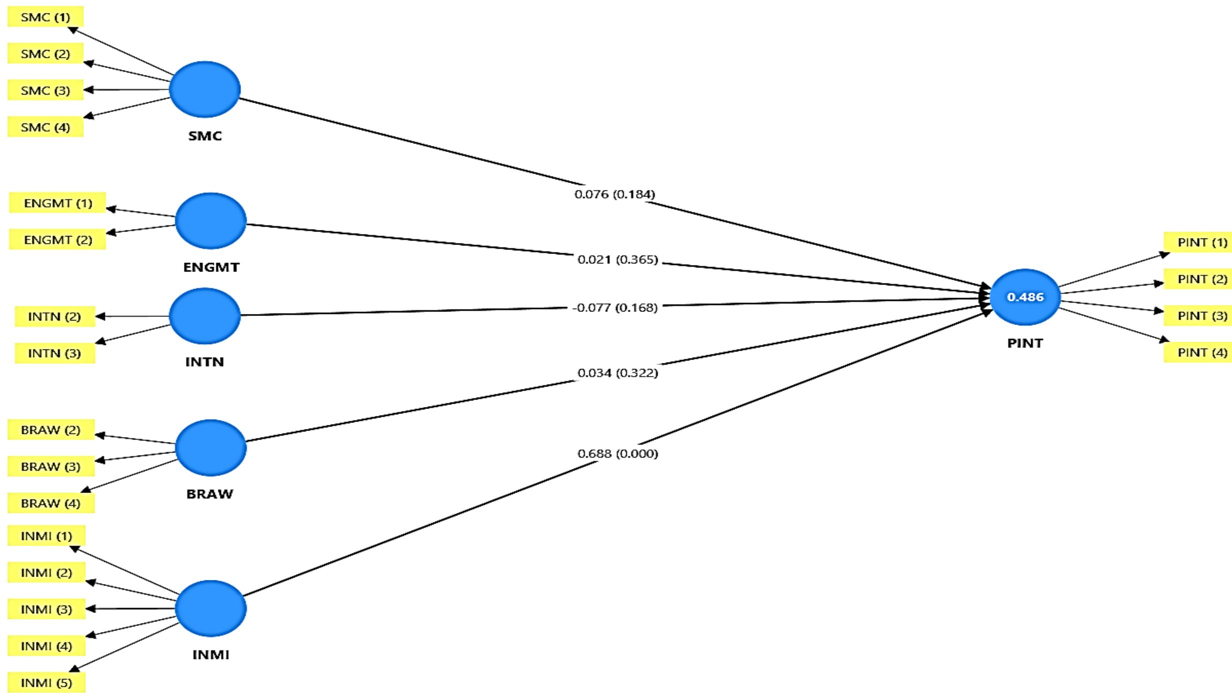

Figure 2 Part label-upper Measurement model including t values
Source: SMART PlS 4

5. Discussion

The Dominant Role of Influencer Marketing

Influence marketing was found to be the only statistically significant factor in explaining purchase intention among the youth in Addis Ababa, as this path had the highest value of path coefficients ($\beta = 0.688$) with a large effect size ($f^2 = 0.691$). This aligns with results obtained by Ismael et al. (2025) and Aji et al. (2020), as they note that influencers are regarded as credible opinion leaders whose endorsement provides authenticity not possible to obtain through advertising. In Ethiopia, where personal trust plays an important role when making purchase decisions, influencers may play the same role of social proof that traditional word-of-mouth marketing plays in this regard. The fact is that many consumers of Addis Ababa are newcomers to online shopping and have no experience and trust standards developed by e-commerce markets.

This is in line with what Karunasingha and Abeysekera (2022) discovered where parasocial relationship enhances purchase likelihood since the endorser acts as the peer who gives the recommendation and not an advertisement. The most popular platform among the sample group was YouTube (40.4%), followed by X/Twitter (30.9%) and TikTok (14.3%). This means that influencer video content whether long form or short form works effectively for this generation. A limitation to note here is that influencer marketing should work only if there is brand alignment and content authenticity between brands and influencers (Singh et al., 2023).

Positive but Insignificant Effects of Content, Engagement, and Brand Awareness

Social media content (H1: $\beta = 0.076$, $p = 0.184$), engagement (H2: $\beta = 0.021$, $p = 0.365$), and brand awareness (H4: $\beta = 0.034$, $p = 0.322$) were all directionally positive but statistically non-significant. From the ELM perspective, central route determinants – quality of content, engagement, and brand awareness – seem to play a role in purchase intentions, although not significant enough to become so in this sample. The logic behind their positive correlation with purchase intention is understandable as quality content decreases information asymmetry (Shien et al., 2023), engagement leads to the development of emotional connections between consumer and brand (Algharabat et al., 2023), and brand awareness decreases perceived purchase risk (Fajri et al., 2021). These determinants might have indirect effects on purchase intention via trust, value perception, or attitude development, which was not tested by this study but worth exploring in future research.

The relatively low factor loadings of SMC3 (0.564) and SMC4 (0.578) indicate that generic or pure promotional content has little persuasive power with young consumers from Addis Ababa. Simply being active on the platform and sharing promotional material is insufficient. To stimulate central route processing, brands require creative and information-rich content.

The Negative Interaction Path

The interaction construct (H3: $\beta = -0.077$, $p = 0.168$) generated a negative but statistically insignificant connection to purchase intention. This finding is surprising. In contrast to passive activities like liking and sharing, interaction entails dialogue and therefore ought to theoretically decrease purchase ambiguity and increase trust. The negative but statistically insignificant value can be attributed to unique characteristics of Addis Ababa's new e-commerce market. In an environment where there is insufficient communication infrastructure and poor customer care services, brand interactions could create frustrations for consumers from inconclusive answers, delays, and unmet expectations. Alternatively, the explanation can be time based, whereby the impact of interaction on trust and purchase intention may not be direct and instantaneous but may take time to manifest.

Theoretical and Contextual Contributions

All in all, the findings provide a context-specific utilization of ELM in the case of Ethiopian digital market. The peripheral route of persuasion, which is triggered by the influencer's credibility, trustworthiness, and authenticity, prevails in the process of purchase intention formation; meanwhile, none of the components related to the central route of persuasion achieves statistical significance. This finding implies that in the case of low-trust and immature e-commerce context, peripheral stimuli can have a disproportionate impact on consumers' decisions, which occurs since the cognitive apparatus needed to evaluate the information via the central route of persuasion (experience in the brand and previous purchase) is yet to be developed. The research enriches the existing literature, which is predominantly based on data from Asia and Western markets.

6. Conclusions and Recommendations

Influencer marketing is determined to be the main factor affecting the online purchasing intention of young consumers in Addis Ababa, Ethiopia. The five-dimension SMM constructs account for 48.6% variance in purchase intention. The findings of the PLS-SEM revealed satisfactory predictive validity (Q^2=0.455), good model fitness (SRMR=0.015), and no multicollinearity problem (max. VIF=2.176). It is assumed that social media content, engagement, interaction, and brand awareness do not affect purchase intention directly; these factors may influence the dependent variable indirectly through certain mediating variables like trust, perceived value, and attitude.

The most important conclusion that can be drawn from this research for the marketers is the need to develop collaboration with trusted and target-audience-related influencers. Honest recommendations that reflect the real connection between the influencer and the brand prove themselves better than promotional actions. Marketing efforts should involve more than just regular posts: stories, videos, pictures, and culturally relevant formats on YouTube and TikTok may influence customers' behavior. Engagement and interaction initiatives have to be aimed at developing relations rather than converting consumers at once.

These results confirm the importance for policymakers and those involved in e-commerce activities to improve the country’s digital infrastructure since the availability of effective payment systems, logistics, and the internet is essential to convert positive attitudes about SMM into online purchases in line with the objectives of the Digital Ethiopia 2030 strategy.

7. Limitations

This study is subject to several limitations that warrant acknowledgment. firstly, the cross-sectional nature of the research means that although it is able to capture consumer perceptions at one point in time, it will fail to show causality between influencer marketing, social media marketing, and purchase behavior. Secondly, since the sample population in this study was selected from young consumers in Addis Ababa only through purposive sampling, then the findings of the study might fail to be generalizable to consumers elsewhere or in different age groups in Addis Ababa. Thirdly, even though the use of PLS-SEM methodology enabled the researcher to test hypotheses, this method of analysis is bound by some limitations because of its inherent nature to measure consumer behavior qualitatively.

8. Suggestions for Future Study

Considering all these limitations, there are some suggestions for future research. First of all, there is a need to conduct longitudinal research in order to establish the temporal sequence and make causal links between SMM dimensions and purchase intention possible. Moreover, future research needs to conduct surveys among larger and more diverse samples, including different geographical locations in Ethiopia, age groups and urban/rural areas. What is more, the combination of quantitative research with qualitative or mixed methods (interviews/focus groups), will allow studying psychological and cultural processes behind consumers' response to SMM. Finally, future research should introduce such mediators as trust, risk perception, attitude, moderators such as digital literacy, expertise and the type of social media used, and other unexplored constructs of SMM.

Abbreviations

SMM	Social Media Marketing
ELM	Elaboration Likelihood Model
PLS-SEM	Partial Least Squares Structural Equation Modeling
CTA-PLS	Confirmatory Tetrad Analysis (PLS)
SMC	Social Media Content
ENGMT	Engagement
INTN	Interaction
BRAW	Brand Awareness & Perception
INMI	Influencer Marketing (Impact)
PINT	(Online) Purchase Intention
AVE	Average Variance Extracted
CR / ρc	Composite Reliability
VIF	Variance Inflation Factor
SRMR	Standardized Root Mean Square Residual
NFI	Normed Fit Index
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
R^2	Coefficient of Determination
Q^2	Stone-Geisser's Predictive Relevance
f^2	Effect Size
CI	Confidence Interval
SPSS	Statistical Package for the Social Sciences

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Author's Contributions

Eyob Ketema Worku: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review and editing.
Lemlem Kefyalew: Conceptualization, Methodology, Validation, Writing – review and editing, Supervision.

Statements and Declarations

Consent to Participate

Informed consent was obtained from all individual participants included in the study prior to data collection. Participants were informed of the study's purpose, the voluntary nature of their involvement, and their right to withdraw at any time without consequence.

Consent for Publication

Not applicable. This manuscript does not contain any individual person's data, images, or identifiable information requiring separate publication consent.

Declaration of Conflicting Interests

The authors declare that there is no conflict of interest with respect to the research, authorship, and/or publication of this article.

Declaration of Generative AI and AI-Assisted Technologies

During the preparation of this manuscript, the author(s) used AI tools, namely Gemini and Claude, to improve the language, grammar, clarity, and readability of the text. These tools were not used to generate original research content, data, analysis, interpretations, or conclusions. After using these tools, the author(s) reviewed and edited the content as needed and take full responsibility for the accuracy, integrity, and originality of the published article.

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