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AI-Driven Personalisation and Customer Engagement in Social Commerce: Evidence from Kosovo

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Abstract

Background: The study aims to examine the role of artificial intelligence-oriented personalisation in customer interaction of social commerce platforms in the developing market, such as Kosovo. **Objectives:** A quantitative design was used, and 312 active users were sampled, with surveys offered to all demographic segments. **Methods/Approach:** The customer's behaviour was conceptualised using the Technology Acceptance Model, the Stimulus-Organism-Response theory, and the Uses and Gratifications Theory. **Results:** The findings reveal a strong, positive correlation between AI-based personalisation and engagement. AI-based personalisation has significantly improved satisfaction, loyalty, and purchase intent. Age and education were ranked among the most critical moderators, and gender differences were not substantial. **Conclusions:** The study is informative for both theory and practice, as it provides insights into strategies for maximising customer contact through prudent personalisation under new market conditions.

Keywords: Artificial Intelligence; social commerce; customer experience; personalization algorithms; technology acceptance.

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Introduction

The commercialisation of virtual space has accelerated over the last decades, and social commerce has become an omnipresent paradigm that enables social interaction mechanisms alongside foundational e-commerce functionality (Kumar & Reinartz, 2016). It can be described as the radical shift from transactional-oriented web purchasing to peer-influence-based, social-proof-based, and intelligence-driven business experiences, aimed at simplifying the buying process (Hajli, 2015). Artificial intelligence has become one of the most significant providers of customised experiences customers receive in this dynamic of change, and it has revolutionised their engagement with digital trade platforms. The following presents the context, along with a list of opportunities and challenges, for social commerce sites using Artificial intelligence (AI) personalisation strategies. The first native social commerce application in Kosovo is Kossvo, which has quickly gained popularity thanks to its AI-driven design that enables customisation of the user experience. Prior research highlights that Kosovo's enterprises and consumers are undergoing rapid digital transformation, creating favourable conditions for the adoption of advanced digital and AI-enabled commerce solutions (Istrefi-Jahja & Zeqiri, 2021).

The platform combines traditional e-commerce processes with social media, enabling users to discover products through recommendations from friends, interact with others in online communities, share their purchase experiences, and receive personalised content generated by artificial intelligence. Social communication and intelligent personalisation systems combine to form Kossvo, the ideal sample for exploring how AI will impact social commerce customer interactions. Part of the literature demonstrates that there is abundant data to support the efficacy of individualisation within the usual e-commerce scenario (Ansari et al., 2000; Li, 2019); however, in the context of studies that consider the implementation of AI personalisation in social commerce, there is scarce data when it comes to addressing the emerging market environment.

However, over the last 20 years, the world of digital commerce has undergone a fundamental shift, and social commerce has been among the most revolutionary developments. More peer-to-peer, social, and product-discovery by algorithms is social commerce, not transactional e-commerce. Such a hybrid model has shifted from merely virtual buying to a social-influenced decision, in which consumer behaviour is dictated by trust, social involvement, and a chain of recommendations. The answer to all of it is artificial intelligence (AI), which enables platforms to personalise users' experiences through tailored recommendations, adaptive design, real-time content, and conversation-based support. Not only has all of this transformed the way people interact with platforms, making it more convenient, but it has also led to new emotional and behavioural interactions. Whereas AI-powered personalisation has been systematically analysed for mainstream e-commerce, it has never been analysed for social commerce platforms, particularly in emerging markets.

Most research studies focused on mature markets, leaving knowledge gaps in the operations of algorithm-based personalisation in markets where internet infrastructure, cultural processes, and trust in technology vary. It is a special case in Kosovo: the country is a post-war society quickly adopting digital technologies, is young, and lacks a well-developed retail base, making it an ideal location to experiment with the role of AI personalisation in establishing contact with consumers. This paper addresses these research gaps by offering a more specific empirical investigation of how AI-mediated personalisation affects the customer experience in the social commerce system Kossvo has designed. It is considered across various dimensions of AI personalisation, including recommendation systems, interface customisation, content

curation, and interactive chatbot features. It considers a conglomerate of indicators of customer engagement, including platform usage behaviour, social engagement behaviour, purchase intentions, and overall customer satisfaction levels. These three theories are arguably complementary and are synthesised into a single theoretical framework to provide a detailed theoretical basis for analysis. The model of user acceptance of AI features, based on the perceived usefulness and ease-of-use constructs, is called the Technology Acceptance Model (TAM). The Stimulus-Organism-Response (S-O-R) theory sheds light on psychological processes by which AI personalisation attributes generate internal user reactions and stimulate behavioural responses. The Uses and Gratifications theory can provide insights into how personalisation in AI can be used to satisfy various user needs and motivations when the conditions of social commerce are met. The quantitative research design is applied based on structured questionnaires from a survey of 312 active Kossvo users in the large cities of Kosovo. These eight quarterly questionnaires would capture seasonal variation. They should take place between the fourth quarter of 2023 and the eighth week of data collection, as they would provide an adequate sample size to reflect diverse demographic characteristics. The statistical test involves descriptive statistics, correlation tests, multiple regression modelling, and structural equation modelling to examine the interrelationships between AI personalisation features and customer involvement outcomes.

The work is novel in three main ways. Firstly, it examines the value of AI-based personalisation in the context of social commerce, where empirical studies are less abundant than in mainstream e-commerce. Secondly, it places the analysis in the developing market of Kosovo, with its particular socio-cultural and infrastructural idiosyncrasies, thereby extending the knowledge frontier. Thirdly, the paper connects three conceptual models: the Technology Acceptance Model (TAM), the Stimulus-Organism-Response (S-O-R) theory, and the Uses and Gratifications Theory (UGT) to provide a multi-level account of how AI personalisation influences user interaction. The paper combines these perceptions and, thereby, provides a clear picture of the psychological processes and behavioural outcomes associated with the concept of personalisation in social commerce.

Literature review

Artificial intelligence in e-commerce and social commerce

From streamlining processes to advanced intelligence that can reveal subtle patterns, predict outcomes, and deliver single-minded personalisation to the end-user experience, the contribution of artificial intelligence within those solutions for digital commerce has shifted from an enabler to a force unto itself. Early AI implementations for e-commerce were primarily focused on inventory management and deploying simple recommendation engines. However, newer implementations can be integrated with natural language processing, computer vision, machine learning algorithms, and deep neural networks that empower multi-point personalisation (Kumar et al., 2019). Personalisation via AI is the methodical customisation of platform characteristics, content characteristics, and recommendations to individual user attributes, preferences, and behavioural patterns (Adomavicius & Tuzhilin, 2015). As emphasised by Zakota (2023), AI-driven decision-making introduces both substantial benefits and inherent risks, requiring careful consideration of transparency, user trust, and potential unintended consequences—factors that are highly relevant in AI-personalised social commerce environments. Recent systematic reviews emphasise that AI-driven personalisation represents a central mechanism of digital service

innovation, shaping how value is co-created between platforms and users (Marić et al., 2024).

It is generally an activity that involves all forms of information: explicit (user-related, such as preferences, ratings, demographics), implicit (user behaviour-related, such as browsing history, click rates, dwell times), and contextual (time, place, device properties). That is then subjected to a sequence of rubric algorithms that generate experiences that, in theory, meet a user's demands and inclinations. The shift from mainstream e-commerce to social e-commerce brings added complexity, as the personalisation made available by AI is being asked to deliver on it. Peer-to-peer, user-generated content, social influence, and social forces constitute social commerce platforms that can have a colossal influence on personal decision-making to buy (Busalim & Hussin, 2016). Recent evidence suggests that habitual social media interactions, such as the routine use of 'Like' features, can further lower psychological barriers to recommendation intention and promote more active engagement behaviours (Kato, 2021). With those social components in place, not only is personalisation driven by social signals, but privacy, algorithmic authentication, and transparency also come into play.

Research indicated that AI social commerce personalisation requires higher-order network power, as well as knowledge of consumer preferences. When Zhang and Benyoucef (2016) argued that social presence, social support, and relationship quality were antecedents of social commerce success, Wang et al. (2016) argued that peer recommendations and social proof mechanisms played a critical role in influencing purchase decisions. The intelligence systems that operate under such conditions must therefore be able to record the complex effects of interactions between individual traits and those of society.

Customer engagement theory and measurement

Customer engagement is a multifaceted construct encompassing the cognitive, emotional, and behavioural dimensions of customer relationships with platforms, products, or brands. Cognitive engagement means attention, absorption, and cognitive processing of interaction with a platform. Emotional involvement comprises excitement, fun, and love for the platform's society. The behavioural involvement manifests as active contributions, content generation, social sharing, and purchasing activities. In social commerce, customer interactions take on a new dimension in terms of social behaviours and community participation (Busalim & Hussin, 2016).

Recent behavioural analytics studies further emphasise the importance of usage frequency and user segmentation in predicting engagement outcomes, showing that demographic variables and behavioural patterns jointly shape customer responses to digital platforms (Ho et al., 2023). Peer communication, content sharing, contributions to the community, and social influence activities are included in social behaviours of engagement that transcend ordinary individual-platform relationships. The social dimension of this collection opens new possibilities for measuring engagement, rendering analytic frameworks cumbersome because of network and social-class influences. Modern customer engagement measurement models have integrated indicators across engagement dimensions. Platform utilisation frequency, session length, content-interaction rates, social sharing activity, and purchasing behaviour are all behavioural metrics. Attitudinal dimension measures include levels of satisfaction, key loyalty intentions, likelihood of recommending, and signs of emotional attachment. Recent research also highlights the value of combining behavioural and attitudinal markers to capture the multidimensional aspects of engagement (Hollebeek et al., 2014). The relationship between AI personalisation and customer

engagement is multimodal. Custom experiences have the potential to make a person feel more relevant, process information more cognitively, be more satisfied with platform interactions, and create stronger emotional ties with platform communities (Wang et al., 2016). The effectiveness of personalisation will vary depending on the accuracy of the algorithms, perceptions of user control, privacy concerns, and cultural factors that may vary widely across other market environments.

Technology acceptance in AI-enhanced platforms

The Technology Acceptance Model (TAM) offers an uncomplicated theoretical backdrop to investigate user adoption of the AI-strengthened capabilities of online platforms. TAM claims that technology adoption intent is primarily determined by perceived usefulness (the extent to which users perceive that technology will improve performance) and perceived ease of use (the extent to which users perceive that technology will be easy to use). These basic constructs were comprehensively validated across many technology adoption scenarios and augmented to account for additional variables specific to technology domains. In AI personalisation cases, TAM has been augmented with trust, privacy concerns, and personalisation quality as additional predictors of adoption intent. Trust is related to users' beliefs in the trustworthiness, correctness, and beingness of AI systems, while privacy concern is connected to information collection, utilisation, and safeguarding practices. Personalisation quality covers personalisation relevance, precision, and recency of personally tailored recommendations and content. The latest research has revealed that cultural and demographic variables are important moderators of the relationships between technology acceptance and other variables.

The younger generation has higher levels of technology acceptance, educational attainment, income, and cultural beliefs about technology and privacy, which affect adoption patterns (Venkatesh et al., 2016). Such moderating effects are particularly valuable for emerging markets, where technology adoption patterns may differ significantly from those in mature markets. Platforms for social commerce pose a special technology-acceptance challenge by integrating social and commercial functionality. Users must accept AI personalisation facilities and social interaction mechanisms simultaneously, which may give rise to a conflict between the value of personalisation and a sense of social authenticity (Lu et al., 2020). At the same time, platform-based peer communities may accelerate or slow individual technology acceptance processes based on peers' attitudes and behaviours toward AI features.

Social commerce dynamics and regional characteristics

Social commerce is the combination of social media and e-commerce capabilities, and it currently enables businesses to operate in the social interactions sphere. The interaction can be used to create novel value through peer recommendations, social proof, peer-group-based product discovery, and sharing-based consumption models that exploit network effects to deliver optimised experiences to users. The social component of commerce is transforming the traditional buyer-seller relationship in fundamental ways through peer-to-peer channels, potentially shaping purchasing decisions. Social influence takes place in a wide range of forms, such as requests from a trustworthy authority, imitation of others' conduct in the peer group, social pressure toward the group's views, social testimony from the group, and peer ratings.

The adoption and success of social commerce are highly dependent on geographic factors. Developing markets have a social rate of penetration higher than that of advanced markets due to factors such as the absence of physical retail infrastructure, social network sensitivities, mobile-first internet adoption, and

favourable demographics for online platforms. These contextual aspects permit the imaginative use of AI personalisation, yet there are data quality issues, technology infrastructure support, and cultural acceptability of algorithmic decision-making. The Kosovo social commerce environment reflects the synthesis of key attributes of new market economies and the peculiarities of its newest, just-emerging post-conflict economy. Robust youth demographics, growing net penetration, the lack of established retail outlets, and the dominance of social network culture all favour the adoption of social commerce platforms. Nevertheless, technology adoption behaviour can be shaped by economic constraints, lack of digital payment infrastructure, and fear of confidentiality, spurred by prior exposure to spying.

AI personalisation components and mechanisms

State-of-the-art personalisation systems with AI leverage several components that work together to tailor the user experience. Recommendation systems are a key feature of personalisation, and they use collaborative filtering, content-based filtering, and hybrid methods to recommend products, content, or relationships that are suitable for users. These systems consider patterns of user activity, preference, and context to provide differentiated recommendations, preferably based on individual interests and needs. Interface personalisation is the practice of adapting the platform layout, feature salience, and navigational structure based on individual usage habits and preferences (Kramer et al., 2007). It may incorporate a customised home page layout, an individually customised menu structure, customised content ordering, and context-sensitive feature presentation that maximise the efficiency and satisfaction of the user experience. Advanced recommender systems increasingly rely on data-mining techniques to enhance predictive accuracy and relevance, as demonstrated in applied system-development research (Mydyti, Kadriu & Bach, 2023).

Content personalisation comprises selecting, ordering, and displaying textual, visual, and multimedia content based on individual users' interests and interaction behaviour (Adomavicius & Tuzhilin, 2015). Personalised news streams, customised product catalogues, focused promotional material, or individual community material that injects additional relevance and potential for interaction are all encompassed. Conversational AI systems offer personalised interaction experiences through natural language and machine learning. The systems can provide individualised support, product advice, and recommendations based on each user's history, preferences, and current interaction context.

Hypothesis development

The Technology Acceptance Model (TAM) explains how individuals can embrace AI characteristics based on perceived usefulness and perceived ease of use, as well as other factors relevant to AI contexts, such as trust and privacy concerns. The stimulus-Organism-Response (S-O-R) theory provides insight into psychological processes, in which AI personalisation features (stimuli) influence internal user states (organism) and subsequently yield changes in behaviour (response). It enables exploration of the mechanisms that connect AI attributes and the effects of interaction, clarifying the mechanisms behind the perceived relationships. UGT explains why users adopt AI-optimised features in social commerce application innovations. This theory assumes that users' media and technology choices are active and determined by what is necessary to meet criteria, including utilitarian gratifications (efficiency, convenience) and hedonic gratifications (entertainment, social connection). Both types of gratification can be increased through AI personalisation, leading to greater relevance and a more personalised experience.

Key findings indicate that personalisation in AI has a significantly positive impact on customer interactions in many cases, and that the mechanisms of customised recommendations exert the most decisive influence on user actions. Effectiveness varies widely across demographic groups, and younger, more educated users tend to be more sensitive to AI's capabilities. The results have functional implications for extending theory and refining social commerce platform design and marketing strategy.

Based on theoretical integration and literature analysis, it was possible to form five main hypotheses:

- H1: AI-powered personalisation capabilities have a positive impact on customer engagement behaviour on social commerce sites.

The personalisation enabled by AI has wholly changed the interaction between customers and platforms, including how recommendations are made, the kinds of content shown, and the experiences. Cognitive, emotional, and behavioural engagement (customer engagement) has been shown to increase with perceived relevance and ease of interaction with the platform. Previous literature indicates that personalisation enables greater user engagement, satisfaction, and loyalty by reducing cognitive load and increasing perceived value (Ansari et al., 2000). In social commerce, social influence and social sharing prevail, and AI personalisation can enhance engagement by matching the product discovery with social interactions and community engagement (Busalim & Hussin, 2016). Empirical developments in recommender-system design further show that data-driven models significantly strengthen decision-making outcomes, reinforcing the expectation that recommendation mechanisms exert the most substantial behavioural influence (Mydyti et al., 2023). Thus, it is also possible to assume that AI-based personalisation has a notable positive impact on customer interaction in social commerce environments.

- H2: Personalised recommendation systems will have a more significant effect on customer engagement than other elements of AI personalisation.

Recommendation systems are consistently cited as the most potent force of engagement among other personalisation mechanisms (interface customisation, content curation, and conversational AI) (Adomavicius & Tuzhilin, 2015). Such systems use collaborative filtering, content-based algorithms, and hybrid algorithms to propose products and services that best match user preferences, thereby enhancing purchase intent and platform stickiness (Ansari et al., 2000). Personalised recommendations in social commerce not only reduce search costs but also align with social proof and peer endorsement, generating additional perceived trust and relevance (Zhang & Benyoucef, 2016). It has been indicated that, although other AI personalisation features can improve the user experience, recommendations elicit the most significant behavioural responses in browsing, sharing, and purchasing. Therefore, recommendation systems will have a greater impact on engagement than any other personalisation element.

- H3: The relationship between personalisation of AI and customer engagement depends on the user demographic characteristics.

Moderating factors have been shown to include demographic characteristics such as age, education, gender, and cultural orientation (Lu et al., 2020). Younger users are generally more responsive to AI features, as they are more digitally literate and comfortable with technology (Kshetri, 2017), and higher levels of education usually correlate with a greater understanding and appreciation of AI-driven recommendations (Kumar et al., 2021). Demographic diversity is even more important in a developing market, where different social and cultural groups have varying levels

of trust in and adoption of technology (Busalim & Hussin, 2016). As a pointer, younger populations in digitalising societies are more likely to utilise AI-personalised commerce due to mobile-first internet usage and peer consumption patterns (Li, 2019). The demographic factor in this relationship will define the character and the direction of the relationship between AI personalisation and customer interactions.

- H4: Technology acceptance factors mediate the relationship between the AI personalisation characteristics and the customer engagement results.

The Technology Acceptance Model (TAM) suggests that perceived usefulness and perceived ease of use are the most critical variables affecting technology adoption and subsequent behaviour change (Venkatesh et al., 2016). Other constructs, such as trust, privacy, and the quality of personalisation, also mediate user engagement with AI-based systems (Lu et al., 2020). For example, when users perceive AI personalisation as helpful and trustworthy, they are more willing to engage cognitively, emotionally, and behaviourally on social commerce platforms (Kumar et al., 2019). On the other hand, privacy concerns can undermine mediation by diminishing the desire to use personalised functions (Wang et al., 2016). It has been proven that TAM constructs mediate the relationship between AI personalisation properties and engagement outcomes. Thus, technology acceptance factors can be considered as essential mediators of the AI personalisation-engagement relation.

- H5: Patterns of utilisation of social commerce affect the efficacy of AI personalisation on engagement with customers.

The frequency of use and the length of tenure on a platform affect how users perceive and respond to AI personalisation features. It has been demonstrated that the more often people use recommendation systems and adaptive interfaces, the greater the benefits they bring and the greater the accuracy of personalisation, because accumulated data on interactions improves accuracy (Ricci et al., 2022). In the same way, users who have been using AI systems for a long time are more likely to show engagement as trust and familiarity with the system grow. Within the framework of social commerce, it is more likely that daily or heavy users will rely on AI recommendations in decision-making and may be less affected by personalisation than non-users (Busalim & Hussin, 2016). Moreover, the modes of social sharing and peer interactions on these platforms intensify the impact of AI capabilities through social confirmation of algorithmic recommendations (Zhang & Benyoucef, 2016). In this way, the effectiveness of AI personalisation in increasing customer engagement varies greatly depending on platform usage patterns.

Methodology

This paper adopts a positivist, quantitative, cross-sectional survey design to test the associations between AI-based personalisation features and customer engagement behaviours on the social commerce platform Kossvo. The chosen approach was positivist because the research aims involved quantifying relationships among observable variables, conducting hypothesis tests, and extrapolating the results to broader groups (Creswell & Creswell, 2018). The design allows us to analyse the relationships between variables at a particular moment in time. It gives us an idea of how effective AI personalisation is today, but it also has weaknesses in establishing causal links over time. This may be relevant because the AI personalisation study is in the discovery stage of the social commerce environment and requires pre-existing knowledge before the longitudinal study begins. The deductive research methodology is based on the design of theories from existing literature, followed by the formulation of a hypothesis, which is then tested through statistical research. This would enable the theory to experiment at the small scale of social commerce

enabled by AI within young markets and perhaps develop theoretical insights and orientations.

Population and sampling strategy

The target demographic comprises active users of the Kossvo social commerce platform who are familiar with AI personalisation features. Active users are those who have logged in to the platform at least twice in the past month and have used personalised recommendations, personalised content, or adaptive interface features at some point during their time on the platform. Stratified random sampling was used to achieve representative coverage of important demographic and usage features. The variables of stratification were: age groups (18-25, 26-35, 36-45, 46+ years), gender distribution, educational levels (secondary, bachelor, master and doctoral), geographic regions in Kosovo (Pristina, Prizren, Peja, Mitrovica, Gjilan) and frequency of using the platform (daily, weekly, monthly users). The sample size calculation was based on G*Power 3.1.9.7 statistical software, with a medium effect size (F2 = 0.15), significance level (0.05), and desired power ($1 - \beta = 0.80$). A multiple regression analysis of eight predictor variables indicated that the minimum required sample size is 277 respondents. A target population of 350 respondents was set to account for non-response and incomplete surveys. The inclusion criteria were that participants were aged at least 18 years, had used the Kossvo platform for at least 3 months, had used AI personalisation functions, were able to complete surveys in Albanian or English, and provided informed consent. Platform workers who had not worked on the platform for less than 1 month, and surveys with less than 85% completion, were excluded.

Research instrument

The structured online questionnaire used for data collection was created specifically for this study, and measures based on validated scales from the existing literature were modified to fit the social commerce and AI personalisation context. The survey comprised 30 questions across six broad categories: demographics; platform behaviour; AI personalisation experience; customer engagement behaviours; technology acceptance factors; and purchase intentions. Four-item scales evaluated the AI personalisation experience in terms of the perceived accuracy of offered recommendations, the relevance of personalised content, the effectiveness of interface customisation, and the utility of conversational AI capabilities. However, they were adjusted to AI capabilities and the social commerce settings of the time and operationalised customer engagement in multidimensional scales that measure cognitive engagement (attention, absorption), emotional engagement (enthusiasm, connection), and behavioural engagement (participation, sharing, purchasing). The scales were modified based on the work of Hollebeek et al. (2014) and expanded to social commerce-specific behaviours, i.e., peer recommendation and community contribution. Technology acceptance factors included perceived usefulness, perceived ease of use, trust, and privacy concern, based on existing TAM research. Items were customised to directly respond to AI customisation attributes in a social commerce setting, making them relevant and readable to the study participants. All questions were answered on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree) to provide respondents with sufficient response variance without making the task cognitively complex. Based on the goals, the questionnaire was developed in English and then translated into Albanian using back-translation procedures to ensure the translated version remained semantically and culturally appropriate.

Data collection procedures and timeline

The data were collected over eight weeks, from September to November 2023, through various distribution channels to maximize response rates and sample representativeness. Guidance was primarily delivered through in-platform notifications to qualified Kossvo users, supported by email invitations to subscribed users and by social media promotion from official platform accounts. The rewards for taking part were platform credits worth between €5 and € 15 and access to premium functionality for a month. These rewards would motivate participation, yet leave the quality of answers unchanged and reduce selection bias toward the most active users. Response tracking procedures monitored daily achievement rates, demographics, and geographical representation to maintain a sufficient balance of the sample over stratification variables. Specific reminders were delivered to underrepresented groups to achieve the preferred sample stratification. Data quality assurance methods included attention-check questions, response-time checks, IP address verification to prevent duplicate responses, and logical consistency checks. Poor-quality surveys were not analysed to ensure data integrity and analytical validity.

Pilot testing and instrument validation

Pilot testing was conducted with 45 Kossvo users across a range of demographic segments to assess questionnaire clarity, completion time, and preliminary psychometric properties. Pilot participants provided feedback on item understanding, survey length, and the technical functionality of the online survey platform. Based on pilot testing results, minor modifications have been made to improve item clarity and reduce completion time from 18 to 12 minutes. Reliability analysis with Cronbach's alpha indicated acceptable internal consistency for all constructs ($\alpha > 0.70$), and factor analysis supported the expected factor structures, with adequate item loadings (> 0.60). Content validity was determined by reviewing the content with three experts specialising in digital marketing, consumer behaviour, and artificial intelligence technologies. Experts reviewed the relevance of the items, alignment with the theory, and appropriateness of the context, leading to minor wording changes to increase precision and clarity.

Statistical analysis plan

Statistical analysis followed a systematic process, beginning with descriptive statistics to characterise sample demographics and variable distributions. Missing data analysis assessed missingness patterns and magnitudes, and suitable imputation methods were used when the missingness exceeded 5% for any variable. Preliminary analyses included normality tests, outlier detection, multicollinearity assessment, and reliability analyses of all measurement constructs. Construct validity was assessed with confirmatory factor analysis (CFA) with maximum likelihood estimation and standard model fit indices (CFI, TLI, RMSEA, SRMR). Hypothesis testing was conducted using hierarchical multiple regression to analyse the relationship between AI personalisation features and customer engagement outcomes, while controlling for demographic and usage features. Structural equation modelling (SEM) was used to examine the complete theoretical model of the research, including mediating pathways and moderating effects. All analyses were performed using statistical software packages such as SPSS and AMOS, with significance levels set at $p < 0.05$ for the primary hypotheses and $p < 0.01$ for the exploratory analyses. Effect sizes were interpreted according to Cohen's conventions, and practical significance was determined in parallel with statistical significance.

Results

Sample Characteristics and Descriptive Statistics

Data cleaning procedures yielded a final sample of 312 valid responses (an effective response rate of 89.1% of the target sample). The demographic analysis showed a fairly even spread across key descriptors (Table 1), with a slight skew towards younger, better-educated users, which is consistent with Kossvo's primary user base.

Table 1
Sample demographics (*n* = 312)

Characteristic	Category	n	%
Age	18–25	120	38.5
	26–35	99	31.7
	36–45	66	21.2
	46+	27	8.6
Gender	Female	165	52.9
	Male	147	47.1
Education	Secondary school	59	18.9
	Bachelor's degree	143	45.8
	Master's degree	89	28.5
	Doctoral degree	21	6.7
City (region)	Pristina	129	41.3
	Prizren	59	18.9
	Peja	52	16.7
	Mitrovica	38	12.2
	Gjilan	34	10.9
Platform usage frequency	Daily	132	42.3
	Weekly	111	35.6
	Monthly	69	22.1
Platform tenure (months)	Mean (SD)	14.7	(8.3)

Source: Authors' work

Age distribution was as follows: 38.5% of respondents were in the 18-25 years age group (*n* = 120), 31.7% in the 26-35 years age group (*n*=99), 21.2% in the 36-45 years age group (*n* = 66), and 8.6% above 45 years (*n* = 27). The respondents' profile was consistent with the gender profile of social commerce use in regional markets (female respondents: *n* = 165, 52.9%; male respondents: *n* = 147, 47.1%). A high level of education was recorded, with 45.8% of respondents holding first university degrees (n = 143), 28.5% holding university master's degrees (n = 89), 18.9% holding educational levels (n = 59), and 6.7% holding doctoral degrees (*n* = 21). Use of the platform was extensive, with 42.3% of users accessing the web page daily (*n* = 132), 35.6% weekly (*n* = 111), and 22.1% monthly (*n* = 69). Use of the platform continued for an average of 14.7 months (*SD*=8.3) for 78.2% which includes major AI personalisation for conversational support.

Reliability and validity assessment

Reliability testing of internal consistency revealed acceptable to excellent reliability for all constructs in the questionnaire. Cronbach's alpha coefficients are as follows: Artificial Intelligence Personalisation Experience: a = 0.876; Customer Engagement: a

= 0.893; Technology Acceptance: α = 0.847; Purchase Intentions: α = 0.825. These exceed the recommended cut-off points (α > 0.70) and indicate the internal consistency of each construct. Confirmatory factor analysis demonstrated a good fit of the proposed measurement model: χ^2 (df = 165) = 287.34, $p < 0.001$, CFI = 0.926, TLI = 0.913, RMSEA = 0.049 (90% CI: 0.039-0.058), SRMR = 0.052. All standardised factor loadings were greater than 0.60, and most items exceeded 0.70, indicating strong item-construct relationships. Convergent validity was determined based on average variance extracted (AVE) values >= 0.50 for all constructs, and discriminant validity was determined based on values of the square root of AVE greater than inter-construct correlations. Composite reliability values ranged from 0.831 to 0.901, exceeding the generally suggested 0.70 cut-off and further supporting measurement model adequacy.

Mediation analysis

Structural equation modelling was used to analyse mediating pathways between AI personalisation features and customer engagement, via technology acceptance factors. Indirect effects through the mediating variables of perceived usefulness and trust yielded an adequate fit for the mediation model (CFI=0.911, TLI=0.895, RMSEA=0.054, SRMR=0.058). In line with hypothesis H4, perceived usefulness accounted for 34.7% of the overall influence between AI personalisation and customer engagement (β = 0.187, 95% CI: 0.098-0.289, $p < 0.001$). Overall, Trust mediated additional effects, accounting for an additional 18.3% of the total relationship (β = 0.098, 95% CI: 0.034-0.174, $p < 0.01$). Combined mediating effects accounted for 53% of the total influence of AI personalisation, suggesting significant indirect pathways. Privacy concerns had adverse mediating effects (β = -0.064, 95% CI: -0.125 to -0.018, p < 0.05), indicating that the potential benefits of personalisation may be lost due to privacy-related concerns. However, the negative mediation only accounted for 11.2 per cent of the total effect, suggesting that positive factors are much stronger than privacy concerns in this sample.

Correlational analysis

Pearson's correlation analysis showed significant positive associations between AI personalisation elements and customer engagement measures (Table 2).

Table 2
Correlation analysis

Variable 1	Variable 2	Pearson r	p-value
Personalized recommendations	Behavioural engagement	0.634	< 0.001
Interface adaptation	Cognitive engagement	0.578	< 0.001
Content personalization	Emotional engagement	0.543	< 0.001
Perceived usefulness	Overall engagement	0.597	< 0.001
Trust	Personalisation components (range)	0.421–0.518	< 0.001
Age	AI personalisation acceptance	-0.284	< 0.001
Age	Technology adoption	-0.312	< 0.001
Education	Engagement behaviours	0.267	< 0.001
Education	Purchase intentions	0.235	< 0.01

Source: Authors' work

The highest correlation was between personalised recommendations and behavioural engagement ($r = 0.634$, $p < 0.001$), followed by interface adaptation and cognitive engagement ($r = 0.578$, $p < 0.001$), and content personalisation and emotional engagement ($r = 0.543$, $p < 0.001$). Technology acceptance factors showed moderate-to-strong correlations with both AI personalisation experience and customer engagement. Perceived usefulness was found to be most highly correlated with overall engagement ($r = 0.597$, $p < 0.001$), and trust was found to be associated in a meaningful way with all personalisation components ($r = 0.421$ to 0.518, $p < 0.001$). Demographic variables showed distinct patterns of correlation with key study variables. Age showed negative correlations with AI personalisation acceptance ($r = -0.284$, $p < 0.001$) and technology adoption ($r = -0.312$, $p < 0.001$), and education showed positive associations with engagement behaviours ($r = 0.267$, $p < 0.001$) and purchase intentions ($r = 0.235$, $p < 0.01$).

Hypothesis testing

Table 3 presents a structured overview of all hypotheses tested in the study, the statistical methods used to evaluate them, the key numerical results, and the conclusions drawn from each test. The table is organised into four primary columns: the hypothesis statement, the statistical test or analytical path applied, the corresponding statistical results, and a concise conclusion indicating whether the hypothesis was supported.

The first part of the table (H1) shows the overall effect of AI personalisation on customer engagement, including the explained variance (R^2), model significance, and a general conclusion about the strength of the direct relationship. Hierarchical multiple regression analysis supported the key research hypothesis (H1), which posited a positive effect of AI personalisation on customer engagement. The complete model explained 47.2% of the variance in customer engagement ($R^2 = 0.472$, $F(8,303) = 34.15$, $p < 0.001$). H1 is therefore supported.

The second part (H2) compares the individual AI personalisation components by displaying their standardised regression coefficients (betas), t-values, and significance levels. This allows the reader to see which component has the most decisive influence on engagement. All components had significant positive effects, with personalised recommendations predicting the most substantial effect ($\beta = 0.324$, $t = 6.78$, $p < 0.001$), followed by interface adaptation ($\beta = 0.251$, $p < 0.001$), content personalisation ($\beta = 0.187$, $p < 0.001$), and conversational AI ($\beta = 0.143$, $p < 0.01$). H2 is supported, as the recommendations show the most significant effect.

The third section (H3) presents the moderating role of demographic variables, showing which demographic factors (age, education, gender) significantly change the strength of the personalisation–engagement relationship. Moderation analysis supported the hypothesis that demographics affect the effectiveness of AI personalisation. Age was a significant negative moderator ($\beta = –0.198$, $t = –3.45$, $p < 0.01$), whereas education was a significant positive moderator ($\beta = 0.156$, $t = 2.79$, $p < 0.01$). Gender effects were not significant ($p > 0.05$). H3 is therefore partially supported—age and education moderate the relationship, whereas gender does not.

The fourth section (H4) summarises the mediation analysis, indicating how technology acceptance factors—such as perceived usefulness and trust—transmit the effect of AI personalisation onto engagement. The table lists the indirect beta values and their statistical significance: perceived usefulness showed a significant indirect effect ($\beta = 0.187$, $p < 0.001$), and trust also exhibited a significant indirect effect ($\beta = 0.098$, $p < 0.01$). Combined, these mediators accounted for 53% of the total

indirect effect. H4 is supported, confirming that technology acceptance factors mediate the relationship between personalisation and engagement. Table 4 presents detailed results for the mediation analysis testing hypothesis H4.

The final row (H5) displays moderation effects related to usage patterns, including differences between daily, weekly, and monthly users, as well as long-term user tenure. Analysis of platform usage patterns found that the effectiveness of AI personalisation varies according to usage frequency and platform tenure, supporting hypothesis H5. Responses to AI personalisation were strongest among daily users ($\beta = 0.287$, $p < 0.001$), followed by weekly users ($\beta = 0.201$, $p < 0.01$) and monthly users ($\beta = 0.143$, $p < 0.05$). Platform tenure also moderated the effect, with users with more than 12 months of experience showing significantly stronger engagement responses ($\beta = 0.234$, $p < 0.001$). These findings indicate that heavier and longer-term users derive greater benefit from AI personalisation, thus confirming H5.

Table 3
Hypothesis Testing

Hypothesis	Statistical test/path	Results	Conclusion
H1: AI personalisation → Customer engagement (direct)	Hierarchical regression / SEM	$R^2 = 0.472$; $F(8,303)=34.15$; $p < 0.001$	AI personalisation has a significant positive effect on engagement; the model explains 47.2% of the variance.
H2: Recommendations > other AI components	Multiple regression (component betas)	Personalized recommendations $\beta = 0.324$, $t = 6.78$, $p < 0.001$; Interface $\beta = 0.251$, $p < 0.001$; Content $\beta = 0.187$, $p < 0.001$; Conversational AI $\beta = 0.143$, $p < 0.01$	Recommendation systems show the largest beta.
H3: Demographics moderate the effect of AI personalisation	Moderation analysis	Age moderator $\beta = -0.198$, $t = -3.45$, $p < 0.01$ (negative); Education moderator $\beta = 0.156$, $t = 2.79$, $p < 0.01$; Gender ns	Age and education moderate effects; gender is not significant.
H4: Technology acceptance mediates AI personalisation → engagement	SEM mediation	Perceived usefulness indirect $\beta = 0.187$, $p < 0.001$; Trust indirect $\beta = 0.098$, $p < 0.01$; Combined mediators 53%	TAM factors mediate a large part of the relationship.
H5: Usage patterns moderate personalisation effectiveness	Moderation/subgroup analysis	Daily users $\beta = 0.287$, $p < 0.001$; Weekly $\beta = 0.201$, $p < 0.01$; Monthly $\beta = 0.143$, $p < 0.05$; Tenure (12+ months) $\beta = 0.234$, $p < 0.001$	More substantial effects for heavier/longer-term users.

Source: Authors' work

Table 4
Mediation Analysis

Mediator	Indirect effect (β)	95% CI	p-value	% of total effect (reported)
Perceived usefulness	0.187	0.098 to 0.289	<0.001	34.7%
Trust	0.098	0.034 to 0.174	<0.01	18.3%
Privacy concerns (negative mediator)	-0.064	-0.125 to -0.018	<0.05	11.2% (negative share)
Combined mediators	(sum of indirect paths)	—	—	**53.0%** of total effect

Source: Authors' work

Additional Subgroup Insights (Exploratory)

Exploratory subgroup analyses revealed notable variations in the effectiveness of AI personalisation across different user categories. Younger users (18–25 years) exhibited the strongest favourable responses to AI features (β = 0.398, p < 0.001), whereas older users (>45 years) displayed weaker but still significant effects (β = 0.186, p < 0.05). Mid-range effects were observed among the 26–35 and 36–45 age groups (β = 0.267 and β = 0.223, respectively; both p < 0.01).

Differences were also evident across educational levels. Users with higher education demonstrated more pronounced engagement responses to AI personalisation than those with only secondary schooling. The most substantial effects were observed among users with a master's degree (β = 0.367, p < 0.001), followed by those with a bachelor's degree (β = 0.298, p < 0.001) and those with a doctoral degree (β = 0.276, p < 0.01). Secondary-education users showed a significant but relatively modest effect (β = 0.189, p < 0.05).

In contrast, no statistically significant differences emerged across major urban regions in Kosovo ($F(4, 307) = 1.83$, $p > 0.05$), suggesting that urban digital infrastructure and cultural technology adoption patterns are sufficiently homogeneous to produce similar responses to AI personalisation across the country's principal cities.

Additional Behavioural Outcome Analysis (Exploratory)

Analysis of results from the purchase-intention process revealed positive, significant relationships with the AI personalisation experience. Users who reported a high level of satisfaction with personalisation showed significantly higher purchase intentions ($M = 5.89$, $SD = 0.76$) than users with low satisfaction ($M = 3.45$, $SD = 1.23$; $t = 15.67$, $p < 0.001$). This association was significant after adjustment for demographic and usage variables ($\beta = 0.456$, $p < 0.001$). An actual analysis of purchasing behaviour using platform transaction data from consenting subjects (n = 267) confirmed the purchase-intention results. Users in the highest quartile of AI personalisation satisfaction made 3.7 ($SD = 2.1$) purchases per month compared with 1.2 purchases ($SD = 1.4$) for users in the lowest quartile ($F(3,263) = 32.48$, $p < 0.001$). Social sharing behaviours were also associated with AI personalisation experience in significant ways. Users with high personalisation satisfaction were more likely to share products (OR=2.34, 95% CI: 1.67-3.28, $p < 0.001$), recommend the platform to friends (OR = 3.12, 95% CI: 2.01-4.84, $p < 0.001$), and participate in community discussions (OR = 2.78, 95% CI: 1.89-4.09, $p < 0.001$).

Discussion and conclusion

Summary of findings

The research's significant findings show that AI-based personalisation is much more effective at increasing customer engagement in social commerce settings, and the effect sizes (R2 = 0.472) are higher than those reported in classical e-commerce studies. This enhanced effectiveness may reflect the synergistic combination of individual personalisation benefits with social interaction mechanisms that characterise social commerce environments. The demographic analysis reveals significant variations in AI personalisation effectiveness across user segments, with younger, more educated users demonstrating stronger responses to AI features. These patterns suggest the need for adaptive implementation strategies that account for user characteristics, potentially involving simplified AI interfaces for less technologically sophisticated users while providing advanced features for early adopters. The research suggests that platforms should invest equally in technical AI capabilities and trust-building mechanisms, recognising that algorithm performance alone is insufficient without corresponding user acceptance and confidence.

Theoretical implications and contributions

The results of this study support the theoretical model of the Technology Acceptance Model, Stimulus Organism Response Theory, and Uses and Gratifications Theory in explaining the personalisation effect of artificial intelligence in the social commerce environment. The significant positive relation between AI personalisation features and customer engagement ($R2 = 0.472$) indicates that these conceptualisations together provide strong explanatory power for understanding user reactions to intelligent systems in a social commerce context. The Technology Acceptance Model constructs (perceived usefulness and trust) emerged as significant mediating variables of the interaction of AI personalisation and customer engagement. The fact that perceived usefulness has only a 34.7% total effect verifies TAM expectations while also widening the model's applicability in the AI era. The finding implies that users' appraisals of AI personalisation features align with those of traditional usefulness appraisals. Nevertheless, the processes of usefulness appraisal may differ from those in the old technology adoption model.

The mediating role of trust accounts for 18.3% of the total effect and has significant implications for understanding the AI acceptance issue in social commerce. While in classic e-commerce settings trust is mainly concerned with transactional security, social commerce trust extends to additional dimensions, including algorithmic transparency, the genuineness of relationships among users, and the integrity of the social world (or community). It is revealing that trust is identified as an important mediator of AI personalisation effects, encompassing users' trust in AI systems and extending beyond functional capabilities to social and relational dimensions. Via the previously shown process from AI personalisation triggers (stimuli) to internal psychological states (organism) to behavioural engagement reactions (response), Stimulus-Organism-Response theory is empirically validated. Perceived usefulness and trust are examined for their mediating effects, and customer engagement behaviours comprise both the "response" and "organism" elements.

The results of this study are consistent with and build on previous literature on the effectiveness of AI personalisation in digital commerce. We found a significant positive correlation between AI personalisation and customer engagement ($r = 0.634$ for recommendations), which is much stronger than the effect sizes in many traditional e-commerce experiments, indicating that personalisation gains in social commerce

might be directly inflated by social influence and peer effects. The results of our study indicate that best-practice customised recommendation systems yield better results than other components of the AI-based system, supporting previous literature in e-commerce (Ansari et al., 2000) and underscoring the need to extend the study to the social commerce context. However, the significant results of interface adaptation and content personalisation in this study suggest that social commerce users may be more open to comprehensive personalisation than conventional e-commerce users. The demographic patterns found in this study are consistent with some aspects of current technology acceptance research, including age effects on AI personalisation acceptance. Nevertheless, unlike some earlier results, no significant gender difference is observed, which may be explained by shifting gender dynamics in the technology-adoption process or by differences in the Kosovo market. The evidence in favour of a mediating role of trust in significant parts of AI personalisation effects implies that social commerce contexts generate additional trust requirements that platforms will have to address through appropriate communication and design approaches.

Practical implications for platform development

The findings of the research provide specific advice to developers of social commerce platforms on enhancing the design of AI-based personalisation strategies. Since the effect of personalised recommendation systems is often much larger, platforms ought to invest in more sophisticated recommendation algorithms rather than other areas of personalisation when resources are limited. Nonetheless, since various personalisation elements can have a profound influence, it can be concluded that the most successful solutions are general ones that blend recommendations, interface customisation, and content personalisation. Perspectives on the mediating effect of perceived usefulness require platforms to demonstrate the real-life benefits of AI personalisation elements by educating users, providing transparency, and enabling performance feedback loops. For users, the AI benefits are unlocked only when they are aware that artificial intelligence functionality enhances their platform's user experience, reduces search costs, or increases purchase satisfaction. These findings align with recent system-development research, which demonstrates that data-mining-based recommendation models substantially improve decision-making quality and user relevance (Mydyti et al., 2023).

Regional and cultural context issues

The case of Kosovo in the research can provide much information on the efficiency of AI personalisation in new post-conflict markets with high rates of digital change. Geographic position in Kosovo did not play a decisive role in the effectiveness of AI personalisation, indicating that the development of urban digital infrastructure has already reached a mature level, capable of applying AI uniformly across large population centres. Nevertheless, the critical role of educational level in the success of AI personalisation poses acute issues for the implementation in new markets. It includes the finding that increased reactions to AI traits among individuals with university education are more likely to indicate that locations may need to invest in user education and digital literacy to ensure that the advantages of personalising it to the greatest extent possible are conveyed to a significant percentage of the population. The mechanisms of social interaction and the personalisation benefits may yield more effective relationships than were estimated by more individualistic cultures. The post-conflict situation is also a possible factor in perceptions of trust and privacy concerns regarding AI personalisation. The fact that privacy mediates only 11.2 per cent of the adverse effects, compared to the utilitarian benefits, indicates

that the utilitarian benefits are far greater than privacy concerns, which could be an indicator of pragmatic attitudes towards technological adoption in contexts where economic opportunities matter more than privacy concerns.

Limitations and Future Approach

These are some limitations of the research findings. This is because the design is cross-sectional and therefore does not support causal inference regarding the relationship between AI personalisation and customer engagement. However, it supports causal inference, with reasonable theoretical support and statistical controls. The longitudinal studies would yield causal knowledge and enable examination of the impacts of AI personalisation over time as users become more competent and confident in intelligent systems. The single-platform offering with contextual richness cannot easily be applied to other social commerce platforms that may feature different features, user bases, or technology implementations. The multi-platform comparative study would enable a more detailed understanding of the efficiency of AI personalisation across different technical and social conditions. Although the geographical constraints of Kosovo are suitable for studying new market environments, they limit the extent to which the findings can be generalised to other cultural or economic contexts.

The indicators of customer engagement are self-report measures, supplemented with behavioural data where possible, which increases the likelihood of response bias. The latter study, which will involve objective behavioural data, will also help develop a better understanding of the impact of AI personalisation on actual user behaviour, rather than perceived or intended behaviour. The results of this study offer several fruitful directions for future research. Longitudinal studies may assess the utility of AI personalisation over time as the user base grows and algorithms improve their performance through machine learning.

Such a study can offer insights into the state of ideal implementation methods and the sustainable development of user relations. The experimental research designs would allow causal inference by controlling the manipulation of some personalisation characteristics of AI. By isolating the effects of individual elements, randomised controlled trials could identify the most suitable compounds for personalisation features across different user classes and use contexts. Studies of the harmful or unintended consequences of AI personalisation, such as filter bubbles, decreased exploration behaviour, and privacy concerns, would provide a more well-rounded perspective on the trade-offs of AI implementation and guide conscientious development practices.

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Appendix: Research Questionnaire

Section A: Demographic Information

1. What is your age?
    - o 18–25 years
    - o 26–35 years
    - o 36–45 years
    - o 46 years and above
2. What is your gender?
    - o Male
    - o Female
    - o Prefer not to say
3. Which is your highest level of education?
    - o Secondary school
    - o Bachelor's degree
    - o Master's degree
    - o Doctoral degree
4. Which is your present employment status?
    - o Student
    - o Employed full-time
    - o Employed part-time
    - o Self-employed/Entrepreneur
    - o Unemployed
5. Are you presently residing within what part of Kosovo?
    - o Pristina
    - o Prizren
    - o Peja
    - o Gjilan
    - o Mitrovica
    - o Gjakova
    - o Others

Section B: Social Commerce Usage

6. On which social media do you use regularly to browse or shop?
    - o Daily
    - o Several times a week
    - o Once a week
    - o Few times a month
    - o Rarely or never
7. What are your most frequent social media sites where you shop? (Select all that apply)
    - o Facebook
    - o Instagram
    - o TikTok
    - o WhatsApp Business
    - o YouTube
8. How many years have you been buying or searching for products via social media in Kosovo?
    - o Less than 6 months
    - o 6 months to 1 year
    - o 1–2 years; More than 2 years

Section C: AI Personalisation Experience

(Please indicate your level of agreement: 1 = Strongly Disagree, 5 = Strongly Agree)

9. The product suggestions that I get on social media are pertinent to my interests.
   1 – Strongly Disagree
   2 – Disagree
   3 – Neutral
   4 – Agree
   5 – Strongly Agree
10. The features of the platform are modified to my personal preferences.
   1 – Strongly Disagree
   2 – Disagree
   3 – Neutral
   4 – Agree
   5 – Strongly Agree
11. My needs are specific to the content that I view (posts, promotions, advertisements).
   1 – Strongly Disagree
   2 – Disagree
   3 – Neutral
   4 – Agree
   5 – Strongly Agree
12. The application of the chatbot or AI assistant is beneficial and personal.
   1 – Strongly Disagree
   2 – Disagree
   3 – Neutral
   4 – Agree
   5 – Strongly Agree
13. The customization of these sites gives an indication of the Kosovo shopping culture.
   1 – Strongly Disagree
   2 – Disagree
   3 – Neutral
   4 – Agree
   5 – Strongly Agree

Section D: Customer Engagement

Cognitive Engagement

14. The full attention is grabbed by using the platform.
15. I am distracted by looking through products or content.
16. I tend to forget about time during the use of social commerce platforms.

Emotional Engagement

17. I am excited to work with these platforms.
18. I like the customised shopping functions.
19. I belong whenever I am interacting with the social commerce groups in Kosovo.

Behavioural Engagement

20. I comment, share or like product-related posts.
21. On these platforms, I suggest other products or services.
22. I tend to buy goods according to the recommendations on the site.

Section E: Technology Acceptance

Perceived Usefulness

23. Personalisation benefits of the platform enhance how I shop.
24. Personalisation on AI assists me in searching for products faster.
25. The value of my shopping experience is enhanced through personalised functions.

Ease of Use

26. The AI services of these sites are user-friendly.
27. The personalised features do not take much effort to learn to use.
28. I find the customised choices easy.

Trust

29. I will rely on the site to give sound suggestions.
30. I think that the AI features are in my best interest as an end user.
31. I am sure I will trust the personalisation provided by these websites.

Privacy Concerns

32. I care about the way my personal information is gathered to be personalised.
33. My concern is with the manner in which the platform utilises my data in AI features.
34. I am not comfortable with revealing personal information, regardless of how beneficial this would make the recommendations.