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# Customer perceptions driving the adoption of artificial intelligence products in Ethiopian market

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## Abstract

Artificial intelligence (AI) is revolutionizing how businesses function. Products with AI integration are the newest trend in several stores. In these stores, consumers interact with totally automated technology. As a result, it's important to carefully consider the factors that led to consumers' intention to buy these products. This paper attempts to investigate the factors influencing the customer intention to buy AI-integrated products in Ethiopia. A survey questionnaire is used to gather data from different customers located in different shopping centers in the capital city. A simple random sampling technique from different accessible shopping centers was used and a sample of 255 respondents was utilized or an actual response rate of 85%, were obtained in the analysis. Partial list square structural equation modeling (PLS-SEM) was used to analyze the data. The study finds customers' behavioral intentions are highly influenced by Perceived usefulness, Perceived ease of use, attitude, subjective norm, and enjoyment. However, perceived cost and performance risk were found insignificant. This study offers important academic and managerial implications in the fields of business and technology. Business and policy makers needs to address affordability and digital literacy gap to enhance AI acceptance in Ethiopian market. Consequently, this study adds to the expanding body of research on emerging trends in services using AI-based technologies.

**Keywords** Artificial intelligence, Ethiopian customers, Technology, Behavior intention

## 1 Introduction

The terms "artificial intelligence" and "cognitive technologies" have already become commonplace in the fields of business, science, and technology [24]. Recent improvements in computing power have sped up the development of artificial intelligence (AI) technologies like machine learning, speech recognition, and natural language processing. It should come as no surprise that demand for intelligent products built with AI technologies is increasing [1]. Artificial intelligence (AI) is being used more and more in everyday goods and services that people use, such as insurance policies based on automated risk assessments, product offers on e-commerce websites, and price comparison tools. This



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technology promises to improve our societies and the lives of consumers. Innovative goods and services, like self-driving automobiles, may be made possible by it. Additionally, it can aid in the advancement of fields like science and medicine.

AI also has a significant impact on how consumers choose products and services, how they interact with businesses, and the risks associated with those products and services. According to Gonzalez Garca et al. (2017), intelligent products are physical items that possess the capacity for autonomous activity and decision-making. Because of the widespread use of digital technologies, considerable advancements in algorithmic skills, access to richer data, and rising processing power, the adoption of AI has significantly increased over the previous five years. Demand side factors like the implementation of digital platforms and the emergence of other disruptive technologies like blockchain and cloud computing are also contributing to the increasing importance of AI [3].

Artificial Intelligent product, which are found in retail stores are embedded with technologies such as sensors, microprocessors, and software that enable them to perform autonomous actions, make decisions, and communicate with their environment or users without constant human intervention (Raff et al. 2020). These products can collect and analyze data, learn from user behavior or environmental conditions, and adapt their functions accordingly to improve performance, efficiency, or user experience. Items like smart appliances that optimize energy use, wearable health devices that monitor and respond to biometric signals, and industrial machines that predict maintenance needs. Their ability to act independently and respond intelligently to changing conditions positions them as key components in the growing ecosystem of the Internet of Things (IoT) and smart systems, driving innovation across industries and reshaping the way products interact with users and other systems.

Emerging economies have been able to adopt basic AI solutions due to a growing number of technology users, early developments in fundamental machine learning algorithms, and a reduced burden of legacy technologies. Ethiopia, a developing country, has made advances in the use of technology in business. Online shopping has replaced traditional brick-and-mortar shopping among Ethiopian customers [51]. This is because of investments by the government of Ethiopia in the telecom sector that have led to penetration of the internet in the country. Mobile app purchases are on the rise because of the quick adoption of smartphones. Businesses have realized the need to embrace AI in order to improve the consumer shopping experience.

Despite the potential advantages of intelligent products, consumers in developing countries confront a number of difficulties [61]. Affordability perceptions are still a significant problem since intelligent products frequently have high costs that make them unaffordable for large portions of the population [51]. Additionally, perceived ease of use, attitude subjective norms, and in general digital literacy and experience with cutting-edge technologies can hinder effective use, particularly for older or less educated consumers [52].

Intelligent products are cutting-edge IT products, thus from the perspective of both businesses and customers, it is crucial to comprehend the variables influencing the behavioral intention of utilizing intelligent products based on AI [47]. The study is important since AI is a new technology in emerging nations and because retailers are unsure of how consumers will react to products using AI. Therefore, it is important to comprehend how consumers want to utilize these AI technologies.

## 2 Literature and hypotheses

### 2.1 Theoretical framework of the study

The Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT) are the theoretical foundations for the majority of studies on the utilization of innovative products [26]. Although many acceptance theory variables are dealt with similarly across many different models and there is considerable overlap, there is not much consistency across these different systems. Based on the identified construct variables, we employed the two most popular models, TPB and UTAUT, to understand the consumer acceptability of AI-based intelligent products.

#### a) Theory of planned behavior (TPB)

A psychological theory that connects ideas and behavior. According to the theory, an individual's behavioral intentions are shaped by three fundamental factors: attitude, subjective norms, and perceived behavioral control. The most proximal predictor of human social behavior, in turn, is behavioral intention, which is a core principle of TPB. Three categories of factors—behavioral beliefs, normative views, and control beliefs—influence human behavior. In their respective categories, behavioral beliefs result in an attitude toward the activity that is either favorable or negative, normative beliefs establish a subjective norm, and control beliefs are concerned with perceived behavioral control.

The TPB has been utilized in studies on the acceptability of innovative products that look at exogenous variables like social influence. Similar to this, there are a number of external elements that have been studied in academic work that are present in intelligent products. TPB was used to explain consumer intention toward the use of smart technologies [10, 40], wearable devices [15, 39], intelligent transport systems [6, 27], and smart home devices [39, 46].

#### b) Unified theory of acceptance and use of technology (UTAUT) 2

The TRA, TAM, and TPB, which are representative technology acceptance theories, were redefined from an integrated perspective to create the UTAUT [41]. According to this theory, the influence of the three additional constructs—hedonic motive, cost/perceived value, and habit—underpins people's use of technology. The findings of earlier studies in the technology and marketing domains found that the perceived hedonic nature of the outcome (such as perceived enjoyment) was a significant predictor of consumer technology use [11, 42], provided justification for the inclusion of this construct. Cost was included in this model for a variety of reasons, including its relative importance in the context of consumer product use as opposed to business technology use. Because consumer technology comes with tangible expenses, using it implies a stronger attitude of responsibility. Technology use increases in intensity as costs decrease.

The UTAUT was used to explain the acceptance of mobile devices [5, 7], Health care systems [16, 25], artificial intelligence education [4, 32].

Based on the above two theory's constructs attitude, subjective norms and perceived behavioral control (behavior intention) are taken from theory of planned behavior. Other constructs perceived ease of use, usefulness, enjoyment, performance risk (performance expectancy) and cost are taken from UTAUT 2. Together these theory's reveal

psychological and systematic factors driving artificial intelligence products usage behavior intention in Ethiopia market.

## 2.2 Behavior intention

The adoption of new technologies, innovations, or devices by an individual or organization is referred to as behavior intention (Faqih 2022). Many academics believe that the main predictor of actual behavior or purchase is intention. In other words, consumers who express a want to purchase a certain good are more likely to do so than consumers who do not show such a desire. Intention is linked to attitudes from a loyalty perspective, whereas purchase or action is linked to behavior loyalty. Knowing the attitudes, evaluations, and internal factors that ultimately lead to buy intent is crucial to forecasting customer behavior.

The level of a consumer's willingness to purchase an AI-enabled product is taken into account in this study as their behavior intention. A purchasing intention does not always result in a transaction. Only a small portion of consumers who indicated an intention to buy something will really complete the transaction (Indiani and Fahik 2020).

## 2.3 Perceived usefulness

Customers may react favorably or adversely to artificial intelligence products since behavioral intent depends on cognitive choice. The "like/dislike nuance" would thus depend on whether the tradeoff is advantageous to the potential buyers in comparison to other product types. This study believes that the usability and utility of the technology have some influence on the capacity to persuade consumers to use AI products. This is consistent with Davis' definition of perceived usefulness (PU) from 1989, which is the idea that using the products would improve one's performance. In the past, researchers have validated the construct of perceived usefulness, and they were found to influence the intention of buying artificial intelligence products [29, 30]. Therefore, it is expected that

**H1** Perceived usefulness positively and significantly influences customers' behavioral intention to use AI-powered products in the Ethiopian market.

## 2.4 perceived ease of use

According to Davis [14], perceived ease of use refers to "the extent to which a person believes that using a particular system would be free from effort." Although it is believed that AI products would have positive effects, for certain customers the ability to understand and be comfortable with the interaction medium may prove to be intimidating. The PEU, in short, is connected to the "user-friendliness" of the product [53]. Potential customers would choose to buy AI products if the trouble outweighs the advantages of buying the product.

It is a construct related to how someone evaluates the effort required to understand and use a technology. As a result, it relates to a person's abilities, as well as to their age, gender, and background in general. Prior studies validate a positive correlation between customers' attitudes toward technology and perceived ease of use. The adoption of smart retail technologies is significantly influenced by perceived ease of use [37], perceived ease of use had a favorable impact on consumers' attitudes toward wearable fitness

technology [12]. The AI product's usability refers to how simple it is to use and communicate with the system. Therefore, we propose that

**H2** Perceived ease of use positively and significantly influences customers' behavioral intention to use AI-powered products in the Ethiopian market.

### 2.5 Attitude

It is the degree to which a person has a favorable or unfavorable appraisal of the behavior of interest. It requires taking into account how the consideration will affect the results. Technology frequently triggers conflicting emotions that lead to anxiety [32]. Technology anxiety, or worry about being dependent on or addicted to technology, had a detrimental effect on consumers' use of sensory-enabling technology [9].

Prior studies indicated that favorable feelings or desire to adopt technological products are positively associated with overall attitudes about technology [34]. According to [35], a person is more likely to have positive attitudes or be more eager to buy new technology items the more positively they feel about technology in general. Thus we propose

**H3** Attitude positively and significantly influences customers' behavioral intention to use AI-powered products in the Ethiopian market.

### 2.6 Subjective norm

It is the idea of the general public's acceptance or disapproval of the activity [28]. It has to do with a person's opinions about whether peers and significant others believe the individual should engage in the behavior. The degree to which a person believes "that most people who are important to him think he should or should not perform the behavior in question" [17], indicating social influences. For new types of technology, such as wearable devices, it has shown to be especially crucial for acceptability and usage behavior [43].

According to empirical studies, there is conflicting evidence about how Subjective Norm influences how people use technology [43]. Some found that Subjective Norm significantly influences Actual System Use, while others non-significant [14]. However, there may be a significant impact of Subjective Norm on Actual System Use in the context of AI. Therefore, we hypothesize

**H4** Subjective norms positively and significantly influences customers' behavioral intention to use AI-powered products in the Ethiopian market.

### 2.7 Enjoyment

Individuals' intentions to shop are influenced by a variety of motivational factors, such as overcoming boredom, peer pressure, and status consciousness [39]. In other words, it isn't always to satisfy a desire for goods or services. Shopping orientation could not exclude happiness, whether it came from utilizing technology or from the real enjoyment of having the goods brought to the door. The "feeling of joy, elation, and pleasure" connected to the individual's act of acquiring an AI product might be used to describe this satisfaction. Therefore, we hypothesize that

**H5** Enjoyment positively and significantly influences customers' behavioral intention to use AI-powered products in the Ethiopian market.

### 2.8 Perceived cost

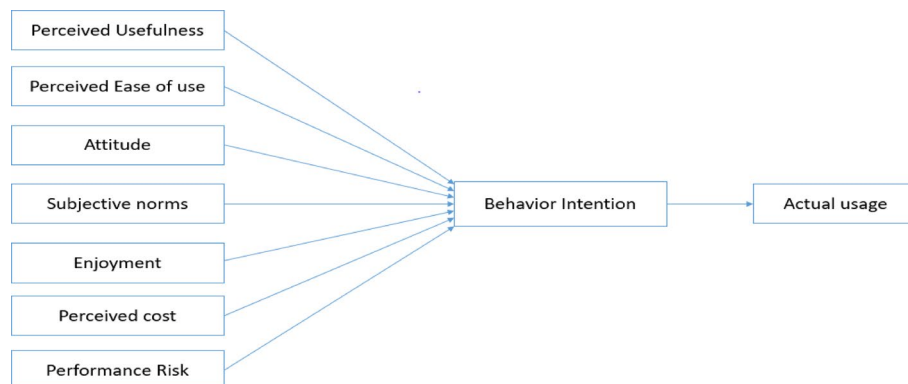
The price paid to purchase a product is known as the perceived financial cost. Many academics have identified the cost of information technologies as a key element influencing users' behavioral intentions [21, 33, 45]. Luarn and Lin [33] found that the perceived financial cost had significantly negative effects on users' behavioral intention in a study of personal adoption of mobile banking. Wu and Wang [44] also found that user adoption of mobile commerce is considerably hampered by users' perceptions of cost. In their investigation of the link between customer attitude and the price of value-added services, Hung et al., (2003) found a negative correlation between these two factors and consumer attitudes about the use of WAP services. According to Luarn and Lin, a customer's behavioral intention may be influenced by financial cost considerations. Cost has also been identified as a significant barrier to adoption. Therefore, we propose that

**H6** Perceived cost positively and significantly influences customers' behavioral intention to use AI-powered products in the Ethiopian market.

### 2.9 Performance risk

A person's subjective evaluation of the attributes, degrees of attributes, or outcomes of a product is referred to as perceived performance [31]. It is described as "the potential for the product to not perform as anticipated and/or to not provide the desired benefits." Performance risk is the potential for a product to be unsatisfactory if it falls short of the buyer's expectations. Performance risk was found to have a negative impact on attitude [22] and purchase intention. Therefore, if customers are concerned that the product won't function as they had hoped, their expectations won't be met, and a negative attitude is likely to result (Fig. 1).

**H7** Performance risk negatively and significantly reduces customers' behavioral intention to adopt AI-powered products in the Ethiopian retail market.



**Fig. 1** Conceptual Framework of Factors Influencing AI Adoption Intention

### 3 Methodology

#### 3.1 Sample and data collection

This study employed a quantitative research approach to examine the proposed hypotheses. Data were collected from regular customers of various shopping centers in Addis Ababa, Ethiopia's capital city. To ensure broad participation, a hybrid data collection method was used, combining paper-based questionnaires and online surveys (Google Forms).

A simple random sampling technique was applied across multiple accessible shopping centers to gather responses. To enhance participation, respondents' phone numbers were collected, enabling the distribution of Google Form questionnaires via random selection. Additionally, the survey link was shared through WhatsApp groups and email to maximize reach and ensure a diverse sample. This multi-channel approach facilitated efficient data collection while maintaining randomization and accessibility for participants.

The sample size for the study was determined based on the guideline proposed by Hair et al. (2016), which recommends a minimum of 10 observations per survey item. With the questionnaire comprising 30 items, the minimum required sample size was calculated as 300 respondents. A total of 300 questionnaires were distributed to ensure adequate statistical power, from which 255 valid responses were obtained, yielding an 85% response rate. This sample size meets the recommended threshold for robust data analysis while accounting for potential non-responses.

#### 4 Research instrument

The objective of this study is to assess the behavioral intention of customers towards AI products in Ethiopia, an emerging economy. Therefore, items for this study on behavioral intention, perceived usefulness, Attitude perceived ease of use were adopted from Venkatesh and Davis, 2000. Subjective norm [48], effort expectancy [43], enjoyment [2, 32], perceived cost [23] and performance risk [36] were adopted. The items were measured on a 5-point Likert scale which ranged from strongly agree (5) to strongly disagree (1). The questions related to demographic characteristics were also asked (Fig. 2).

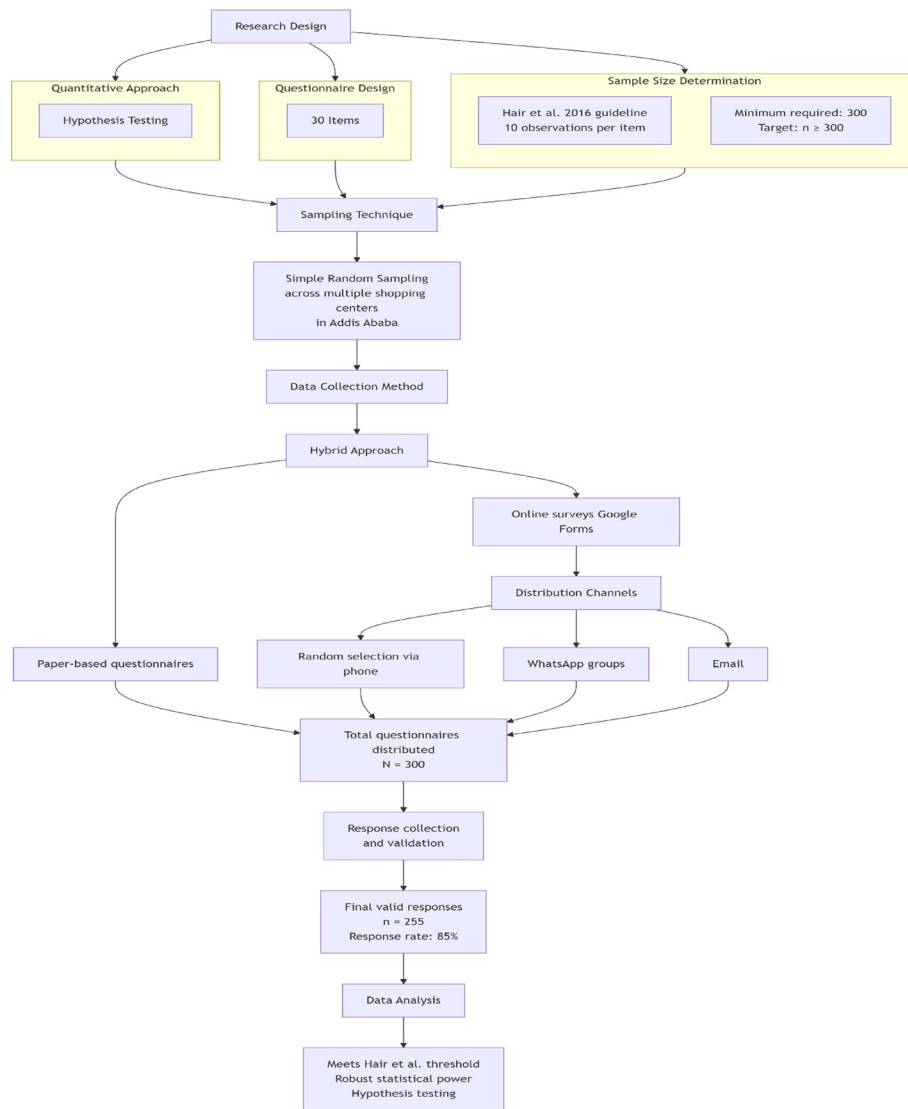
### 5 Results

#### 5.1 Demographic profile of respondents

The demographic profile of respondents reveals that the majority were male (79.01%), aged 21–35 years (63.97%), and held an intermediate (10 + 2) education (31.96%). A significant proportion were unmarried (57.51%), and most reported a family income above 10,000 Birr (35.29%), followed by those earning 6,000–10,000 Birr (29.41%). Few respondents were over 51 years (5.79%), held a Ph.D. (2.51%), or were separated/widowed (1.35%), indicating a sample skewed toward younger, educated, and middle-to-higher-income individuals (Table 1).

#### 5.2 Measurement model

A measurement model was evaluated using confirmatory factor analysis (CFA). A look at the outer measurement model yields several validity and reliability findings. For items to meet indicator reliability, factor loadings must be higher than 0.7 [19]. Only 4 items in total had to be excluded based on these choice criteria. Bootstrapping was used to test



**Fig. 2** Visual Overview of the Quantitative Research Design

the significance for the residual items, and all factor loadings show significance at the level of  $p < 0.05$ . All items, their loadings, and average variance are displayed in Table 2.

This reliability indicator reveals requested values for all constructs by examining the internal consistency and reliability of scales with Cronbach's alpha [13].

The composite reliability indicator is the other internal consistency metric; it provides a high level of reliability when all values are greater than the threshold of 0.7 [8]. As we continued with the investigation, we looked at the average variance extracted (AVE) values to investigate convergent validity. Every construct has an AVE above 0.5, which is in accordance with the literature's suggestion and requirement [18]. The Fornell-Larcker criterion, which requires that the AVE of the relevant construct must exceed the squared bivariate correlation with other components related to the research model, is also used to demonstrate discriminant validity [18]. This criterion and discriminant validity are met appropriately. Table 3 shows that discriminant validity.

**Table 1** Participant's characteristics

		Frequency	Percent
Gender	Female	82	20.99
	Male	173	79.01
Age	a) 15–20	29	10.16
	b) 21–35	162	63.97
	c) 36–50	44	20.08
	d) More than 51	14	5.79
Education	Didn't complete high school	37	16.9
	High school	50	22.82
	Intermediate (10 + 2)	70	31.96
	Bachelor degree	57	15.35
	Master's degree	23	10.46
Marital status	Ph.D	18	2.51
	Married	90	41.14
	Unmarried	162	57.51
Family income (Birr)	Separated/Widow	3	1.35
	Under 3000	30	11.76
	3000–6000	60	23.52
	6000–10000	75	29.41
	Above 10,000	90	35.29

### 5.3 Structure model

Structural equation modeling (SEM) was performed using Smart Pls 4.0. Software. SEM is used to test the hypotheses of the Structural Model. The structural model analysis in Smart PLS-SEM was conducted through a three-step validation process following Hair et al. (2019): first, examining path coefficients and effect sizes via bootstrapping to determine relationship significance and strength. Second, evaluating the model's explanatory power through the coefficient of determination ( $R^2$ ); and third, assessing predictive relevance ( $Q^2$ ) using blindfolding techniques to verify the model's out-of-sample predictive capability, thereby ensuring comprehensive validation of the theoretical framework.

After establishing the scales' psychometric properties, we tested the hypothesized model. The bootstrapping approach was used with a resample of 5,000 samples to examine the  $R^2$ , beta ( $\beta$ ), and corresponding t-values in order to evaluate the structural model. The adjusted R square value shows that the seven construct latent variables potentially explain 58% of the behavior intention in Ethiopia's customers. The goodness-of-fit indices for the hypothesized full model suggest a good overall fit ( $\chi^2 = 1018.6.05$ , p-value = 0.000, SRMR = 0.067, NFI = 0.714).

The SRMR [20], which is defined as the difference between the observed correlation and the model-implied correlation matrix, accepts values of less than 0.08 as acceptable. NFI values above 0.9 frequently signify an acceptable fit. The statistical (bootstrap-based) inference of the discrepancy between the empirical covariance matrix and the covariance matrix proposed by the composite factor model was evaluated by exact model fit (Fig. 3).

### 5.4 Hypothesis testing

Structural equation modeling (SEM) can test the hypothesis by looking at the probability value. The results of all hypotheses are reported in Table 4. Hypothesis H1, perceived use (PU) shows a positive significant influence on customer behavior intention (EP) at 0.05 level of significance. This indicates that the direction of PU to BI is positive. Thus,

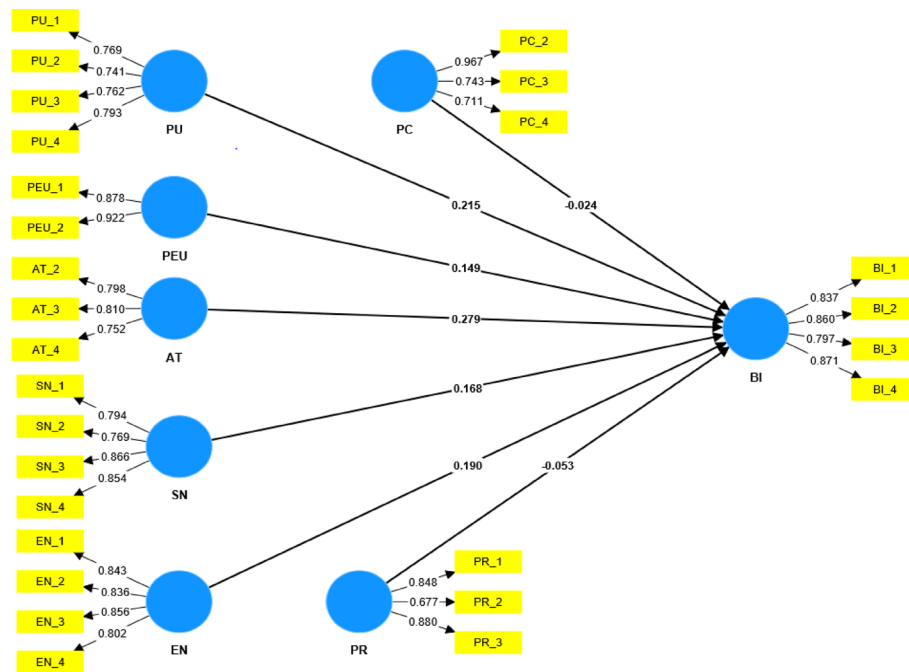
**Table 2** Construct reliability and validity

Variable		Cronbach alpha value	Composite reliability	Average variance
<i>Behavior intention</i>		0.862	0.863	0.619
BI1	0.837			
BI2	0.860			
BI3	0.797			
BI4	0.871			
<i>Perceived usefulness</i>		0.771	0.785	0.588
PU1	0.769			
PU2	0.741			
PU3	0.762			
PU4	0.793			
<i>Perceived ease of use</i>		0.770	0.794	0.811
PEU1	0.878			
PEU2	0.922			
<i>Attitude</i>		0.792	0.691	0.619
AT1	0.798			
AT2	0.810			
AT3	0.752			
<i>Subjective norm</i>		0.839	0.844	0.675
SN1	0.794			
SN2	0.769			
SN3	0.866			
SN4	0.854			
<i>Enjoyment</i>		0.855	0.864	0.696
EN1	0.843			
EN2	0.836			
EN3	0.856			
EN4	0.802			
<i>Perceived cost</i>		0.797	0.723	0.664
PC1	0.967			
PC2	0.743			
PC3	0.711			
<i>Performance risk</i>		0.765	0.813	0.651
PR1	0.848			
PR2	0.777			
PR3	0.880			
Overall		0.806	0.797	0.665

Source: Author's own work

**Table 3** Correlation and discriminant validity

	AT	BI	EN	PC	PEU	PR	PU	SN
AT								
BI	0.851							
EN	0.616	0.653						
PC	0.133	0.122	0.113					
PEU	0.689	0.634	0.437	0.036				
PR	0.140	0.162	0.151	0.631	0.051			
PU	0.540	0.641	0.679	0.092	0.472	0.095		
SN	0.511	0.671	0.412	0.116	0.574	0.114	0.354	



**Fig. 3** Structural model. The Structural Model with Path Coefficients

**Table 4** Hypothesis testing

Hypothesis	Path direction	Path coefficient	t-statistics	P	Result
H1	PU → BI	0.215	4.202	0.000**	Supported
H2	PEU → BI	0.149	2.935	0.002**	Supported
H3	AT → BI	0.279	4.473	0.000**	Supported
H4	SN → BI	0.168	2.694	0.002**	Supported
H5	EN → BI	0.190	3.101	0.001**	Supported
H6	PC → BI	-0.024	0.490	0.312	Not Supported
H7	PR → BI	-0.053	1.110	0.133	Not Supported

\*\*Significance at  $p < 0.05$ . Source: Author's own work

hypothesis H1 is accepted. Hypothesis H2 shows a significant influence of perceived ease of use (PEU) on behavior intention (BI) at a 0.05 level of significance. Thus, this hypothesis is accepted. For hypothesis H3, attitude has a positive significant impact on behavior intention.

Similarly, in Hypothesis H4, the effect of social norm (SN) on behavior intention (BI) reports a significant value at 0.05 level of significance. It indicates that there is a positive relationship between social norms and BI. In hypothesis H5, the effect of enjoyment (EN) on behavior intention (BI) reports a significant value at a 0.05 level of significance. It indicates that there is a positive relationship between SN and BI. In other cases, hypotheses H6, and H7 in the analysis of the effect of perceived cost (PC) and performance risk (PR) report an insignificant value at a 0.05 level of significance. Therefore, hypotheses 6 and 7 are not accepted. From the findings, one can observe that there was a good model fit and five out of seven hypotheses were significant.

## 6 Discussion and conclusion

The physical and online retailing spaces are transforming as a result of AI-based technologies and techniques such as robots, chatbots, bots, augmented reality, virtual reality, machine learning, deep learning, computer vision, cognitive conversation commerce, and the internet of things. The next revolution in retail is being driven by AI Integrated Products. Consumers in these retail establishments deal with totally automated technologies. As a result, it's critical to carefully consider the factors that led to consumers' intention to purchase AI-powered automated products.

Therefore, prior to implementation, behavior intention with respect to technology readiness must be understood. The study indicates that Ethiopian consumers' perceptions of AI products in the retail sector are strongly influenced by factors such as perceived usefulness, ease of use, attitude, social influence, and enjoyment. These results are consistent with the previous findings [48, 49, 54] (Sohn and Kwon 2020) and well-known technology adoption models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which highlight that users are more inclined to embrace technology when it is seen as helpful, easy to use, and supported by social norms. The notable role of enjoyment suggests that in Ethiopia, hedonic factors such as engaging features like virtual try-ons or AI-based product suggestions are crucial in shaping customer experiences and promoting adoption. This emphasizes the need for AI solutions in retail to be not only functional but also enjoyable, user-friendly, and socially relevant.

Interestingly, the research found that perceived cost and performance risk had little impact on how Ethiopian customers view AI products this contradicts with previous findings that perceived cost have significant impact on behavior intention [55]. However, the findings on the impact of performance risk is consistent with the previous findings [50]. This differs from trends seen in other markets, where high costs and concerns about reliability often hinder adoption. In Ethiopia, this may suggest that although consumers are price-conscious, their enthusiasm for trying new technologies outweighs concerns about expense. Likewise, the minimal effect of performance risk could point to either a limited understanding of AI's potential drawbacks or a general trust in retail technologies. Nonetheless, this does not eliminate the need for caution—retailers and policymakers should still work to ensure transparency around costs and the reliability of AI tools to maintain consumer trust and encourage sustained adoption [56–63].

The findings shows consumers are optimistic, innovative, and unafraid of using items with artificial intelligence (AI), which is good for retailers and companies who make products with AI integrated in. Customers are generally favorable to new retail AI products. Due to the products' automation and lack of human operational effort, this study concluded that the risks associated with cost and performance are not significant. However, this contradicts previous findings [38, 45]. Customer service departments that actively support customers with security-related issues should definitely exist. Retail store managers should create methods to alert customers about fraud and unauthenticated data usage as well as steps to address these issues. To increase the perceived ease of use of AI-based technology in retail businesses, managers must also instruct the customers in its use.

Retail managers must make sure that the technical support team is knowledgeable and available in the shop to handle both minor and severe emergencies. The language used in

technical manuals, display boards, hoardings, and signage for technical assistance with AI-based products is straightforward, clear, and user-friendly. Local language voice-based assistance should be offered to make shopping for products more comfortable for customers.

The PU, PEU, AT, SN, and EN play a crucial role in the behavior intention. Retail managers should therefore make sure that the AI-based products are made to offer the customer a joyful, enjoyable, adventurous, exciting, and stress-relieving experience while they buy. The AI products, including chatbots, speech recognition, robotic shopping carts, mobile apps, and automation, should be made to give users a fun experience. To make customers feel special, store managers should make sure that they receive individualized advice, specials, and adverts based on their specific purchasing needs.

This study has theoretical implications since it offers a thorough framework for examining consumer behavior intentions toward products with embedded AI. To theoretically describe the psychological process of consumers' intention, the proposed framework theoretically combines the system-specific constructs of TAM with the individual-specific constructs of Attitude, social norms, Enjoyment, perceived cost, and perceived risk.

By including the customers' unique viewpoints and AI-specific factors in a single proposed model, this research fills the theoretical gap in the literature on artificial intelligence and provides value to the field of study. By empirically examining the customers' intention towards AI products, it adds value to the existing literature on the adoption of new technologies and responds to the need for scholarly work in this area.

Therefore, this research contributes to the growing field of study on emerging trends in services employing AI-based technology. The findings of this study have consequences for the body of knowledge about retail management, customer behavior, and information systems.

## **7 Limitation and future research direction**

This research is the first step in figuring out how consumers in Ethiopia, an emerging market, feel about products with embedded AI. This study has limitations because it was a cross-sectional survey of customers in Ethiopia with a geographic restriction. As a result, consideration must be taken when extending the findings to other contexts. With demographic parameters like gender, age, education level, and income group analyzed on a comparative basis, this study can be expanded to other developing nations with a variety of cultural backgrounds additional variables can be added to conduct additional studies. Since the model was only evaluated in the Ethiopian context, it offers up new study opportunities in other developing nations and environments.

Based on the analysis and findings additional research topics like "Beyond Perception: Measuring the Actual Adoption Rate of AI Products in Ethiopia and the Chasm Between Intention and Use, The Role of Mobile Technology as a Gateway for AI Adoption in Ethiopia, Indigenous Knowledge Systems vs. Artificial Intelligence: A Study of Trust and Integration in Ethiopian different sector and Perception and Efficacy of AI-Driven Fintech Solutions: A Study on Financial Inclusion and Trust in the Ethiopian Banking Sector can be studied.

### **Author contributions**

A. Biruk Tessema, B. Esayas Degago Demissie, C. Dr. Swati Prasad, D. Dr. Esubalew Melese, E. Dr. Edina Molnár All authors contributed significantly to the development of this manuscript. A, B, & C, D. conceptualized the study design and led the overall coordination of the research process, contributed to the data collection and initial data analysis, participated

actively in the literature review, theoretical framework development, manuscript drafting and supported the data interpretation and contributed to refining the discussion and conclusions. E. supported the data interpretation and contributed to refining the discussion and conclusions, provided critical revisions, ensured the methodological rigour, and assisted in finalising the manuscript for submission. All authors reviewed and approved the final version of the manuscript.

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#### Data availability

The survey data analyzed in this study are not publicly available due to participant confidentiality but are available from the corresponding author upon reasonable request.

#### Declarations

##### Ethics approval and consent to participate

This study was reviewed and approved by the Research Ethics Committee of the Hope Enterprise University College. All procedures performed in this study involving human participants were conducted in accordance with the ethical standards and guidelines of the committee. Informed consent was obtained from all participants prior to data collection. Informed consent was obtained from all individual participants involved in the study. Prior to their participation, each respondent was provided with a detailed information sheet outlining the purpose of the research, the procedures involved, the anticipated duration, and their right to withdraw at any time without consequence. Participants were explicitly informed that their responses would remain anonymous and confidential, would be used solely for academic research purposes, and that aggregated findings might be published in scholarly articles. Consent was confirmed by the participants' voluntary completion of the survey after reviewing the information, ensuring that the study was conducted ethically and in accordance with the principles of the Declaration of Helsinki.

##### Consent for publication

By agreeing to participate in this study, participants hereby provide their consent for the data collected to be used in aggregated and anonymized form for publication in academic and professional channels. All responses have been treated with strict confidentiality, and no personally identifiable information has been or will be included in any published material, including scholarly articles, reports, conference presentations, or public summaries of the research. Participants acknowledge that the findings may be used for educational and research dissemination purposes while ensuring their anonymity and privacy are fully protected.

##### Competing interests

The authors declare no competing interests.

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