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Artificial Intelligence and Its Ethical Implications for Marketing

Ana Rita Gonçalves [1], Diego Costa Pinto [1], Paulo Rita [1*], Tamara Pires [1]

[1] *NOVA Information Management School (NOVA IMS), Universidade Nova de Lisboa, 1070-312 Lisboa, Portugal.*

Abstract

Despite the recent developments in AI, ethical questions arise when consumers contemplate how their data is being treated. This paper develops a conceptual model building on the theory of acceptance, risk, trust, and attitudes towards AI to understand the drivers that lead consumers to accept AI, considering consumers' ethical concerns. The model was empirically tested with 200 consumers of AI marketing services. The findings reveal that perceived risk significantly impacts attitudes toward AI, ethical concerns, and perceived trust and suggest a significant association between perceived risk, ethical concerns, and social norms. This research provides important theoretical and managerial implications for the ethical aspects of AI in marketing by highlighting the ethical and moral questions surrounding AI's acceptance.

Keywords:

Artificial Intelligence; Risk; Trust; Attitude; Ethical Concerns; Social Norms.

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1- Introduction

Artificial intelligence (AI) has led to changes in several domains, such as marketing strategies, business models, customer service, and behaviors [1, 2]. For example, marketers adopt AI to better understand and anticipate what consumers want and, consequentially, make optimal decisions and improve the lifetime value of customers [3], representing the potential to reduce costs and increase revenues [4, 5].

While AI has reshaped the customer experience [6], employees and consumers resist adopting it [2, 7]. These concerns with AI appear to be well-founded, as the progress in AI's capacity has become more evident over the years [8]. AI is an agent capable of undertaking progressively difficult cognitive tasks, demonstrating a solid ability for data analysis, learning from, and autonomous decision-making [9]. Companies have increasingly relied on AI's predictive capabilities to build ultra-customized services that enhance engagement, relevance, and satisfaction [10]. Nevertheless, such great capacity of AI has quickened exaggerated views on the subject and its potential to impact consumers' daily lives [11]. Past research on the acceptance of AI has revealed that consumers tend to prefer human labor to AI [12] and fear that AI is unethical [1, 13].

One of the potentialities of AI is better predicting what customers want [14]. Recent developments in AI enable the automation of consumer chores and provide personalized content through the emergence of big-data-driven and micro-targeting marketing offerings [15], contributing to consumers' efficient decision-making. However, if AI can substantially predict their preferences, consumers can also understand it as a loss of autonomy with ethical implications for their choices and evaluations [16]. Although AI can be viewed as a neutral instrument to be assessed based on efficiency and accuracy, this approach ignores the societal and individual issues that might arise when AI is applied [17].

* **CONTACT**: prita@novaims.unl.pt

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Furthermore, there is a lack of regulation in the field [18], generating ethical and moral questions [19]. Thus, this research adds to the literature by drawing attention to the ethical and moral dilemmas regarding AI's theories of user acceptance. In order to do so, it sheds light on the ethical aspects involving consumers' trust, risk, and attitude toward AI. Furthermore, while prior studies only assessed individuals' levels of acceptance and satisfaction regarding AI [20], this study includes ethical aspects in the theoretical model, testing how AI might affect consumers' perceptions.

By doing so, this research contributes to the marketing and ethics literature, at least in two significant ways. First, it contributes to research on acceptance theory [20, 21] by considering the ethical implications of the interaction with AI. Second, this research adds to recent studies on consumers' interaction with new technologies [1] by providing a more nuanced perspective on how ethical considerations can impact society and consumers' risks and perceptions of AI.

2- Literature Review

2-1- Artificial Intelligence and Technology Acceptance

Over time, researchers have been trying to understand and explain end users' adoption and acceptance of AI [9, 22, 23]. Nowadays, customers rely more on Artificial Intelligence and are willing to sacrifice their autonomy and control over circumstances to receive better services and more precise choices [1]. Hence, researchers have focused their studies on understanding what impacts these developments might have on humans. Muller [24, 25] particularly concentrated his studies on predicting AI's future and its ethical risks. For instance, AI could only become harmful by how it is used, meaning that if used for the sole purpose of consumer benefits or how it might benefit the organization [26]. Conversely, humans can be biased when analyzing large amounts of data [27]. The theoretical background of artificial intelligence is presented in Table 1.

Table 1. Theoretical background on Artificial Intelligence

Topic	Research	Reference
Customer experiences in the age of artificial intelligence	A theoretical model drawing on the trust-commitment theory and service quality mode. The findings indicate the significant role of trust and perceived sacrifice as factors mediating the effects of perceived convenience, personalization, and AI-enabled service quality and also reveal the significant effect of relationship commitment on AI-enabled customer experience.	[1]
Data privacy: Effects on customer and firm performance	A field study with actual customers of 15 companies across three industries demonstrates consistent effects across four types of customer data vulnerability. It confirms that violation and trust mediate the effects of data vulnerabilities on outcomes.	[19]
User acceptance of information technology: toward a unified view	The paper makes several recommendations for future research, including developing a deeper understanding of the dynamic influences studied here, refining the measurement of the core constructs used in UTAUT, and understanding the organizational outcomes associated with new technology use.	[21]
Risks of Artificial Intelligence	The book evaluates predictions of the future of AI, proposes ways to ensure that AI systems will be beneficial to humans, and then critically evaluates such proposals	[24]
Ethics of Artificial Intelligence and Robotics	Provides a general explanation of the ethical issues, outlines existing positions and arguments, then analyses how this plays out with current technologies, and finally, what policy consequences may be drawn	[25]
AI4People	Introduces the core opportunities and risks of AI for society; presents a synthesis of five ethical principles that should undergird its development and adoption; and offers 20 concrete recommendations – to assess, develop, incentivize, and support good AI – which in some cases, may be undertaken directly by national or supranational policymakers, while in others may be led by other stakeholders.	[26]
Right/Wrong: How Technology Transforms Our Ethics	Juan Enriquez reflects on the evolution of ethics in a technological age. He points out that, contrary to common wisdom, technology often enables more ethical behaviors. Technology challenges old beliefs and upends institutions that do not grow and change.	[28]
Patience Is Not a Virtue: The Design of Intelligent Systems and Systems of Ethics	The paper takes a functionalist stance that ethics is the set of behaviors that maintain a society. It explores the basis of sociality and autonomy to explain moral intuitions concerning AI systems.	[29]
Ethical Artificial Intelligence - An Open Question	The paper briefly analyses the concerns and potential solutions to solve the ethical issues presented and increases awareness of AI safety as another related research interest.	[30]
Artificial intelligence and life in 2030: One hundred year study on artificial intelligence	A long-term investigation of the field of Artificial Intelligence and its influences on people, their communities, and society. It considers the science, engineering, and deployment of AI-enabled computing systems.	[31]
You look Like a Thing and I Love You	Consumers rely on AI for recommendations, translations, and to put cat ears on users' selfie videos daily. They also trust AI with matters of life and death, on the road and in hospitals. But how smart is AI? The book shows how these programs learn, fail, and adapt and how they reflect the best and worst of humanity.	[32]

Over the last decade, several core theories in technology acceptance have been developed to better explain user acceptance of information systems like AI. First, the Theory of Reasoned Action (TRA) is considered one of the most fundamental theories explaining human behavior. This theory seeks to explain what influences and drives consumer behavior by predicting it based on two premises: the attitude toward the behavior—the positive or negative feelings of the individual influencing their behavior—and subjective norms, which are described as the perception of how peers believe that they should or should not behave [33, 34].

Second, the Theory of Planned Behaviour (TPM) predicts behavioral intentions to engage in a specific behavior at a specific time and place. Compared to the TRA, TPM evaluates another factor – Perceived Behavioural Control [21]. The authors postulate that behavior is under volitional control. TPB considers important factors influencing behavior intention and adoption: attitude, subjective norms, and perceived behavior control [34, 35].

Third, the Technology Acceptance Model (TAM), the theory presented by Fred Davis in 1986, is an adaptation of TRA specifically tailor-made for users' information system technology acceptance. The theory aims to explain why users decide to adopt technologies or not by evaluating several factors that influence their decision. However, in this case, the authors excluded attitude from the primary factors [21]. TAM was developed to predict the adoption of IT systems by evaluating when and how users will use them, assessing the perceived ease of use, which explains if the use of the system will not present many difficulties; Perceived Usefulness, which indicates the extent to which the individuals believe that the system will help improve their tasks; and how they influence the behavioral intention [36].

Finally, the Technology Acceptance Model (TAM 3) is an evolution of the previous model. Venkatesh et al. [21] kept investigating the world of IT systems' acceptance. Regardless, technology adoption still poses a barrier for several organizations due to the system's complexity and how it became central to organizational operations. The low adoption of systems causes severe losses to organizations. This theory focuses on the factors that influence perceived usefulness and perceived ease of use that leads to behavioral intention [37].

In summary, although core theories of acceptance were developed, the context of new information systems has raised concerns about data and privacy, especially with the implementation of AI [38-40]. However, none of the previous theories included ethical concerns in their models.

2-2- Artificial Intelligence and Consumers' Ethical Concerns

Consumer AI experience, according to Puntoni et al. [17], includes four types of interactions, namely, data capture, where consumers endow individual data to AI; classification, when consumers receive AI's personalized predictions; delegation, when AI substitutes the consumers in some tasks; and, finally, social, when consumers communicate with AI. Hence, the diversity of interactions consumers might have with AI throughout the day is countless [10]

With the advance in technology and computing capabilities, companies must adapt to developments. Adapting to and adopting them for daily tasks and products brings a new way of creating value for the customer and the company itself [41]. With the help of AI technologies such as machine learning, voice recognition, and natural language processing, enterprises make better and more precise decisions [42]. For instance, a content recommendation system such as Netflix that uses big data for behavioral targeting provides consumers with choices, they are likely to enjoy without the effort of having to sift through all the content to find their preferences. This facet allows users to discover their current choice and others they might be interested in. This capability would not be possible if it were not for these new techniques [16]

As prior research suggests [43-45], several technologies have quickly replaced human decision-making by providing better inputs. This innovation implies that customers may benefit from the outcomes of decisions made by digital assistants, which efficiently match personal preferences with accessible possibilities without suffering from the cognitive and affective fatigue that decision-making can cause [16]. Nevertheless, research tells us that consumers can also derive pleasure from their own decisions, and when they feel that they do not have that ability, it can lead to adverse reactions and consequences, impacting the quality of choice and consumer satisfaction [46].

As shown, there are conflicting feelings about the development and deployment of AI, and ethical challenges and opportunities rise [47]. Past research has highlighted the role of trust and perceived sacrifice to better understand AI-Enabled customer experiences. Some studies highlight major sacrifices such as the lack of human interaction, loss of privacy, loss of control, time consumption, and possible negative feelings where trust plays a crucial role [48, 49].

Ethical issues regarding AI go beyond the accumulation of data and concerns the use of information to manipulate behavior, whether online or offline, in a way that manipulates self-will and conscious choice. For example, with enough data and interaction, an algorithm can target a specific individual and present them with the right inputs that could likely influence their behavior [25]. Companies take advantage of this to maximize their profits by exploiting behavioral biases, deceptions, and addiction generation. The ethical concerns stem not only from advertising and the message delivered to customers but also overconsumption and purchase addiction resulting from its application [50]. The idea is to use machines to detect patterns humans cannot see and aid marketers in decision-making [51].

Depending on the researcher's judgment, there is no clear understanding of what would be ethical [52]. Ethical decision-making involves evaluating moral awareness and issues that occur by recognizing their existence and identifying their circumstances [53]. AI, in compliance with ethics, brings major benefits, preventing the misuse and underuse of technology. It brings perks by enabling organizations to take advantage of social values that can help to identify what would be morally acceptable by society. Conversely, it helps companies anticipate and possibly avoid costly mistakes from actions that might be considered unethical or unacceptable [26]. A group of researchers believes that what they call Ethics' dual advantage can only work in an environment of trust and clear responsibility. People are more prone to accept technologies if the benefits that come with them are higher than the possible risks [26]. Consumers believe that all they do is driven and motivated by their selves, not a sum of all the inputs they are exposed to.

Developments in technologies such as AI promptly enable AI to have more responsibilities in decision-making and act alone on matters. Thus, it increases the concern about safety and human benefits [54]. The perceived risk that comes with it is enhanced, making people question whether some machines should be doing what they do and if such technologies should be developed. People begin to question whether machines will outsmart humans [24].

2-3- Conceptual Model and Hypotheses Development

As mentioned in the previous section, consumer behavior models have undergone several changes. Based on the first TAM model and considering other factors: Ethical Concerns, Trust, and Risk, this paper analyzes how those variables influence consumer behavior toward using AI and their perception.

H1. *Attitude toward AI is negatively impacted by perceived risk.*

A person's attitude towards something is understood by their positive or negative feelings about the performance of the target behavior [20]. Nowadays, companies can collect consumer data in almost every interaction of consumers' daily lives. They use information consumers intentionally provide or collect from the "shadows" consumers leave behind in their daily lives. This process can result in a feeling of exploitation by consumers despite AI's capacity to forecast and meet preferences, primarily because they are unaware of AI's operating principles [17].

Even though consumers are willing to share some of their personal information and, therefore, accept some level of risk. The truth is that they are not yet in a state where they can understand what personal information companies can collect and in what ways it is used. Therefore, consumers believe there is some probability of suffering a loss in interacting with AI [19, 55].

H2. *Attitude toward AI positively influences perceived usefulness.*

Decision-making is not always easy for consumers. When presented with several options, they tend not to know what to choose and abstain from them [56]. AI can better predict what customers want [14] by helping firms expect what they will buy (Davenport et al. [4]), representing an opportunity for consumers to make their choices more effortless, practical, and efficient and reducing their search costs [8]. AI and its applications master big data processing to tailor suggestions to certain offerings or actions, leading to easier and less exhausting processing for humans [57].

As technology continues to expand and consumers' perceived need for using AI shifts, the role of AI continues to develop. The way consumers perceive the usefulness of a system or the benefits they might gain with it is highly impacted by attitudes and positive feelings toward them [23].

H3. *Perceived risk influences perceived trust.*

Consumers sometimes feel exploited when interacting with AI. These consumers' perceptions come mostly from how AI operates, namely, through intrusive and avoidable data acquisitions, how information is aggregated over time and across contexts, and the lack of transparency and associated regulation [17, 58].

Regardless, data is useless if humans do not know how to retrieve information from it. On the other hand, data holds the insights needed for decision-making. Decisions are essentially made based on instincts, years of experience, and their domain, but sometimes this might differ from what is appropriate for the moment. Studies have shown that trusting beliefs influence the perceived risk and the trust itself reduces uncertainty, which is assumed to be similar to risk [59].

Perceived risk and trust are crucial factors in consumers' behavior and the adoption and usage of AI. However, most individuals do not understand how the process works and, thus, blindly trust AI and companies. However, a lack of trust and understanding hinders AI adoption [55].

H4. *Ethical concerns are higher when there is a higher perceived risk.*

According to Foxman and Kilcoyne, privacy risks and control influence consumers' perceptions of privacy violations [60]. Almost all consumers have a digital footprint, which, with time, only becomes more extensive and accurate about their behavior and preferences. Just by having a presence online, consumers lose their anonymity. Brands can easily access consumers' information on those platforms. Consumer perceptions of privacy depend on two factors [60]: knowledge and control. For instance, when they post something on social media, companies can access this, thus collecting the consumers' information to provide better products or services. On the other hand, consumers have limited knowledge of how their information is used overall, causing a loss of control [61]. This data capture experience that consumers undergo makes them lose and perceive a loss of personal control, fueled by a lack of transparency [62]. Not surprisingly, this raises deep ethical concerns about AI, such as AI biases, ethical/moral judgment, and cybersecurity [47].

H5. *Social norms are influenced by perceived trust.*

Social Norms correspond to an expectation about the appropriate behavior that occurs in the group individuals are part of [20]. Trust, on the other hand, is based on the person's belief about the characteristics of another person [63].

Research has found trust useful in adopting new technologies and social norms, significantly predicting consumers' willingness to interact with AI devices [64, 65].

H6. *Social Norms are positively influenced by ethical concerns.*

As products and services empowered by AI become more present in consumers' lives, the mixed feelings associated with AI technologies also grow, especially due to the inherent challenges [47], radically influencing what society perceives as being ethical in the new landscape [28].

H7. *Social Norms have positive effects on Perceived Usefulness.*

Supporting routine decisions with AI helps with the accuracy of potential outcomes. Humans can be biased when it comes to analyzing data. However, due to its ability to efficiently deal with large amounts of data, AI mitigates possible biases and extends explanations beyond humans' perceptions [27].

The conceptual model considered in this study is shown in Figure 1.

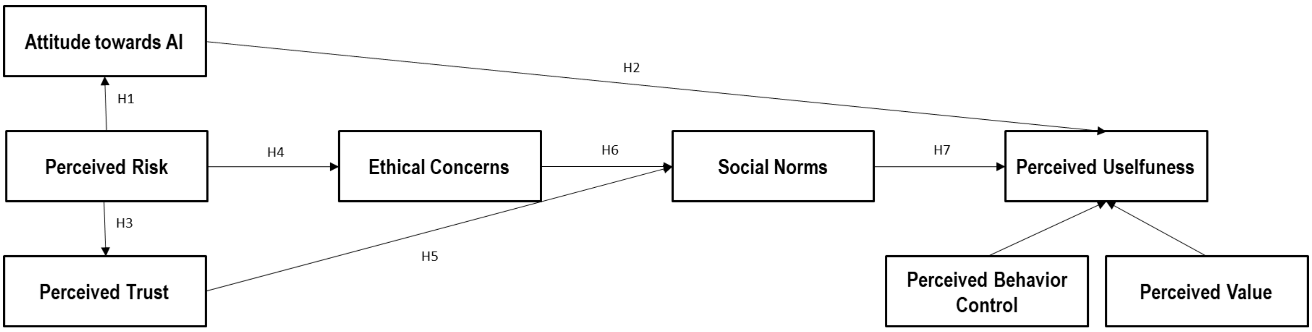

Figure 1. Conceptual Model

3- Materials and Methods

A questionnaire based on constructs previously studied by authors such as Venkatesh & Davis [66] was designed to test the model. Quantitative research was conducted to evaluate the previously stated hypotheses to examine consumers' perceptions of AI and its effects on them.

The survey was distributed on Qualtrics to anyone with some knowledge in the field. In other words, anyone who has had or has contact with any AI tool. A brief explanation of the concept, including the terms used in the survey, was given. Respondents were also required to answer demographic inquiries.

3-1- Measurement

The measurement items came from previous studies on individuals' acceptance of technologies, featuring studies from Venkatesh & Davis [66], Rahman [67], Yang & Jolly [68], Taylor & Todd [69], and others listed in Table 2. Multiple items were used to measure each factor. A seven-point Likert scale with anchors ranging from "*Strongly disagree*" to "*Strongly agree*" and from "*Completely unlikely*" to "*Very likely*" was used for each item.

Table 2. Measurement Items

Construct	Item	Measurement Item	Reference
Perceived Trust	PT1	I feel I can rely on the AI tool to do what it is supposed to do	[65]
	PT2	I believe the AI tool provides accurate information	
Perceived Usefulness	PU1	Using the AI product would improve my daily work performance	[66]
	PU2	Using the AI product would help my daily work	
	PU3	Using the AI product would enhance effectiveness in my daily work	
	PU4	I would find the AI product useful in my daily work	
Attitude	A1	Use of the AI product in everyday life would be bad/good	[67]
	A2	Use of the AI product in everyday life would be useless/useful	
	A3	Use of the AI product in everyday life would be desirable/ undesirable	
	A4	Use of the AI product in everyday life would be ineffective/ effective	
	A5	Use of the AI product in everyday life would be unpleasant/ pleasant	
	A6	Use of the AI product in everyday life would be irritating/likable	
	A7	Use of the AI product in everyday life would be helpful/ worthless	
Subjective Norms/Social Influence	SN1	People who influence my behavior would think that I should use the AI product	[23, 68]
	SN2	People who are important to me would think that I should use the AI product	
	SN3	People around me will take a positive view of me using the AI product	
	SN4	People around me would think that I should not use the AI product	
Perceived Behavioural Control	PBC1	Using the AI product is entirely within my control	[67, 69]
	PBC2	I have enough ability to use the AI product	
	PBC3	I do not have the necessary knowledge to use the AI product	
	PBC4	I have the resources, knowledge, and ability to use the AI product	
Behavioural Intention	BI1	I intend to recommend that other people use the AI product	[67]
Perceived Value	PV1	Compared to the fee I would need to pay; the AI product offers value for money	[23, 70]
	PV2	Compared to the effort I would need to put in, the AI product is beneficial to me	
	PV3	Compared to the time I would need to spend; the AI product is worthwhile to me	
	PV4	Overall, the AI product delivers good value	

4- Results and Discussion

4-1- Sample Characteristics

The research sample comprised 50.2% male and 44.2% female respondents aged between 21 and 47 years. Regarding education, most respondents (89) had a bachelor's degree, and the second highest group (58) held a master's degree (Tables 3 to 5). The survey was conducted from November 2020 to June 2021. The survey was distributed online and mainly on a university campus. Out of 215 respondents, 200 completed the questionnaire entirely.

Table 3. Gender (Questionnaire respondents)

		Frequency	Percent	Cumulative Percent
Valid		6	2.8	2.8
	Female	95	44.2	47
	Male	108	50.2	97.2
	Other	6	2.8	100
	Total	215	100	

Table 4. Education (Questionnaire respondents)

	Frequency	Percent	Cumulative Percent
Valid	9	4.2	4.2
Bachelor's Degree	89	41.4	45.6
High School Degree (or equivalent)	19	8.8	54.4
Less than High School Degree	15	7	61.4
Master's Degree	58	27	88.4
Some College	25	11.6	100
Total	215	100	

Table 5. Age (Questionnaire respondents)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	14	1	0.5	0.5	0.5
	16	7	3.3	3.4	3.9
	17	2	0.9	1	4.9
	18	10	4.7	4.9	9.8
	19	3	1.4	1.5	11.3
	20	7	3.3	3.4	14.7
	21	18	8.4	8.8	23.5
	22	39	18.1	19.1	42.6
	23	33	15.3	16.2	58.8
	24	17	7.9	8.3	67.2
	25	14	6.5	6.9	74
	26	11	5.1	5.4	79.4
	27	10	4.7	4.9	84.3
	28	3	1.4	1.5	85.8
	30	2	0.9	1	86.8
	31	3	1.4	1.5	88.2
	32	6	2.8	2.9	91.2
	34	6	2.8	2.9	94.1
	35	1	0.5	0.5	94.6
	36	1	0.5	0.5	95.1
	38	3	1.4	1.5	96.6
	44	5	2.3	2.5	99
	46	1	0.5	0.5	99.5
	47	1	0.5	0.5	100
	Total	204	94.9	100	
Missing	System	11	5.1		
Total		215	100		

4-2- Assessment of the Measurement Model

Structural Equations Modeling was employed using Partial Least Squares Structural Equations Modeling to evaluate the research model's hypotheses (Figure 2). SEM is a second-generation multivariate data analysis method that tests theoretically supported linear and additive causal models. PLS-SEM is a soft modeling approach to SEM with no assumptions on data distribution [71]. This approach evaluates causal relationships by integrating statistical data with qualitative causal hypotheses [72]. For the current work, a two-step process was used: 1) reliability and validity of the measurement model; and (2) structural model assessment.

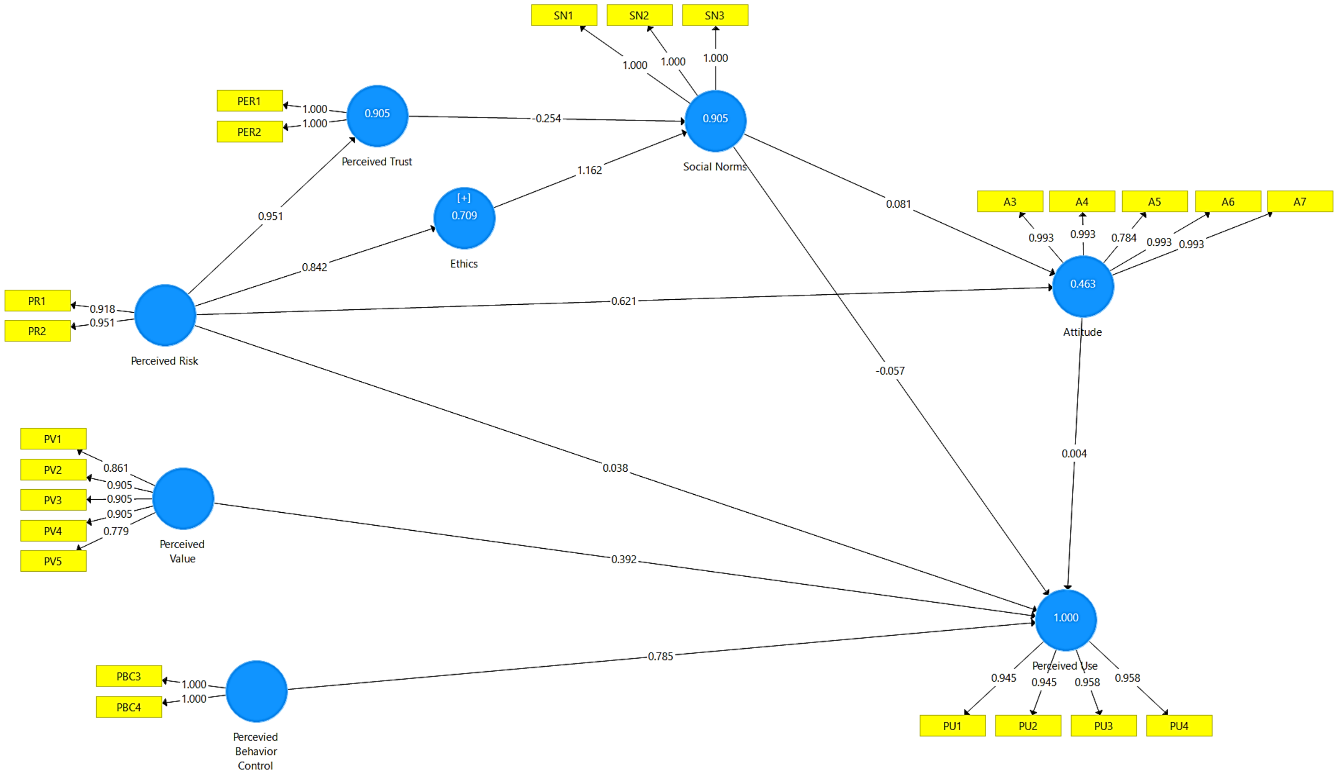

Figure 2. PLS-SEM Model

As Hair et al. [73] recommend, internal consistency, convergent validity, and discriminant validity were assessed since the model only includes reflective constructs. Construct reliability and validity were studied to evaluate the quality and consistency of the data (Table 6). The first validate if the input data can explain the reality, and validity refers to what extent the results are corrosive and passive to be accepted [74].

Table 6. Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Attitude	0.974	0.983	0.981	0.911
Ethical Concerns	0.911	0.966	0.920	**0.392**
Perceived Risk	0.857	0.896	0.933	0.874
Perceived Trust	1.000	1.000	1.000	1.000
Perceived Usefulness	0.965	0.970	0.975	0.906
Perceived Value	0.941	1.375	0.941	0.761
Perceived Behavior Control	1.000	1.000	1.000	1.000
Social Norms	1.000	1.000	1.000	1.000

The composite reliability is all above 0.8, which can be considered a valid threshold. Regarding the average variance extracted (AVE), the threshold is above 0.5 [75], and in the data set, only ethical concerns had values below the threshold (Table 7). However, the Cronbach Alpha values were all above the 0.7 threshold.

Table 7. Fornell-Lacker Criterion (Discriminant Validity)

	A	E	PR	PT	PU	PV	PBC	SN
A	0.955							
E	0.748	0.626						
PR	0.678	0.842	0.935					
PT	0.698	0.864	0.951	1.000				
PU	-0.017	0.117	-0.027	-0.022	0.952			
PV	-0.017	0.378	-0.026	-0.022	0.682	0.872		
PBC	-0.014	-0.017	-0.022	-0.018	0.945	0.407	1.000	
SN	0.522	0.942	0.710	0.750	0.148	0.499	-0.026	1

The Heterotrait- Monotrait ratio (HTMT) was used to assess the discriminant validity (Table 8). Kline considers the threshold 0.85, whereas Teo et al. assume 0.90 [76]. From the data, fewer values are above that threshold, so it is possible to consider that the true correlation between the constructs should differ.

Table 8. **Heterotrait-Monotrait Ratio (HTMT)**

	A	E	PR	PT	PU	PV	PBC	SN
A								
E	0.687							
PR	0.734	0.771						
PT	0.704	0.732	**1.011**					
PU	0.018	0.418	0.030	0.023				
PV	0.015	0.718	0.026	0.019	0.496			
PBC	0.015	0.234	0.024	0.018	**0.969**	0.199		
SN	0.526	**0.945**	0.753	0.750	0.168	0.577	0.026	

4-3- Measurement of Reliability and Validity

A correlation matrix was assessed to prove discriminant validity, and the AVE was evaluated against it. In Table 9, the results show that the AVE exceeded the correlation for each latent variable, except for ethical concerns, where the AVE was 0.392.

Table 9. **Correlation Matrix**

	A	E	PR	PT	PU	PV	PBC	SN
A	1							
E	0.7481	1						
PR	0.6784	0.8418	1					
PT	0.6979	0.8637	0.9513	1				
PU	-0.0172	0.1169	-0.0270	-0.0225	1			
PV	-0.0165	0.3779	-0.0262	-0.0217	0.6819	1		
PBC	-0.014	-0.0172	-0.0219	-0.0183	0.945	0.4065	1	
SN	0.5218	0.9424	0.7096	0.7495	0.1477	0.4988	-0.0259	1

4-4- Structural Model and Hypothesis Testing

The structural model indicated no multicollinearity for most of the variables. The model's variance inflation factors (VIF) were measured and the analysis revealed that the VIF for some factors: A → PU (1.8851), A→PR (2.0145); PR→E (1.0000); PR→PT(1.0000) A→SN(2.0145); were lower than the threshold value of 3.3 [77], but when it comes to PR→PU (4.5382); E→SN(3.9374); PT→SN(3.9374); PV→PU(3.5342); PU→SN(5.9785) which could be used to eliminate non-significant items. Nevertheless, they are lower than 5 (Table 10).

The structural model assessment and the hypothesis testing were done with a bootstrapping procedure with 5000 iterations where the path coefficient ranged from 0.0000 to 0.8428. The bootstrapping technique with 5,000 iterations is used to estimate the PLS path model at a 0.05 significance level [73]. It was assessed by looking at the significance of path coefficients and the variation explained (R^2) of the dependent constructs. Calculating with bootstrapping allows for testing the statistical significance of the PLS-SEM results, such as path coefficients, Cronbach's alpha, HTMT, and R^2 values [78].

The R^2 values of the independent variables, attitude toward AI (0.463), perceived trust (0.905), ethical concerns (0.709), social norms (0.905), and perceived usefulness (≈1), were also higher than the minimum threshold [79]. The model is important to explain a significant amount of the variation in the core constructs, which shows that the framework is composed of adequate drivers of perceived usefulness, including ethical implications.

Table 10. Bootstrapping: Mean, STDEV, T-Values, P-Values

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Attitude → Perceived Usefulness	0.0042	0.005	0.021	0.1985	0.8428
Ethical Concerns → Social Norms	1.1617	1.1326	0.3385	3.4317	0.0006
Perceived Risk → Attitude	0.6206	0.5333	0.2778	2.2335	0.0260
Perceived Risk → Ethical Concerns	0.8418	0.8074	0.1745	4.8231	0.0000
Perceived Risk → Perceived Trust	0.9513	0.9434	0.0886	10.7395	0.0000
Perceived Risk → Perceived Usefulness	0.0379	0.0196	0.0261	1.4511	0.1474
Perceived Trust -> Social Norms	-0.2539	-0.2192	0.3861	0.6575	0.5112
Perceived Value → Perceived Usefulness	0.3921	0.3828	0.1887	2.0779	0.0382
Perceived B. Control → Perceived Usefulness	0.785	0.7846	0.1466	5.3561	0.0000
Social Norms → Attitude	0.0814	0.061	0.1578	0.5163	0.6059
Social Norms → Perceived Usefulness	-0.0567	-0.0382	0.0444	1.2772	0.2021

Perceived Risk has proven to be a driver of attitude toward AI ($\beta_{PR}\rightarrow_{A}$=0.6206, p=0.0260). However, attitude toward AI failed to prove to be a driver of perceived usefulness $\beta_{A}\rightarrow_{PU}$=0.004, p=0.8482). These results support H1, i.e., perceived risk negatively impacts the attitude toward AI, but reject H2.

Furthermore, perceived risk was proven to be a driver of perceived trust ($\beta_{PR}\rightarrow_{PT}$=0.9513, p=0.000). These results suggest that perceived risk is a better driver of perceived trust and supports H3. Nonetheless, perceived trust was not proven to be a driver of social norms $\beta_{PT}\rightarrow_{SN}$=-0.2534, p=0.5112), consequently rejecting H5.

Finally, perceived risk is also demonstrated to be a driver of ethical concerns ($\beta_{PR}\rightarrow_{E}$=0.8418, p=0.000), showing that consumers' ethical concerns are higher when there is a higher perceived risk (H4). In addition, ethical concerns are shown to be a driver of social norms ($\beta_{E}\rightarrow_{SN}$=1.1617, p=0.006), i.e., social norms are positively influenced by ethical concerns (H6). These results indicate that ethical concerns are the main driver of social norms.

As mentioned, the variation explained in social norms is 91%. Nonetheless, social norms do not positively influence perceived usefulness, and thus, H7 is rejected.

Overall, the model explains approximately 100% of the variation of perceived usefulness, four out of seven hypotheses were supported, and the corresponding null hypotheses were rejected. An overview of the research model and achieved results are depicted in Table 11 and Figure 3.

Table 11. Summary of hypothesis results

Hypothesis	Supported or Not Supported
H1	Supported
H2	Not Supported
H3	Supported
H4	Supported
H5	Not Supported
H6	Supported
H7	Not Supported

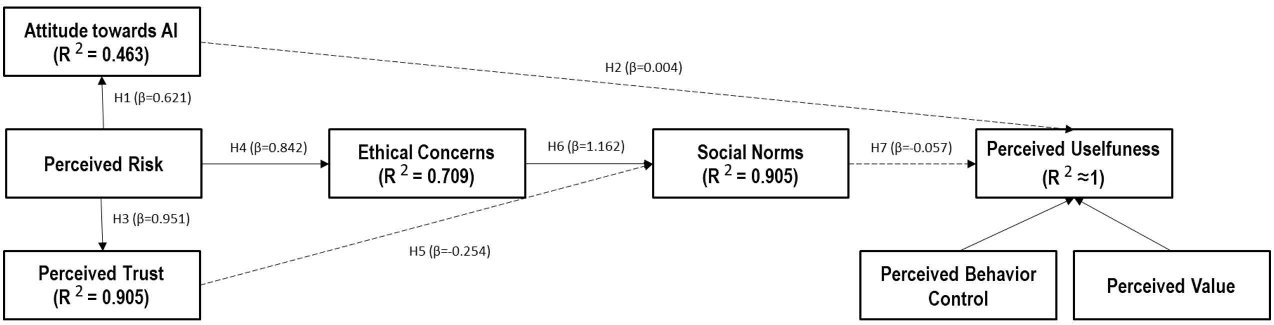

Figure 3. Results of Structural Equation Modelling (non-significant paths in dashed lines)

4-5- Discussion

This study contributes to the field by presenting a new conceptual model for ethics and AI. Given AI's presence in today's consumers' lives and the ethical concerns that arise with it, the model allows us to understand the implications for consumers' perceptions of and acceptance of AI. This model answers an urgent call for research on AI ethics [47].

The findings provide a new conceptual model to study the acceptance of AI, adding ethical concerns to the equation. The results indicate that the new conceptual model strongly predicts ethical concerns, social norms, and perceived usefulness. A key contribution of this research is extending an acceptance model [21] by including risk, trust, attitudes towards AI, and ethical concerns constructs to account for a full understanding of consumers' perceptions of AI. To the best of the authors' knowledge, this research is the first to draw attention to the ethical and moral dilemmas regarding AI's theories of user acceptance, as prior studies only assessed individuals' levels of acceptance and satisfaction regarding AI [20].

The study's results reveal that perceived risk significantly impacts attitudes toward AI, ethical concerns, and perceived trust. Therefore, perceived risk plays a crucial role in the model, and it is a key aspect concerning the acceptance of AI, which is aligned with previous studies [55, 80]. In addition, it suggests a significant association between perceived risk, ethical concerns, and social norms, where ethical concerns are the primary driver of social norms. This result confirms the relevance of the study. Due to the inherent difficulties of AI technologies, customers' mixed reactions to them also increase as these goods and services become more prevalent in their lives, which profoundly impacts how society views ethics in this new environment.

In sum, the present study contributes to recent research on consumers' use of new technologies by providing a more nuanced understanding of how ethical issues might affect society as well as their perceptions. The research helps understand the drivers that lead consumers to accept AI or not, thus reducing the risks and increasing trust.

5- Conclusion

Although AI can be considered a neutral tool whose efficiency and accuracy should be evaluated, this approach ignores the social and individual difficulties that may occur when AI is used. Numerous ethical issues are at the core of such AI dilemmas. In addition, AI technology's exponential expansion and pervasive effect make these ethical issues even more critical and urgent. This study aims to contribute to the literature on AI ethics and marketing by extending previous findings and uncovering an important underlying path of ethical applications. Based on the first TAM model and considering other factors, namely, ethical concerns, trust, and risk, this paper analyzes how those variables influence consumer behavior towards the use of AI and how it affects them. This research sheds light on the implications that the ethical concerns of using AI have on the acceptance of that same AI. In addition, the model reinforces that Perceived Risk, Perceived Trust, and Attitude play a fundamental part in consumers' acceptance. This investigation shares a more nuanced view of how ethical concerns might affect society and customers' risks and perceptions, i.e., understanding the forces that cause consumers to accept or reject a technology can reduce risks and increase trust.

Nevertheless, research thus far has revealed that there is still much to be discovered and many aspects to consider. The study showed that AI can indeed help consumers do their daily tasks and that, at some point, they are increasingly becoming attached to it and expect it to do its job appropriately. However, on the other hand, there is some apprehension regarding the power given to this technology and the way it rules human life. Hence, further investigation will be necessary to better clarify the situation of AI and the appropriate compliance for it. Researchers should empirically examine how AI is developing and seek more preventive methods that must be applied to reduce the possibility of bad outcomes.

6- Declarations

6-1- Author Contributions

Conceptualization, T.L., D.C.P., and P.R.; methodology, T.L., D.C.P., and A.R.; investigation T.L.; writing—original draft T.L., D.C.P., and P.R.; preparation, T.L., D.C.P., and A.R.; writing—review and editing, P.R. and A.R.; visualization, A.R.; supervision, D.C.P., and P.R.; funding acquisition, D.C.P., P.R., and A.R. All authors have read and agreed to the published version of the manuscript

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

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6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. Computers in Human Behavior, 114, 106548. doi:10.1016/j.chb.2020.106548.

[2] McLeay, F., Osburg, V. S., Yoganathan, V., & Patterson, A. (2021). Replaced by a Robot: Service Implications in the Age of the Machine. Journal of Service Research, 24(1), 104–121. doi:10.1177/1094670520933354.

[3] Chattopadhyay, S., Shankar, S., Gangadhar, R. B., & Kasinathan, K. (2018). Applications of Artificial Intelligence in Assessment for Learning in Schools. Advances in Educational Technologies and Instructional Design, 185–206, IGI Global, Hershey, United States. doi:10.4018/978-1-5225-2953-8.ch010.

[4] Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42. doi:10.1007/s11747-019-00696-0.

[5] Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., Gupta, M., & Niehaves, B. (2021). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. Government Information Quarterly, 101596. doi:10.1016/j.giq.2021.101596.

[6] Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the Customer Experience through New Technologies. Journal of Interactive Marketing, 51(1), 57–71. doi:10.1016/j.intmar.2020.04.001.

[7] Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to Medical Artificial Intelligence. Journal of Consumer Research, 46(4), 629–650. doi:10.1093/jcr/ucz013.

[8] Guha, A., Grewal, D., Kopalle, P. K., Haenlein, M., Schneider, M. J., Jung, H., Moustafa, R., Hegde, D. R., & Hawkins, G. (2021). How artificial intelligence will affect the future of retailing. Journal of Retailing, 97(1), 28–41. doi:10.1016/j.jretai.2021.01.005.

[9] Pelau, C., Dabija, D. C., & Ene, I. (2021). What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. Computers in Human Behavior, 122, 106855. doi:10.1016/j.chb.2021.106855.

[10] Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. California Management Review, 61(4), 135–155. doi:10.1177/0008125619859317.

[11] Cave, S., & Dihal, K. (2019). Hopes and fears for intelligent machines in fiction and reality. Nature Machine Intelligence, 1(2), 74–78. doi:10.1038/s42256-019-0020-9.

[12] Granulo, A., Fuchs, C., & Puntoni, S. (2021). Preference for Human (vs. Robotic) Labor is Stronger in Symbolic Consumption Contexts. Journal of Consumer Psychology, 31(1), 72–80. doi:10.1002/jcpy.1181.

[13] Leung, E., Paolacci, G., & Puntoni, S. (2018). Man versus Machine: Resisting Automation in Identity-Based Consumer Behavior. Journal of Marketing Research, 55(6), 818–831. doi:10.1177/0022243718818423.

[14] Wertenbroch, K., Schrift, R. Y., Alba, J. W., Barasch, A., Bhattacharjee, A., Giesler, M., Knobe, J., Lehmann, D. R., Matz, S., Nave, G., Parker, J. R., Puntoni, S., Zheng, Y., & Zwebner, Y. (2020). Autonomy in consumer choice. Marketing Letters, 31(4), 429–439. doi:10.1007/s11002-020-09521-z.

[15] Agrawal, A., Gans, J., & Goldfarb, A. (2017). How AI will change strategy: A thought experiment. Harvard Business Review, Harvard University, Massachusetts, United States.

[16] André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., van Boven, L., Weber, B., & Yang, H. (2018). Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data. Customer Needs and Solutions, 5(1–2), 28–37. doi:10.1007/s40547-017-0085-8.

[17] Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and Artificial Intelligence: An Experiential Perspective. Journal of Marketing, 85(1), 131–151. doi:10.1177/0022242920953847.

[18] Smuha, N. A. (2021). From a 'race to AI' to a 'race to AI regulation': regulatory competition for artificial intelligence. Law, Innovation and Technology, 13(1), 57–84. doi:10.1080/17579961.2021.1898300.

[19] Martin, K., Shilton, K., & Smith, J. (2019). Business and the Ethical Implications of Technology: Introduction to the Symposium. Journal of Business Ethics, 160(2), 307–317. doi:10.1007/s10551-019-04213-9.

[20] Momani, A. M., & Jamous, M. (2017). The evolution of technology acceptance theories. International Journal of Contemporary Computer Research (IJCCR), 1(1), 51-58.

[21] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly: Management Information Systems, 27(3), 425–478. doi:10.2307/30036540.

[22] Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. International Journal of Information Management, 49, 157–169. doi:10.1016/j.ijinfomgt.2019.03.008.

[23] Kim, J., Giroux, M., & Lee, J. C. (2021). When do you trust AI? The effect of number presentation detail on consumer trust and acceptance of AI recommendations. Psychology and Marketing, 38(7), 1140–1155. doi:10.1002/mar.21498.

[24] Muller, V. C. (2016). Risks of artificial intelligence. Chapman and Hall/CRC, New York, United States. doi:10.1201/b19187.

[25] Muller, V. C. (2020). Ethics of Artificial Intelligence and Robotics. Stanford Encyclopedia of Philosophy, 1–30, Department of Philosophy, Stanford University, Stanford, United States.

[26] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations. Minds and Machines, 28(4), 689–707. doi:10.1007/s11023-018-9482-5.

[27] Colson, E. (2019). What AI-driven decision making looks like? Harvard Business Review, Harvard University, Massachusetts, United States.

[28] Enriquez, J. (2021). Right/wrong: How technology transforms our ethics. MIT Press, Cambridge, Massachusetts, United States. doi:10.56315/pscf6-21enriquez.

[29] Bryson, J. J. (2018). Patiency is not a virtue: the design of intelligent systems and systems of ethics. Ethics and Information Technology, 20(1), 15–26. doi:10.1007/s10676-018-9448-6.

[30] Pavaloiu, A., & Kose, U. (2017). Ethical artificial intelligence-an open question. arXiv Preprint. arXiv:1706.03021. doi:10.48550/arXiv.1706.03021.

[31] Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., ... & Teller, A. (2022). Artificial intelligence and life in 2030: the one hundred year study on artificial intelligence. arXiv preprint arXiv:2211.06318. doi:10.48550/arXiv.2211.06318.

[32] Shane, J. (2019). You look like a thing and I love you. Hachette, New York, United States.

[33] Hale, J. L., Householder, B. J., & Greene, K. L. (2012). The Theory of Reasoned Action. The Persuasion Handbook: Developments in Theory and Practice, 14(2002), 259–286, SAGE Publication, London, United Kingdom. doi:10.4135/9781412976046.n14.

[34] Lai, P. (2017). The Literature Review of Technology Adoption Models and Theories for the Novelty Technology. Journal of Information Systems and Technology Management, 14(1), 21-38. doi:10.4301/s1807-17752017000100002.

[35] Cudjoe, D., Nketiah, E., Obuobi, B., Adjei, M., Zhu, B., & Adu-Gyamfi, G. (2022). Predicting waste sorting intention of residents of Jiangsu Province, China. Journal of Cleaner Production, 366, 132838. doi:10.1016/j.jclepro.2022.132838.

[36] Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results. Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, Massachusetts, United States.

[37] Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. Decision Sciences, 39(2), 273–315. doi:10.1111/j.1540-5915.2008.00192.x.

[38] Cowan, K., Javornik, A., & Jiang, P. (2021). Privacy concerns when using augmented reality face filters? Explaining why and when use avoidance occurs. Psychology and Marketing, 38(10), 1799–1813. doi:10.1002/mar.21576.

[39] Lau, J., Zimmerman, B., & Schaub, F. (2018). Alexa, Are You Listening? Proceedings of the ACM on Human-Computer Interaction, 2(CSCW), 1–31. doi:10.1145/3274371.

[40] Price, W. N., & Cohen, I. G. (2019). Privacy in the age of medical big data. Nature Medicine, 25(1), 37–43. doi:10.1038/s41591-018-0272-7.

[41] Armour, J., & Sako, M. (2020). AI-enabled business models in legal services: From traditional law firms to next-generation law companies? Journal of Professions and Organization, 7(1), 27–46. doi:10.1093/jpo/joaa001.

[42] Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. Telematics and Informatics, 47. doi:10.1016/j.tele.2019.101324.

[43] Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. International Journal of Information Management, 48, 63–71. doi:10.1016/j.ijinfomgt.2019.01.021.

[44] Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586. doi:10.1016/j.bushor.2018.03.007.

[45] Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping humans in the loop: Pooling knowledge through artificial swarm intelligence to improve business decision making. California Management Review, 61(4), 84–109. doi:10.1177/0008125619862256.

[46] Hermann, E. (2022). Leveraging Artificial Intelligence in Marketing for Social Good—An Ethical Perspective. Journal of Business Ethics, 179(1), 43–61. doi:10.1007/s10551-021-04843-y.

[47] Du, S., & Xie, C. (2021). Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities. Journal of Business Research, 129, 961–974. doi:10.1016/j.jbusres.2020.08.024.

[48] Fortes, N., Rita, P., & Pagani, M. (2017). The effects of privacy concerns, perceived risk and trust on online purchasing behaviour. International Journal of Internet Marketing and Advertising, 11(4), 307–329. doi:10.1504/IJIMA.2017.087269.

[49] Oliveira, T., Alhinho, M., Rita, P., & Dhillon, G. (2017). Modelling and testing consumer trust dimensions in e-commerce. Computers in Human Behavior, 71, 153–164. doi:10.1016/j.chb.2017.01.050.

[50] Lee, N., Broderick, A. J., & Chamberlain, L. (2007). What is "Neuromarketing"? A discussion and agenda for future research. International Journal of Psychophysiology, 63(2), 199–204. doi:10.1016/j.ijpsycho.2006.03.007.

[51] Struhl, S. (2017). Artificial Intelligence Marketing and Predicting Consumer Choice: An Overview of Tools and Techniques. Kogan Page, London, United Kingdom.

[52] Hunt, S. D., & Vitell, S. J. (2006). The general theory of marketing ethics: A revision and three questions. Journal of Macromarketing, 26(2), 143–153. doi:10.1177/0276146706290923.

[53] Treviño, L. K., Weaver, G. R., & Reynolds, S. J. (2006). Behavioral ethics in organizations: A review. Journal of Management, 32(6), 951–990. doi:10.1177/0149206306294258.

[54] Dignum, V. (2017). Responsible Autonomy. Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence. doi:10.24963/ijcai.2017/655.

[55] Hasan, R., Shams, R., & Rahman, M. (2021). Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri. Journal of Business Research, 131, 591–597. doi:10.1016/j.jbusres.2020.12.012.

[56] Schamp, C., Heitmann, M., & Katzenstein, R. (2019). Consideration of ethical attributes along the consumer decision-making journey. Journal of the Academy of Marketing Science, 47(2), 328–348. doi:10.1007/s11747-019-00629-x.

[57] Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. Harvard Business Review, 96(4), 114-123.

[58] Grafanaki, S. (2017). Autonomy Challenges in the Age of Big Data. Fordham Intellectual Property, Media & Entertainment Law Journal, 27(4), 803–868.

[59] Conn, A. (2016). Benefits and risks of artificial intelligence. Future of Life Institute, Massachusetts, United States. Available online: https://futureoflife.org/ai/benefits-risks-of-artificial-intelligence/?cn-reloaded=1 (accessed on January 2023).

[60] Foxman, E. R., & Kilcoyne, P. (1993). Information Technology, Marketing Practice, and Consumer Privacy: Ethical Issues. Journal of Public Policy & Marketing, 12(1), 106–119. doi:10.1177/074391569501200111.

[61] Wang, X., Tajvidi, M., Lin, X., & Hajli, N. (2020). Towards an Ethical and Trustworthy Social Commerce Community for Brand Value Co-creation: A trust-Commitment Perspective. Journal of Business Ethics, 167(1), 137–152. doi:10.1007/s10551-019-04182-z.

[62] Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. International Journal of Information Management Data Insights, 1(1), 100002. doi:10.1016/j.jjimei.2020.100002.

[63] Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. Academy of Management Review, 20(3), 709–734. doi:10.5465/amr.1995.9508080335.

[64] Söllner, M., & Leimeister, J. M. (2013). What we really know about antecedents of trust: A critical review of the empirical information systems literature on trust. Psychology of Trust: New Research, Nova Science Publishers, New York, United States.

[65] Fernandes, T., & Oliveira, E. (2021). Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. Journal of Business Research, 122, 180–191. doi:10.1016/j.jbusres.2020.08.058.

[66] Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46(2), 186–204. doi:10.1287/mnsc.46.2.186.11926.

[67] Rahman, A., Khanam, T., & Pelkonen, P. (2017). People's knowledge, perceptions, and attitudes towards stump harvesting for bioenergy production in Finland. Renewable and Sustainable Energy Reviews, 70, 107–116. doi:10.1016/j.rser.2016.11.228.

[68] Yang, K., & Jolly, L. D. (2009). The effects of consumer perceived value and subjective norm on mobile data service adoption between American and Korean consumers. Journal of Retailing and Consumer Services, 16(6), 502–508. doi:10.1016/j.jretconser.2009.08.005.

[69] Taylor, S., & Todd, P. (1995). Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions. International Journal of Research in Marketing, 12(2), 137–155. doi:10.1016/0167-8116(94)00019-K.

[70] Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer trust, value, and loyalty in relational exchanges. Journal of Marketing, 66(1), 15–37. doi:10.1509/jmkg.66.1.15.18449.

[71] Wong, K. K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. Marketing Bulletin, 24(1), 1-32.

[72] Jung, S., & Park, J. (2018). Consistent Partial Least Squares Path Modeling via Regularization. Frontiers in Psychology, 9. doi:10.3389/fpsyg.2018.00174.

[73] Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). A primer on partial least squares structural equation modeling (PLS-SEM). Sage Publications, London, United Kingdom.

[74] Middleton, F. (2022). Reliability vs. Validity in Research | Differences, Types and Examples. Scribbr. Available online: https://www.scribbr.com/methodology/reliability-vs-validity/ (accessed on January 2023).

[75] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39. doi:10.2307/3151312.

[76] Alarcón, D., Sánchez, J. A., & De Olavide, U. (2015). Assessing convergent and discriminant validity in the ADHD-R IV rating scale: User-written commands for Average Variance Extracted (AVE), Composite Reliability (CR), and Heterotrait-Monotrait ratio of correlations (HTMT). Spanish STATA meeting, 22 October, 2015, Madrid, Spain.

[77] Petter, S., Straub, D., & Rai, A. (2007). Specifying formative constructs in information systems research. MIS Quarterly: Management Information Systems, 31(4), 623–656. doi:10.2307/25148814.

[78] Ringle, C. M., Wende, S., & Becker, J.M. (2022). SmartPLS 4. Oststeinbek: SmartPLS. Bootstrapping. Available online: https://www.smartpls.com/documentation/algorithms-and-techniques/bootstrapping (accessed on January 2023).

[79] Chin, W. W. (1998). Issues and opinion on structural equation modeling. MIS Quarterly: Management Information Systems, 22(1), 7-16.

[80] Solberg, E., Kaarstad, M., Eitrheim, M. H. R., Bisio, R., Reegård, K., & Bloch, M. (2022). A Conceptual Model of Trust, Perceived Risk, and Reliance on AI Decision Aids. Group & Organization Management, 47(2), 187–222. doi:10.1177/10596011221081238.