



# Advertising Benefits from Ethical Artificial Intelligence Algorithmic Purchase Decision Pathways

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## Abstract

Artificial intelligence (AI) has dramatically changed the way organizations communicate, understand, and interact with their potential consumers. In the context of this trend, the ethical considerations of advertising when applying AI should be the core question for marketers. This paper discusses six dominant algorithmic purchase decision pathways that align with ethical philosophies for online customers when buying a product/goods. The six ethical positions include: ethical egoism, deontology (i.e., rule-based), relativist, utilitarianism, virtue ethics, and ethics of care (i.e., stakeholders' perspective). Furthermore, this paper launches an “intelligent advertising” AI theme by examining its present and future as well as identifying the key phases of intelligent advertising. Several research questions are offered to guide future research on intelligent advertising to benefit ethical AI decision-making. Finally, several areas that can be widely applied to ethical intelligent advertising are suggested for future research.

**Keywords** Ethical considerations · Digital marketing · AI Algorithms

## Introduction

Artificial intelligence (AI) has transcended across numerous fields in our lives (Kaplan & Haenlein, 2019, 2020; Russell & Norvig, 2020). Further, AI can dramatically improve individuals and organizations' efficiencies in almost every endeavor (Frankish & Ramsey, 2014). In marketing, AI and its relevant subsets, such as machine learning, deep learning and neural network, can strongly support resolving issues (Jordan & Mitchell, 2015). Nonetheless, ethical considerations in the design and employment of algorithms are indispensable, since it champions fairness and reduction of harm to individuals (Johnson, 2015). Such work is essential

as individuals and organizations attempt to train models on everything from stopping hate speeches online to marketing advertising as well as ensuring more fair and equitable hiring and promotion methods (Kirsten, 2018; Kirsten et al., 2019). To this end, AI and its related technologies are rapidly transforming society and will continue to do so in the coming decades. This social transformation will have profound ethical impact, with these prevailing innovative technologies both enhancing and disrupting individuals and organizations' actions.

AI is the foundation for representing human intelligence processes through the creation and application of algorithms constructed into a robust computing environment (Russell & Norvig, 2020; Xu et al., 2020). Stated simply, AI is undertaken to make computers reflect human brain neural processing. Accomplishing this end necessitates three vital elements, which are computational systems, data management, and algorithms. AI-based algorithms provide machines the capability to make decisions, recognize patterns and draw useful conclusions, which basically means imitating human intelligence (Rodgers, 2020).

Primarily, the goal of an algorithm is to resolve a specific problem, generally defined by someone as a sequence of steps. To accomplish this, the imitation of human cognition and functions, comprised of learning and problem-solving,

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is a prerequisite (Russell & Norvig, 2020). In machine learning or deep learning, an algorithm is a set of rules given to an AI program to help it learn on its own. Whereby machine learning is a set of algorithms that enable the software to update and “learn” from prior results without requiring programmer intervention. Furthermore, deep-learning models can be depicted as a related field to machine-learning models that deals with algorithms stimulated by the structure and function of the human brain called artificial neural networks.

Advertising is a marketing area in which AI-based algorithms may assist in formulating enhancement of planning and strategy (Van Esch et al., 2020). Moreover, ethical considerations in AI are critical in terms of fairness in advertising. A central problem in intelligent advertising is that new algorithmic models are needed to better understand ethical considerations and deliver the “appropriate” advertising for customers at the “right” time. While consumers’ desires, needs and wants can be considered as a foundation of intelligent advertising, it is necessary to analyze consumers’ positions (Li, 2019b) or consumers’ journey. This is important in order to understand consumers’ insights in digital advertising (Kietzmann et al., 2018) predicated on AI technologies (Deng, Tan, et al., 2019). Furthermore, advertising views, comments, and unique visits are a set of soft metrics or minor conversions to measure branding. The set of hard metrics and major conversions pertains to application downloads, sign-ups, and purchases in order to measure selling. According to Deng, Tan, et al. (2019) and Malthouse et al. (2019), hard metrics and macro conversions remain comparatively easy to follow in AI-powered analytics unlike soft metrics and minor conversions. Therefore, a huge marketing challenge is to uncover a method to use AI-powered algorithms to analyze hard metrics and macro conversions from

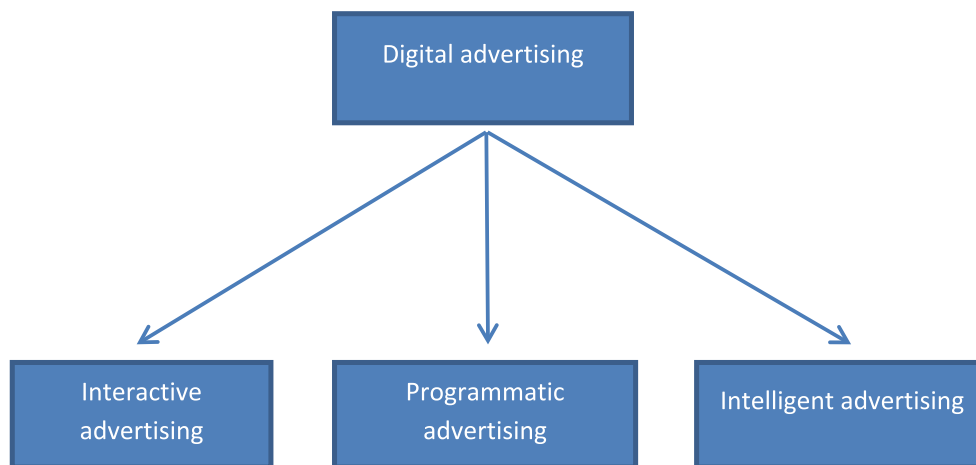
consumer’s actions. In other words, this type of procedure may deliver improved intelligent advertising to better understand the purchase decision process.

According to the aforementioned, marketers and advertisers can adopt AI systems (Kietzmann et al., 2018) to be more effective in understanding and reaching consumers at different stages of the consumer journey (Petro, 2018). To appreciate what AI creates for the advertisers and marketers, one must understand ethical considerations and reach the customers at different stages of the consumer journey.

Therefore, this paper imports a Throughput Model (TPM) a decision-making model that encapsulates AI algorithms that can be utilized to generate six dominant ethical behavioral pathways. Therefore, the TPM (Rodgers et al., 2014) is used in marketing to provide an explanation for individuals and organizations’ algorithmic decisions by touching upon several distinct decision-making aspects. Moreover, AI ethical issues such as bias and deception have already started to have an impact on businesses and individual, which the TPM can speak to by means of its algorithms.

In addition, the TPM addresses online decision-making as a cognitive process, which occurs in the mind of customers prior to a decision choice being made on the Internet. The online decision-making perspective suggests that a decision can be influenced by one of six dominant algorithmic pathways by the context in which it is made. This perspective is focused on learning the factors (i.e., perception and/or information) that bring value to the options (i.e., judgment) before a decision choice is made (see Fig. 1).

TPM is a basic conceptual quantitative model that links the phases of a purchasing process in terms of “perception” (P), “information” (I), “judgment” (J), and “decision choice” (D), where “P” or “I” (or iterations between both)



Source: Adapted from Hairong Li (2019)

Fig. 1 Three-phase of digital marketing

lead to “J,” which then leads to “D” (and/or “P” directly leads to “D”). Hence, understanding the different algorithmic pathways that lead to “D” can help to suitably design a system to uncover consumer decision models. Moreover, the algorithmic pathway that customers link to an option can vary depending on the number of alternatives, the decision maker's mood, her/his former experience with that kind of decision, and so on.

The ethical algorithms can be depicted as follow: (1)  $P \rightarrow D$  represents *ethical egoism*. (2)  $P \rightarrow J \rightarrow D$  portrays the *deontology viewpoint*. (3)  $I \rightarrow P \rightarrow D$  focusses on the *relativist perspective*. (4)  $I \rightarrow J \rightarrow D$  suggests the *utilitarian position*. (5)  $P \rightarrow I \rightarrow J \rightarrow D$  highlights the *virtue ethics viewpoint*. (6)  $I \rightarrow P \rightarrow J \rightarrow D$  represents the *ethics of care philosophy* (or stakeholders' position).

These six pathways are viewed as the most dominant and influential for decision-making dominated by moral perspectives. Although, it is important to note that other pathways in the *TPM* also contribute to the above philosophical positions. Our contention is that the corresponding algorithmic pathway to each noteworthy philosophical view is the most dominant (Rodgers and Gago, 2001). This concept differs from the traditional model.

The traditional model is based on two major assumptions (Tversky & Kahneman, 1981). The first assumption suggests that choices are understood to follow the principle of utility maximization. Utility can be thought of as levels of satisfaction, happiness, or personal benefit. Individuals act to maximize personal subjective benefits by assessing each option aligned with the weighted criteria and choosing the option with the highest total score. The second assumption of the rational model is that individuals' preferences are well-defined and constant over time (Tversky & Kahneman, 1981).

The *TPM* differs from the traditional economic theory (i.e., rational model) because it is (1) a process model (i.e., opens up the black box), (2) similar to a human neural network providing parallel routes in two stages (i.e., IJ and PJ in the first stage and PD and JD in the second stage) (see Fig. 1), (3) inclusive of a symbolic neural network function (i.e., PI) that imitates a Bayesian model (see Fig. 1), and (4) provides different stages representative of human information processing.

Further, this paper is inspired by the following research questions:

- (1) Can the *TPM* represents six algorithmic pathways that influences decision-making?
- (2) Can the six ethical positions of ethical egoism, deontology (i.e., rule-based), relativist, utilitarianism, virtue ethics, and ethics of care (i.e., stakeholders' perspective) be captured in algorithmic pathways?

- (3) Can the algorithmic pathways assist in processing different types of marketing consumer data for implementation?

The *TPM*'s six major ethical algorithmic pathways are discussed later more in detail to indicate their valuable part of any AI-based algorithmic system. The algorithmic pathways help to integrate complex ethical issues into a few central concepts, which can provide widespread commitment to a particular set of values. They can also offer an informal means of holding individuals and organizations accountable to reassure public concerns.

Within this context, the purpose of this article is two-fold. First, this paper sheds light on a particular driver of intelligent advertising in the AI age. In particular, the study focuses on the development of intelligence modelling. Moreover, the research investigates the influence of AI and its related subsets of machine learning, deep learning, and neural networks on advertising. Second, this paper proposes to apply ethical considerations for intelligent advertising to the algorithmic purchase decision pathways of the consumers. This procedure may assist marketers and advertisers in understanding and reaching the appropriate ethical considerations for a particular class of customers at the appropriate time. This approach combines the *TPM* (Rodgers, 2006, 2010) and AI technologies to build the neural network for intelligent advertising based on the consumer's purchase decision algorithms. Further, this model is imbued with ethical considerations with the *TPM* that can assist individuals with a framework enabling them to analyze complicated ethical situations (Rodgers, 2009; Rodgers & McFarlin, 2016).

This paper opens with a brief, general discussion of the relationship between AI and advertising in the AI world and the current issue is expressed. Then, the recent circumstance of intelligent advertising is explained. The next sections present several online algorithmic purchase decision pathways along with ethical considerations for customers and how intelligent advertising can benefit from these algorithms. Finally, the paper concludes by outlining the conclusions, limitations, and future of the research.

## Phase of Digital Marketing

Previous research suggests that the impact of AI on advertising has primarily increased efficiency (Li, 2019b; Rodgers et al., 2021). AI has shifted the way advertisers understand and guide consumers (Kietzmann et al., 2018). AI in advertising is considered the main demand in an e-commerce environment and can assist e-commerce platforms and advertisers in developing ethical responsible apparatuses and meet the online market demand (Qin & Jiang, 2019).

Both practitioners and academics regard AI as an important influence on not only advertising dimensions, such as advertising process, advertising operation, advertising design (Qin & Jiang, 2019), and advertisement production and execution (Lee & Cho, 2019), but also each phase of digital marketing, such as programmatic advertising (Bakpayev et al., 2020; Chen et al., 2019) in the technology world, which has exploded and changed dramatically in recent time. Further, as depicted in the TPM pathways, AI-based algorithms can be adapted to benefit advertisers by transforming big data (including structured and unstructured data) to understand and reach consumers via consumer journey (Petro, 2018).

With the help of AI-based algorithms and machine learning, consumer data can be combined and mined to understand the current customer's insights. That is, data can be collected from various sources by marketers and advertisers in order to connect actively back to consumers. The growth of intelligent advertising (such as interactive advertising and programmatic advertising) can be viewed as outwardly driven by big data, cloud computing and algorithms (Van Esch et al., 2020). Thus, it is important to implement the TPM algorithmic pathways to assist in better understanding how intelligent advertising can deliver personalization and real-time for customers based on their activities or behaviors.

Cho and Lee (2018) and Lee and Cho (2019) advocated for adaptation to a changing environment by implementing digital advertising along with the combination of advertising concepts such as interactive advertising, Internet advertising, online advertising and/or smart advertising. Furthermore, Li (2019b) confirmed that there are three phases of digital marketing, including interactive advertising, the first stage; programmatic advertising, the second stage; and intelligent advertising, the third stage. Similarly, the TPM follows a stage-by-stage process involving innovative attributes (i.e., perception and information concepts), as well as an options stage of digital advertising (i.e., judgment) before a decision choice. For instance, the TPM incorporated stages involve programmatic advertising that uses algorithms to depict digital advertising (IAB, 2014; Li, 2019a).

With the emergence of the Internet, the nature of advertising changes (Lombard & Snyder-Duch, 2001). The marketer is progressively more relying on interactive technologies, which refer to “methods, tools or devices that allow various entities (individuals, machines, or organizations) to engage in mediated communication to facilitate the planning and consummation of exchanges between them” (Varadarajan et al., 2010, p. 97). Furthermore, this process helps reach customers who adopt the Internet as an information source. This type of marketing communication can be ramped up by the implementation of algorithms and interactivity of AI concepts as displayed by the TPM. According to Johnson (2000), interactivity can make advertising more effective.

Based on previous researchers, a model employing an algorithmic process can significantly enhance individuals and organizations' decision making abilities (Heeter, 2000; Li, 2019b; Liu & Shrum, 2002; McMillan & Hwang, 2002; Pavlou & Stewart, 2015).

### Programmatic Advertising

The second phase of digital advertising is programmatic advertising that is considered a rapidly evolving and emerging phenomenon built on an AI infrastructure (Chen et al., 2019). It can be defined as an automated serving of digital advertising based on individual advertising impressive opportunities in real-time (Busch, 2016). This new phase of digital marketing can be automatically bought and sold through data, software or algorithms (IAB, 2014). The TPM-based algorithms, which emphasize six dominant consumers pathways, can provide an elevated insight into this new phase of digital marketing.

According to Chen et al. (2019), programmatic advertising contains a creative platform (PCP) and a content management platform (CMP) in order to assist or mechanize a creative process in the data-driven and consumer-centered marketplace and programmatic buying, which combines a data management platform (DMP) and a demand-side platform (DSP) to solve a fundamental challenge of discovering the best match among a suitable advertisement and a given user in a given situation (Broder, 2008). The main attributes of programmatic advertising are automation and interactivity.

### Intelligent Advertising

Intelligent advertising is the third phase of the first 25 years of digital marketing, as AI has been influenced by different levels of the advertising process (Qin & Jiang, 2019). Although AI technologies can enhance digital advertising from the second phase—programmatic advertising (Chen et al., 2019)—through four steps of the advertising process. These four steps include (1) customer insight discovery, (2) media planning and buying, (3) advertising creation and (4) evaluation of advertising impact (Qin & Jiang, 2019). AI-based algorithms in the TPM appear to be appropriate to capture new attributes of intelligent advertising, such as personalization in prescription of the user's needs and wants (Li, 2019b) or voluntary exposure to the user (Li et al., 2002, 2003).

Many AI systems have been suggested to improve the effectiveness of advertising in the AI age. For instance, a smart AI personalized advertising copy system can be implemented to conduct experiments to test the effect of advertising. Based upon the TPM's six algorithmic pathways, this can generate personalized advertising automatically to meet

a consumer's need through four main components, including advertising copy template generation, advertising words sentiment analysis, template matching and personalized user tag classification (Deng, Tan, et al., 2019). Moreover, similar to the TPM perspective, Malthouse et al. (2019) recommended a multi-objective, multi-stakeholder recommender system that can be considered as a solution for maximizing the value of a two-sided consumers and advertisers' platforms through a recommendation platform which is able to personalize a set of products or services to each user.

## Intelligent Advertising in the AI Age

Adopting AI is the new wave in many subsets of the advertising field. With the power of AI, advertising process (Qin & Jiang, 2019; Van Esch et al., 2020), automatic advertising personalization (Deng, Tan, et al., 2019; Malthouse et al., 2019), and the main foundation of intelligent advertising, such as consumer's insights (Li, 2019b) or consumer decision journey (Kietzmann et al., 2018), are supported to develop rapidly and effectively.

### Advertising Process Power-Driven by AI Technologies

AI influences the advertising process by reorganizing and upgrading the traditional advertising process and improving advertising efficiency (Qin & Jiang, 2019). AI technologies are found that can restructure various steps of the advertising process, such as advertising planning, advertising research, advertising creation, media planning and buying, performance evaluation, copywriting and so forth (Liao, 2017). Besides, according to Jiang and Xin (2019), it can guide advertising activities such as large-scale personalized advertising production (through consumer profiling) and proactive strategies (through algorithms) because AI can impact on a new set of advertising process steps, including customer insight discovery, media planning and buying, advertising creation and advertising impact evaluation.

The current literature is beginning to explore how the advertising process can be reorganized and upgraded when AI technologies have been applied (Qin & Jiang, 2019). The next section provides inroads to the use of organizations' algorithms pertaining to branding and selling.

### New Models, Algorithms of Branding and Selling Supported by AI and Its Subsets

According to Li (2019b), AI power can be tracked and evaluated by metrics and macro-conversions (which measure selling—the immediate effects of advertising) to measure the effectiveness of intelligent advertising instead of soft

metrics or minor conversions (which measure branding—the delayed effect of advertising) used in the previous advertising studies.

There are several researchers who pay attention and apply to AI advertising systems that use hard metrics and macro conversions to generate personalized advertising automatically for the consumer's need (Deng, Tan, et al., 2019) or recommend a two-sided consumer and advertiser platform to personalize a set of product or service to each customer (Malthouse et al., 2019). However, AI tools still require models, which can measure the efficiency of intelligent advertising better in the future.

### Predicting the Consumer's Needs and Wants by AI Technologies

Besides customer's habits, tastes, preferences and interests, needs and wants which can be analyzed from large amounts of multisensory data of customers' insights in real-time are the two main foundations of intelligent advertising. Customer's insights can be understood through AI technologies (such as computer vision, speech recognition and natural language processing) and their integrated processes and systems.

### Advertising Along the Consumer Journey Based on AI

AI can assist marketers and advertisers to better understand consumers' decision journey, which has five stages, including need recognition, initial consideration, active evaluation, purchase and post-purchase (Court et al., 2009). That is, AI can support and transform advertising tasks at each journey stage based on the aforementioned building blocks. For instance, AI technologies assist to understand emerging consumer's needs and wants (via the data from market research, data mining or web analytics that are able to create consumers' profiles), initial consideration (via AI-powered search to increase brand's visibility and emphasizing consideration reasons), active evaluation (via machine-learning and image to recognize customers' trends and patterns and understand customer's thoughts and feelings), purchase (via intelligent purchasing system to alter the purchase process completely) and post-purchase (via AI-enabled Chabot to reduce resolution time for next inquiries or engage with post-purchase actions).

From these previous studies, AI technologies are supported to identify and comprehend the consumer decision journey. However, it is only based on the traditional stages of the consumer decision process. There is a lack of literature for investigating the consumer decision algorithms in the online environment, which can assist AI technologies to better understand the consumer decision journey to help



marketers and advertisers create the efficiency of intelligent advertising better.

The next section explores the new algorithmic purchase decision journeys for online customers that can support intelligent advertising to get in touch with potential customers personally at real-time.

## Online Algorithmic Purchase Decision Pathways

The following literature reviews the online decision process and the advantages and disadvantages of current online decision-making models.

### Online Decision-Making Process Differs from Traditional Decision-Making

Online decision-making process differs from the traditional decision-making process because it is more flexible (Bucklin et al., 2002). That is, online processes are influenced by the Internet AI technological apparatuses (Butler & Peppard, 1998; Gupta et al., 2004). This technology can enhance online customers' experiences in collecting required information, alternatives searching, evaluations of alternatives, purchase options and so forth (Butler & Peppard, 1998; Constantinides, 2004; Moon, 2004). Furthermore, the customers can be assisted in modifying their purchase habits to new complex decision-making environments (Xia & Sudharshan, 2002) as well as buying across channels (Choudhury and Karahanna, 2008; Karimi et al., 2015).

Moreover, customers are also assisted in tracking numerous decision routes to make their final choices (Pavlou et al., 2007). The online customers are more enlightened to consider adding, skipping or reordering the steps of their prior decision-making processes (Dorn et al., 2010). Thus, online purchase decision-making can be a tremendously and self-motivated adaptable avenue (Karimi et al., 2015).

Compared with traditional purchase decision journey, online shopping customers maybe be more forceful, utilitarian and demanding (Koufaris, 2002). According to Court et al. (2009), customers can be more in charge of their situations, obtain appropriate information dynamically and not have to wait for available information offered in different settings by organizations. These previous studies support the TPM algorithmic pathways since buyers' characteristics and decision-making perspectives are different based on their various educations, social status, and philosophical viewpoints (Rodgers, 2006). Moreover, the TPM algorithmic pathways encapsulate customers' motivation, attitudes, personality, perception, lifestyle and knowledge as discussed by Kotler et al. (2018). These attributes may influence the customer's cognitive thinking and guide the selection of an

online customer's particular algorithmic pathway (Karimi et al., 2018).

## Current Online Decision-Making Models

The traditional 5-stage buyer's decision process (i.e., need recognition, information search, evaluation of alternatives, purchase decision, and post-purchase decision) in consumer buying behavior pertains to what customers undergo before, during, and after they buy a product or service (Engel et al., 1968). This traditional model is established by a number of studies including research by Engel et al. (1968), Engel and Miniard (1990); Howard and Sheth (1969) and Karimi et al. (2018). The 5-stage buyer's decision process represents a linear model, which maybe implemented as the standard model for research of consumer behavior (Karimi et al., 2015).

As reported by Karimi et al. (2015), this classical model can be adapted in the online environment. The TPM algorithmic pathways support this classical model in that it covers online consumers various decision-making propensities, which span across their diverse education, social status, viewpoints, etc. Furthermore, other characteristics, such as motivation, attitudes, personality, perception, knowledge and lifestyle (Kotler et al., 2018), can influence the online users' selection of a particular TPM algorithmic pathway. The six algorithmic pathways allow for flexibility in the online environment. Karimi et al. (2015) and Bucklin et al. (2002) acclaimed that online choice options should be more flexible and consist of a series of concerned selections.

Nonetheless, on-line purchasing may contribute to both negative (Chen et al., 2009; Sicilia & Ruiz, 2010) and positive effects (Huang, 2000; Huang et al., 2013). For example, information overloads may delay the final decision (Soto-Acosta et al., 2014) or change the consumer's behavior (Mick, et al., 2004).

Online consumers may make purchase decisions by following distinct different pathways (Pavlou et al., 2007). In regard to the consumers' adaptive abilities, they can add, skip or reorder the stages of the decision-making process (Dorn et al., 2010). As a result, the Internet can impact on every stage of the online decision-making process (McGaughey & Mason, 1998).

In this traditional decision-making model, the customers are considered to move from one stage to the next, finally making a purchase decision (Karimi et al., 2018). However, in the real world, the consumers make their decision process flexibly based on their adaption and respond to decision tasks (Bettman et al., 1998; Payne et al., 1988). This would imply that the traditional model cannot illustrate the complexity of the consumer decision-making processes in the real world since the consumers might move, skip or reorder

among stages (Dorn et al., 2010; Karimi et al., 2013; Langley, 1999).

On the other hand, several earlier theories on predicting behavioral intention have been studied intensively depicting individuals' decision-making. The Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) address individuals' motivational factors as predictors of behavioral intention. Moreover, the processes of TRA and TPB depend on attitudes toward the behavior and social normative perceptions (Ajzen & Fishbein, 1980; Fishbein, 1980). From an information systems theory perspective, the Technology Acceptance Model (TAM) explains how a consumer accepts and uses a technology (Davis, 1989). Operationalization of TRA has been rooted in the concept that attitudes are subject to expectations or beliefs related to attributes of the object and evaluations of those attributes (Fishbein, 1967). This expectancy-value is widely applied in psychology, including attitude theories and decision-making theories, for decades (e.g., Edwards, 1954; Rosenberg, 1956).

Despite their differences, these theories and models suggest that personal beliefs may be reinforced by intentional experiences, thereby shaping behaviors in a particular way, especially as reflected in the TPM algorithmic pathways. These differences and similarities characteristics between these theories and models are described in detail below.

TAM was explored in order to examine customer's behaviors and their connection with consumer's technology acceptance (Davis and Warshaw, 1989). TAM represents the process by which people apply and accept new technology in their behaviors (Davis and Warshaw, 1989). On the other hand, in the TRA and TPB models, decision-makers might consider the activity's implications reflected on being involved in or not involved in a specific behavior (Ajzen, 1991; Fishbein, 1980).

Taylor and Todd (1995) compared the TAM to the TPB and found similar explanatory power of both, as well as differences. While the TAM demonstrates its strength in predicting usage, the TPB suggests a more specific process of behaviors. Shim et al. (2001), Limayem et al. (2000), George (2004), Vijayasathy (2004), Kim and Park (2005) have shown that the two theories emphasize the same element that influences customers' behaviors, that is the attitude toward e-commerce.

According to Ajzen (1991), Davis (1989), and Fishbein (1980), these models explored the elements of planned activities based on consumer attitude and how they impact on customer intention. Nevertheless, the pathways that lead a customer to a particular attitude and intention were not considered in the models, and this is where the TPM algorithmic pathways can extend the literature. In other words, according to the TPM, individuals' cognitive processes leading to decision choices may not be recognized. Moreover, these models

explored customers' perceptions, such as perceived usefulness and perceived ease of use in TAM; attitude and subjective norm in the TRA model; and attitude, subjective norm, and perceived behavior control in the TPB model. These models help to understand customers' behaviors when examining perceptions and to evaluate (judging) before deciding (behavior intention). Nevertheless, they disregard the role of information before judgment and making a final decision; and this is one of the TPM contributions.

In summary, scholars have developed the models above aiming to explore consumer behavior and decision-making, which identify critical factors that affect a customer's shopping behavior in the online environment, especially in a mobile environment (Chen et al., 2018; Cho & Sagynov, 2015; Wang & Yu, 2017). TRA, TPB and TAM have been examined in different online shopping studies for decades (Gupta & Arora, 2017; Paul et al., 2016; Rehman et al., 2019; Tandon & Kiran, 2019). These theories and models can display the influence of individual characteristics, such as perceived behavioral attitude and control, and online clients' behavior (Lee et al., 2007). Furthermore, these characteristics may be shaped by an individual's beliefs (Gefen et al., 2003; Hsu et al., 2006; Lee et al., 2007), which can be grounded in feelings, norms, attitudes, and beliefs (Davis and Warshaw, 1989; Ajzen, 1985, 1991; Fishbein, 1980).

Also, TPM algorithmic pathways contribute to the literature since the aforementioned models do not consider the *stages* that online consumers might follow during their shopping journey. Thus, this paper applies the TPM to demonstrate the different routes that customers might use to shop for different products/services by investigating algorithmic purchase decision pathways.

## Modelling the Online Purchase Decision Pathways Based on the Throughput Model (TPM)

According to the implementation of the TPM and its value in the online environment, algorithms of purchase decision pathways are modelled and may be captured in AI tools, such as machine-learning or deep learning.

### The Throughput Model

TPM was explored by Rodgers (1997; 2020) to clarify six dominant pathways aligned with six dominant ethical theories (Rodgers, 2009; Rodgers & Al Fayi, 2019) that an individual might follow during the decision-making process. This type of modelling is particularly useful since customers have various viewpoints, education or social status. Customers can also modify or move their decision-making through their understanding and considering the benefit of the six dominant routes.

There are four main concepts (including perception, information, judgement and decision choice) which were established to be influential in the decision process (Foss & Rodgers, 2011; Rodgers et al., 2019). First, perception (P) indicates a condition that consists of organizing and classifying information. Following, information (I) represents inbound data from tasting, hearing, seeing, smelling, and touching senses. Data is transferred to relevant and reliable information by higher-level human processes. Later, judgement (J) is a process of ordering and classifying the “perception” and “information” features of the decision-making process employing two different methods, namely (1) compensatory (choosing the highest value choice between two choices) and (2) non-compensatory (modifying the general compensatory method by way of adding and summing the criteria value). Lastly, decision choice (D) relates to the foremost estimated value, which can be a result of a selection dependent on individual capability and intended plans. Figure 2 illustrates six algorithmic ethical pathways to the process of decision-making.

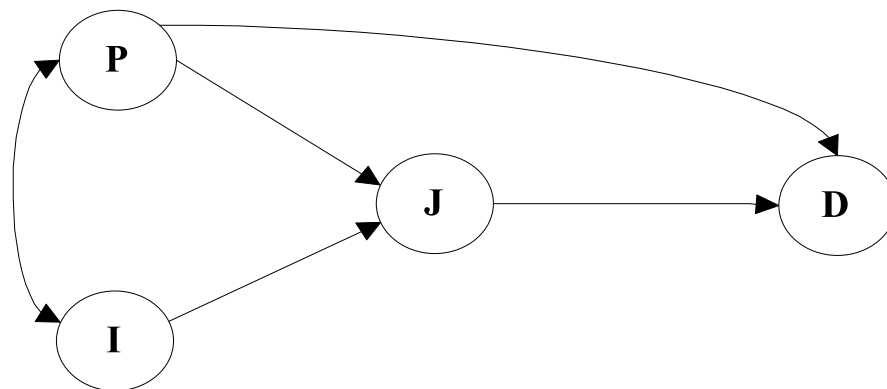
The TPM outlines the following six dominant ethical pathways that influence a decision choice (Rodgers and Gago, 2001).

- (1)  $P \rightarrow D$  depicts the ethical egoism pathway (preference-based), which stresses that individuals are always motivated to act in their perceived self-interest. Here an individual with a certain level of expertise or knowledge plans without the aid of information.
- (2)  $P \rightarrow J \rightarrow D$  describes the deontological pathway (rule-based), which stresses an individual’s perceived understanding of rules, even if the present information may be contradictory.
- (3)  $I \rightarrow P \rightarrow D$  focuses on the utilitarian pathway (principle-based) that is related to consequences, as well as the greatest good for the greatest number of individuals.
- (4)  $I \rightarrow J \rightarrow D$  indicates the relativism pathway, which is exceedingly dependent on changing information that underscores the relativist position, which adopts the notion that people use themselves or the individuals surrounding them as their foundation for defining ethical standards.
- (5)  $P \rightarrow I \rightarrow J \rightarrow D$  stresses the virtue-ethics pathway, which specifies individuals’ practice of good behavioral in terms of their character and honesty in situations to bring about good consequences.
- (6)  $I \rightarrow P \rightarrow J \rightarrow D$  symbolizes the ethics of care (i.e., stakeholders’ viewpoint) perspective pathway, which adopts the available information, and then influences a person’s perception from a relational and context-bound approach toward morality and decision making. Further, it focuses on a willingness to listen to distinct and previously unacknowledged perspectives.

### TPM Value in the Online Environment

Previous literature has shown that the TPM can be applied in the mobile commerce environment (Rodgers, 2010). The TPM might support businesses in understanding, forecasting, and modifying online consumer purchase decisions through the six different algorithmic pathways. This model, which assists people in understanding useful knowledge, offers an in-depth analysis of the various stages affecting decisions so that it allows marketers and organizations to study information and efficient process in several stages before making a decision choice. The TPM can assist to

Where  $P$ = perception,  $I$ = information,  $J$ = judgement, and  $D$ = decision choice.



Source: Rodgers, 1997; 2006

**Fig. 2** The throughput model. Where  $P$  perception,  $I$  information,  $J$  judgement, and  $D$  decision choice



create a conceptual structure, recommend a series of connections and relationships, or develop an algorithmic equation system.

In addition, consumers can be shopping for the same products and the route of each customer can be different from others (Pavlou et al., 2007) because of their adaptive abilities of decision tasks (Bettman et al., 1998; Dorn et al., 2010; Payne et al., 1988). Thus, the customers might have various paths to making final decisions when shopping online (Lian & Lin, 2008; Liu & Wei, 2003; Pascual-Miguel et al., 2015). While the TPM may be used to create enabled robust algorithms of purchase decisions in the online environment, it can explore the purchase algorithmic pathways for online customers when they shop for products/goods.

The next section investigates the online purchase algorithmic pathways based on the TPM.

### Modelling the Purchase Decision Pathways

The 5-stage buyer's decision process can be tailored into the TPM to investigate the six algorithmic pathways in online decision-making behavior (see Fig. 3). First, perception pertains to "defining the problem" (Rodgers, 1997) that can be characterized as "need recognition." In other words, consumer needs can be represented as a subset of perception, which can be recognized and fulfilled through the attainment of products or services.

Second, information can be described as reliable and relevant. In these purchase decision pathways, information source can be viewed as "related product information." Consequently, after delineating the "need," online customers may endeavor to process the information that may stimulate the acquisition of products/services that they intend to purchase. The foundations of this information may commence

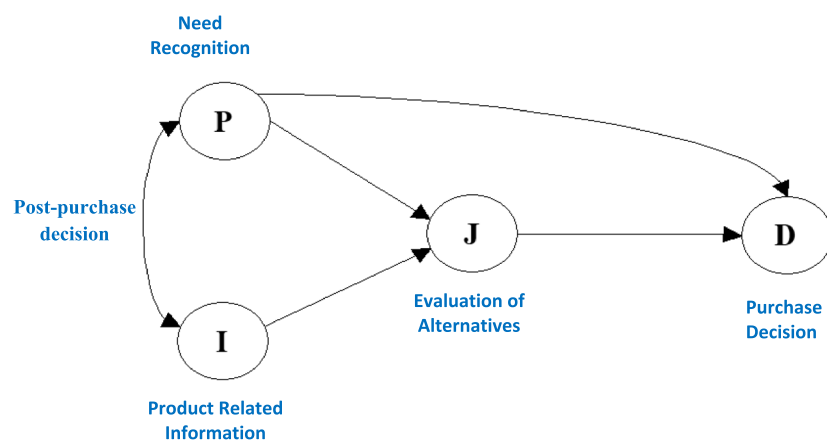
from their personal involvement or come from their reference groups such as relatives, friends, colleagues, public information, etc.

Third, the judgment stage highlights "analyzing perception and information" that can be described as "evaluation of alternatives" to pick the best choice to purchase. In this step, consumers organize the extent of brands or products' criteria/options (consideration set, induced set or awareness set) (Campbell, 1969; Howard & Sheth, 1969; Solomon, 2006) in order to make a comparison among them to purchase. This process is associated with the brands or products that buyers consider acceptable for their next purchase (Howard & Sheth, 1969). In addition, this process may be condensed to a few features grounded on peoples' criteria namely, quality, price, previous exposure, brand awareness and more (Brown & Wildt, 1992; Campbell, 1969; Howard & Sheth, 1969; Roberts & Lattin, 1991).

Fourth, decision choice pertains to "the utmost expected value solution." In this step, individuals may anticipate purchasing products/services that appear to be the choicest for them. Researchers have indicated that online shopping intention may lead to online purchasing decision choices (Taylor & Laohapensang, 2009; He et al., 2008; Pavlou & Fygenson, 2006; Carlos Roca et al., 2009). Hence, decision choice, in this instance, can be referred to as "purchase decision."

The post-purchase decision is portrayed by the TPM coherence relationship of perception and information (i.e., PI). That is, analogous to Bayesian statistic (Bolstad & Curran, 2016), the "information" concept is continuously revising a consumer's perception. That is, prior purchasing decisions (i.e., post-purchase decision) are portrayed by the "information" construct. In addition, consumers' previous decisions are absorbed by information sources, which are underscored by a purchased product or service. Therefore, the PI correlation

**Fig. 3** Algorithmic modeling of consumers' decision processes



Where: P = need recognition, I = information searching, J = evaluation of alternatives, D = purchase decision

Arrows = The hypothesised pathways from one construct to another

Source: Adapted from Rodgers, 2006

operates in part as a post-purchase decision framework that is similar to a neural network.

A neural network is a class of computer software, which is inspired by humans' biological neurons (Barnett & Cerf, 2017). Moreover, neural networks can support machine learning in that it can imitate pattern recognition or match like the PI bond as it learns to decipher a problem (Rodgers, 2020). Finally, this methodology can provide a machine learning apparatus (supervisory or non-supervisory) for consumers' purchasing behavior. The AI machine learning characteristic of the TPM allows the algorithmic pathways the proficiency to robotically learn and improve from experience (i.e., PI) without being openly programmed. Machine learning underscores that the TPM can access data and utilizes it in order to learn from consumers' purchasing behavior.

The six algorithmic pathways demonstrate how customers' decision-making affects different possible routes. Furthermore, the six pathways can be grouped into three different steps in the decision-making process. The proposition of each algorithmic pathway is explained as follows.

One-step decision-making pathway:

1.  $P \rightarrow D$ , quick buying pathway

Two-step decision-making pathways:

2.  $P \rightarrow J \rightarrow D$ , selected buying pathway.
3.  $I \rightarrow J \rightarrow D$ , casual buying pathway.
4.  $I \rightarrow P \rightarrow D$ , impressionable buying pathway.

Three-step decision-making pathways:

5.  $P \rightarrow I \rightarrow J \rightarrow D$ , traditional buying pathway.
6.  $I \rightarrow P \rightarrow J \rightarrow D$ , modern formal buying pathway.

These above-mentioned algorithms may be viewed as machine learning (or deep learning) mechanisms for training how consumers might approach a decision obstacle by using one of six different purchase pathways. Consequently, this technique can be tailored to different types of pathways, which consumers may use in their decision-making processes by implementing apparatuses such as machine learning and neural network algorithms. In other words, these purchase decision algorithms can support intelligent advertising through machine learning and deep learning by capturing consumer insights. The next section discusses how intelligent advertising can benefit from these purchase decision routes.

## Intelligent Advertising Enhancement of Algorithmic Purchase Ethical Decision Pathways Based on Multiple Neural Networks

Based on modelling the purchase decision pathways, the authors suggest several novel ways for marketers and advertisers to apply in intelligent advertising supported by machine learning. To date, a paucity of research has systematically assessed the ethical issues encountered or considered by those using the Internet purchasing habits. This is where TPM, as highlighted by six dominant algorithmic pathways, can assist customers and marketers.

In addition, the ability of consumers to make better quality decisions in online stores is related to their ability to take advantage of the characteristics of online settings that enhance decision quality, while avoiding those which impair it. As discussed previously, the TPM ethical algorithmic pathways provide characteristics that include (1) time constraints, (2) cognitive costs, (3) perceived risks, and (4) product knowledge.

First, the algorithmic pathways (e.g., quick buying pathway) considers *time constraints*, which accounts for the physical effort required to conduct a search (Johnson et al., 2003). Moreover, the typical online consumer is "time starved" and shops online to save time (Bellman et al., 1999). Online consumers also exhibit search and evaluation patterns that are consistent with time constraints (Sismeiro & Bucklin, 2004).

Second, the algorithmic ethical pathways involve *cognitive costs*, which are lower in digital environments since cognitive effort can be shifted to the recommendation agents that are typically obtainable in these environments (Johnson et al., 2003).

Third, based upon a particular algorithmic ethical pathway engaging *perceived risks*, consumers require stronger signals (e.g., brand names, retailer reputation) to lessen risk (Biswas & Biswas, 2004). Further, risk considerations may be offset by the convenience of a particular algorithmic pathway when purchasing online (Bhatnagar et al., 2000).

Fourth, the algorithmic ethical pathways employed can enhance *product knowledge* for consumers. In addition, the Internet coupled with AI algorithms can proficiently research products that are an important source of information (Ratchford et al., 2003).

## Consumer Purchase Decision Pathway Algorithms Driving Intelligent Advertising Tasks

To attract more attention to the opportunities that the algorithmic purchase decision pathways create for advertisers and marketers, it is necessary to understand how the

**Table 1** Intelligent advertising message system to correspond to algorithmic purchase decision pathways

Algorithmic purchase decision pathways and underlying ethical positions	Symbolic purchase decision pathways	Symbolic intelligent advertising message system	Intelligent advertising message system
Quick buying pathway (ethical egoism—preference-based)	$P \rightarrow D$	$A1 \rightarrow A4$	Quick advertising message system
Selected buying pathway (deontology—rule-based)	$P \rightarrow J \rightarrow D$	$A1 \rightarrow A3 \rightarrow A4$	Selected advertising message system
Casual buying pathway (utilitarianism—principle-based)	$I \rightarrow J \rightarrow D$	$A2 \rightarrow A1 \rightarrow A4$	Casual advertising message system
Impressionable buying pathway (relativist-based)	$I \rightarrow P \rightarrow D$	$A2 \rightarrow A3 \rightarrow A4$	Impressionable advertising message system
Traditional formal buying pathway (virtue ethics-based)	$P \rightarrow I \rightarrow J \rightarrow D$	$A1 \rightarrow A2 \rightarrow A3 \rightarrow A4$	Traditional full advertising message system
Modern formal buying pathway (ethics of care—stakeholder position)	$I \rightarrow P \rightarrow J \rightarrow D$	$A2 \rightarrow A1 \rightarrow A3 \rightarrow A4$	Modern full advertising message system

Source Authors generated

purchase decision algorithms link to intelligent advertising tasks during each step of these pathways.

At the input level for machine learning or deep learning, consumer background information and decisions are typically collected and analyzed, which are derived from multiple sources such as the Internet of Things (IoT). Further, at layer 1, customers' needs and wants (need recognition stage) are predicted. Although customers intrinsic "needs" or "wants" are unconscious, implicit, unclear, undefined (Hatton et al., 2017), proxy information from the IoT at times are good indicators (Bhattacharyya & Rahman, 2004; Saldivar et al., 2016). For example, customers' information searching actions may serve as a substitute for product improvement awareness. (Bettman & Park, 1980; Herr, 1989; Rahman & Kharb, 2018). Moreover, this process also enables customers to learn more about a product's features and competing brands when they gather related information (Sachdeva, 2015).

Therefore, marketers and advertisers are more aware of potential customers' propensities. In other words, customers are recognizing their needs for the products or "increasing the brand's visibility and emphasizing key reasons for consideration" (Kietzmann et al., 2018, p. 265).

In layer 2, need recognition and information searching are considered again to determine if they appear or disappear in this step of the consumer journey. Based on the need recognition or information searching realized in this stage, marketers and advertisers can more adeptly correspond to the actions of the consumers.

In the next layer, an evaluation of alternatives (comparison among brands on price, quality, features, etc.) is involved. Evaluation of alternatives involves selecting the brands or products to purchase based on a set of considerations (also called the evoked set or awareness set) (Campbell, 1969; Howard & Sheth, 1969; Solomon, 2006). This consideration set represents brands or products, which are

alternatives narrowed down, depending on various personal criteria such as brand awareness, previous exposure, price, quality, etc. (Brown & Wildt, 1992; LeBlanc & Herndon, 2001; Roberts & Lattin, 1991). The consumer decision is made by considering this reduced set of brands and products (Erdem & Swait, 2004). Hence, this process of advertising chores may instill a higher trust level for customers (Batra & Keller, 2016).

Next, the purchase action (make a transaction, payment, etc.) is encapsulated in layer 4. After evaluating these alternatives, the shoppers may intend to purchase the products/services which they think are suitable for them. Furthermore, this stage depicts how advertisers may consider emphasizing convenience and information about where to buy or offering purchase incentives that can influence customers' responses.

### Intelligent Advertising Message Along with the Consumer Purchase Decision Pathway Algorithms

The algorithmic purchase decision pathways can help marketers and advertisers not only identify the advertising tasks but also select the "more appropriate advertising message" that supports and keenly influences the next actions of potential consumers. Machine learning may help organizations grasp the appropriate steps in the customers' purchase decision pathways. In the AI age, advertising message focuses on personalization and contextualization in real-time (Chen et al., 2019). Therefore, it is important for advertisers to understand their customer's decision journey and advance the appropriate advertising message for them.

According to the six dominant purchase decision pathways in Table 1, AI ethical considerations can support marketers in choosing the appropriate messages for potential consumers (Rodgers et al., 2020). That is, each customer has

his/her different decision path so the list of intelligent advertising for him/her is different from others. For instance, if an individual shops via the quick buying pathway, advertising message 1 (A1) and advertising message 4 (A4) will be delivered in a corresponding need recognition and purchase decision-making stage (A1 → A4), while another customer may follow a modern formal buying pathway, which involves A2 → A1 → A3 → A4.

### Intelligent Advertising Process Along with the Consumer Purchase Decision Pathway Algorithms

AI technologies can assist in a new set of advertising process, which includes consumer insight discovery, advertising creation, media planning and buying, and advertising impact evaluation (Qin & Jiang, 2019). Hence, purchase decision algorithms may influence the four-step process of intelligent advertising.

Consumers' insight discovery refers to the use of analytics technologies to analyze the consumers' digital lifestyles and obtain awareness into the demand of the consumers (what consumers really want) (Qin & Jiang, 2019). Through the algorithmic decision routes, the consumers' digital profiles, which are frequently collected related information such as gender, age, origin, hobbies, recent consumption or purchasing power, are gathered and recorded. By different classification methods, the consumer behavior data can come from multisource and mass information (Liu et al., 2018). This relevant data can be used to match advertising objectives and goals for potential consumers (Qin & Jiang, 2019).

Based on results of consumer insight discovery (Qin & Jiang, 2019) and a development of AI technologies, such as correlation analysis, target semantic extraction, cross-media information retrieval based on sentiment analysis, topic analysis and content (Abbas et al., 2018; Deng, Zhou, et al., 2019), a targeted advertising creation can be combined from the consumers' needs, advertising creative performance, advertising creation and strategic advertising planning (Qin & Jiang, 2019). Purchase decision algorithms assist the marketers in being aware of their consumer's need and activities during the decision journey so that the right advertising creation can be developed for the right customer. For example, the advertising creation for one customer at the need recognition stage may be different from information searching or evaluation of alternatives or purchase decision stage.

Furthermore, the step for media planning and buying enables personalized advertising content to be delivered directly to the consumers based on their behavioral trajectories in daily-use media, online shopping media and information-acquisition media. This step combines the planning and choosing the right combination of advertising channels

with media buying (Qin & Jiang, 2019). When the advertisers understand which stage their customers are in, they can reach their potential customers based on the suitable personalized advertising content at the right channel. For instance, when customers are at the information searching stage, the advertisers might choose the advertising message which is suitable for their need and wants in the previous stage of decision paths and launch it in searching tools which their customers usually use for getting product-related information.

The last step, advertising impact evaluation, depicts "the acquisition of accurate and timely feedback from the ad impact data collected in real-time monitoring of media planning and buying" (Qin & Jiang, 2019, p. 342). With algorithmic purchase decision routes, organizations can realize whether the advertising message may impact their customers. If their customers move to the next stages or come to the final option, the advertising message may work effectively. If their customers do not act or go back to the previous stages, it seems that the advertising message may be inefficient. Based on this result, the advertisers can adjust their advertising plan or message to get in touch with their potential customers more successfully.

### Conclusion and Future Research

This research provides insight into drivers of intelligent advertising, such as intelligence modelling, in the AI era. First, the research explored the stimulus of AI and its related subsets of machine learning, deep learning, and neural networks on advertising. Second, this paper provided a basis to apply ethical considerations for intelligent advertising in customers' algorithmic purchase decision pathways. This technique may assist marketers and advertisers in comprehending and reaching suitable ethical concerns for customers. This process is useful since biased human judgments can influence AI-based systems in two distinct manners. The first is bias in the data that systems are trained from for implementation. A second source of bias transpires in the way algorithms are developed for application. This paper suggests six ethical algorithmic pathways that may address the latter problem. Moreover, algorithms are responsible for assisting customers' online decisions that impact their decision-making more than ever before. Nonetheless, it is becoming progressively apparent that this is not always being done fairly or transparently. Further, not implementing the correct algorithm may trigger harm to customers and influence behaviors in morally dubious ways.

Ethical algorithmic pathways implanted in the TPM refers to the process of evaluating and choosing among purchasing alternatives in a manner consistent with ethical principles. In making ethical decisions, it is necessary to understand

different algorithmic ethical pathways to eliminate unethical options and support the best ethical alternative. Connecting ethical theories to algorithmic pathways allows us to better understand the cognitive and information components that are undergirding decision-making used in AI systems.

In addition, based on the TPM, this article examines a more inclusive comprehension and springboard of the numerous ethical algorithmic purchase decision routes of consumers in the online environment. Further, this paper serves to fill an existing research gap in the literature by illustrating how purchase decision-making ethical algorithms based on the TPM are more transparent and unbiased. Moreover, by emphasizing the different perspectives of purchase decision-making ethical algorithms, this paper advances algorithms for intelligent advertising tasks, messages, and processes.

## Research Implications

From a theoretical perspective, this study contributes to the literature in the following way. This paper commences by stressing that the TPM can designate the buyer's characteristics by showing six dominant ethical algorithmic purchase decision pathways for online consumers. Supplementary, this methodology elucidates each purchase decision pathway in detail. Depending on the type of products/services, this procedure has three levels (i.e., one, two and three-step decision-making algorithmic approaches) for the consumer to decide. Further, this paper provides distinctive insights and a wide-ranging reflection on the utilization of the TPM in consumer purchase decisions. In addition, this decision-making model makes use of neural networks to better explain marketing post-purchase decisions by consumers. Second, this paper explores the significance of these purchase decision algorithms for intelligent advertising. By breaking down the four concepts of the TPM and applying them in the consumer decision-making process in four layers like a neural network, these ethical algorithmic purchasing decision models might support intelligent advertising, which can be used in machine learning and deep learning to predict and approach the right advertising tasks and message for potential shoppers.

The TPM advances the marketing discipline as well as other disciplines since it is a process model that (1) allows ethical considerations and transparency by opening the black box, and (2) imitates human brain neural network function by providing parallel routes in two stages (i.e., IJ and PJ in the first stage and PD and JD in the second stage), (3) includes a figurative neural network function (i.e., PI) that trains perception for selection of certain information for later processing and mimics information updating from outside sources, and (4) provides,

before a decision is made, different cognitive processing stages, which can be broken into several ethical pathways, namely: ethical egoism, deontology (i.e., rule-based), relativist, utilitarianism, virtue ethics, and ethics of care (i.e., stakeholders' perspective).

In summary, the ethical algorithmic pathways' impact on people, organizations, and society shapes practically every question of business and public policy. Nonetheless, core issues, such as bias, transparency, ownership, and consent, can be subject to different meanings in different contexts. Therefore, the six algorithmic ethical pathways may alleviate these problems.

## Practical Implications

From a practical perspective, this study provides insightful recommendations for advertisers and marketers in understanding the six dominant ethical algorithmic purchase decision routes consumer use in the online environment as well as the algorithms for intelligent advertising to understand the advertising tasks, message, and process. These proposed models may assist organizations in predicting their consumers' purchase decision routines as well as exploring the right advertisement for the right customers based on available data on their customers' behavior, which can be supported by AI-enhanced machine learning, neural networks, and deep learning apparatuses. Besides, these ethical algorithmic models might assist advertisers and marketers in understanding the different routes of their target consumers so that they can change the advertising message or task, which might lead their consumers to transfer from the intermediate purchase pathways to the simple pathway.

In summary, AI is part of every individual and organization's life in a variety of ways. It exists in the form of spam filters, recommendation engines, translation services, chatbots, personal assistants, search engines and fraud detection systems. TPM dominate concepts of perception, information, judgment, and decision choice provide the necessary ingredients for diverse ethical decision-making. The TPM six ethical algorithmic pathways can produce differentiated advertising automatically to meet consumers' needs, embracing advertising copy template generation, advertising words sentiment analysis, template matching and personalized user tag classification. AI, along with the TPM ethical algorithmic pathways, can be taught by integrating into every discipline with the understanding the role of ethical considerations. Further, educators, managers, administrators ought to welcome the idea that AI is not overwhelming or an elective topic but utilized as an effective tool to evaluate critical thinking. Finally, customers' edification and understanding of the six ethical algorithmic pathways can better assist in the protection of consumers' privacy rights.



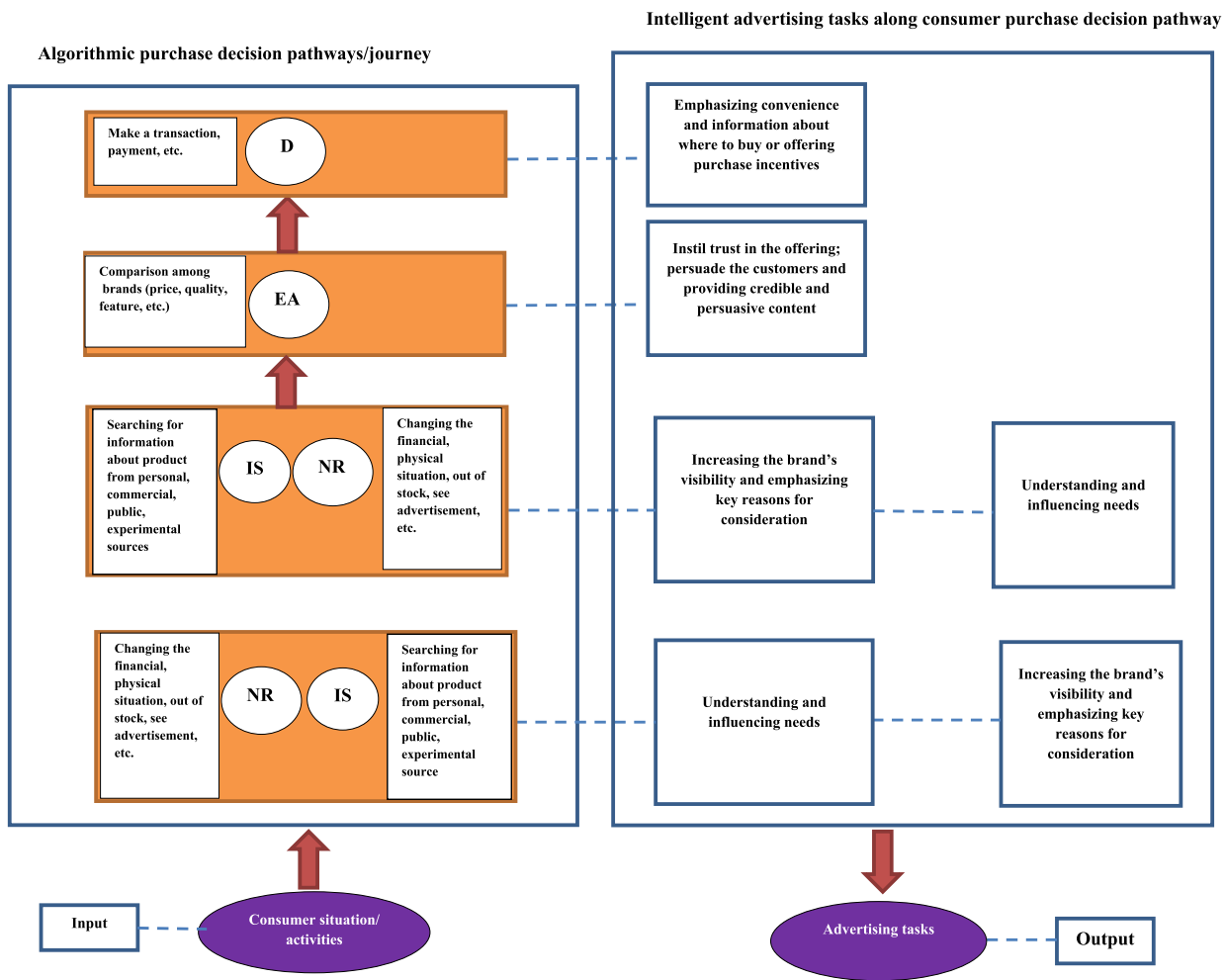
### Study Limitations

Despite the contributions of the study, it has some limitations. First, one limitation relates to the absence of training data for the model applied to machine learning. Nonetheless, in the future, other studies should relate the TPM with machine learning coupled with neural networks and deep learning. Therefore, additional work is required to build the formula for purchase decision-making to provide a complete algorithmic online purchase decision-making model, which may become a powerful tool for organizations. Second, it is necessary to explore the relationship between the algorithmic purchase decision pathways and intelligent advertising

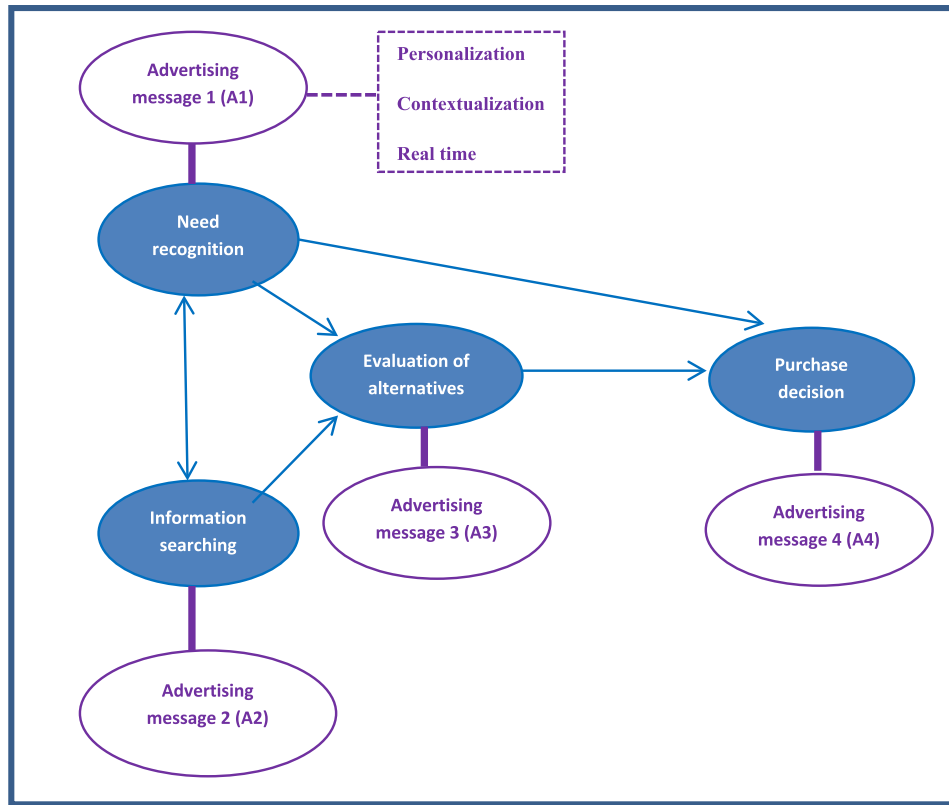
modelling. Finally, another limitation of this study is that the authors have not collected comparable data to test the model. Therefore, future research should include data from different sources to refine the constructs of the purchase algorithmic decision pathway model along with quantitative assessments.

### Appendix

See Figs. 4, 5, and 6.



**Fig. 4** Intelligent advertising task along with the consumer purchase decision pathway algorithms. *NR* Need recognition, *IS* information searching, *EA* evaluation of alternatives, *D* purchase decision. *Source* Authors generated



Source: Authors generated

Fig. 5 Intelligent advertising message system along algorithmic decision pathways

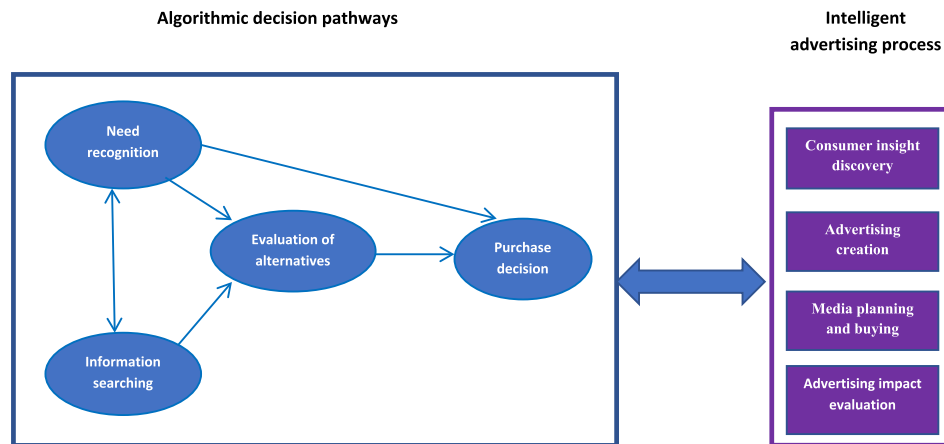


Fig. 6 Intelligent advertising process along with the consumer purchase decision pathway algorithms

**Declarations**

**Conflict of interest** There is no conflict of interest for this paper.

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