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Conceptual Framework—Artificial Intelligence and Better Entrepreneurial Decision-Making: The Influence of Customer Preference, Industry Benchmark, and Employee Involvement in an Emerging Market

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Abstract: Purpose: Technology initiatives are now incorporated into a wide range of business domains. The objective of this paper is to explore the possible effects that *Artificial intelligence* systems have on entrepreneurs' decision-making, through the mediation of customer preference and industry benchmark. **Design/methodology/approach**: This is a non-empirical review of the literature and the development of a conceptual model. Searches were conducted in key academic databases, such as Emerald Online Journals, Taylor and Francis Online Journals, JSTOR Online Journals, Elsevier Online Journals, IEEE Xplore, and Directory of Open Access Journals (DOAJ) for papers which focused on *Artificial intelligence (AI)*, *Entrepreneurial decision-making*, *Customer preference*, *Industry benchmarks*, and *Employee involvement*. In total, 25 articles met the predefined criteria and were used. **Findings**: The study proposes that *Artificial intelligence* systems can facilitate better decision-making from the entrepreneurial perspective. In addition, the study demonstrates that employees, as stakeholders, can moderate the relationship between *Artificial intelligence* systems and better decision-making for entrepreneurs with their involvement. Moreover, the study demonstrates that customer preference and industry benchmark can mediate the relationship between *Artificial intelligence* systems and better entrepreneur decision-making. **Research limitations/implications**: The study assumes a perfect ICT environment for the smooth operation of *Artificial intelligence* systems. However, this might not always be the case. The study does not consider the personal disposition of entrepreneurs in terms of ICT usage and adoption. **Practical implications**: This study proposes that entrepreneurial decision-making is enriched in an environment of *Artificial intelligence* systems, which is complemented by customer preference, industry benchmark, and employee involvement. This finding provides entrepreneurs with a possible technological tool for better decision-making, highlighting the endless options offered by *Artificial intelligence* systems. **Social Implications**: The introduction of AI in the business decision-making process comes with many social issues in relation to the impact machines have on humans and society. This paper suggests how this new technology should be used without destroying society. **Originality/value**: This conceptual framework serves as a valuable organizational spectrum for entrepreneurial development. In addition, this study makes a valuable contribution to entrepreneurial development through *Artificial intelligence* systems.

Keywords: entrepreneurship; decision-making; artificial intelligence; employee involvement; customer preference

1. Introduction

Entrepreneurial development studies are rapidly gathering momentum in the 21st century, due to the growing recognition of its potential in wealth creation and general economic development (Robson et al. 2009). Academics and practitioners acknowledge the immense benefits accrued from entrepreneurial development (Barringer and Ireland 2010).

Entrepreneurs innovate, create new business ideas, and take financial risks in converting perceived opportunities to viable business ideas. As people who employ limited, heterogeneous resources under uncertain conditions in order to cater to customer preferences and make a profit, entrepreneurs engage in largely experimental processes, with context affecting this experimental process (Shane and Venkataraman 2000).

Entrepreneurs can change the economic situation of emerging economies with the right environment and technology tools. Entrepreneurs can utilize the appropriate technology tools to detect business trends and offer valuable insights, which are required for business decisions (Akinyemi and Adejumo 2018).

The impact of technology on entrepreneurial development cannot be overstated, which explains the global commitment to entrepreneurial development. For instance, the Small Business Innovation Research (SBIR) program in the USA remarkably improved the survival and growth rates of Small and Medium Enterprises (SMEs) (Akinyemi and Adejumo 2018). Similar policies have been implemented in European Union states to promote entrepreneurial activities and motivate SMEs to conduct business globally (Akinyemi and Adejumo 2018). Similar policies exist in varying degrees to promote entrepreneurial initiatives in emerging economies. For instance, Ghana has established the Ghana Enterprises Agency (GEA 2021) to improve the knowledge, skill, behavior, and attitudes of individuals and groups who aspire to be entrepreneurs (https://gea.gov.gh (accessed on 23 November 2021)).

The contemporary social and business environment is experiencing an intensive wave of digitalization. Global economies have evolved from brick and mortar to convenience at the click of buttons. This modernization influences business functions and transforms enterprises and societies (Wirtz and Zeithaml 2018). The rapidly improving technology is transforming all business sectors, and as technology becomes better and more convenient, organizations seek ways to utilize it to gain a competitive advantage (Wirtz and Zeithaml 2018).

Technology advancement and its resultant connectivity of the society and business environment continue to lead to the creation of massive volumes of data (Obschonka and Audretsch 2020). A significant feature of data in modern business is a constant exponential growth in volume. Over 90% of all existing data has been generated (IBM 2020). Presently, businesses thrive on the foundations of data and the ability of business organizations to gather, interrogate, manage, and utilize data to differentiate their offerings (George et al. 2014). Businesses use data to obtain a proper understanding of their operations, especially insights into the behavior of their customers, in order to facilitate strategic decision-making.

The decision-making process in business involves understanding the trends and patterns in business growth, which are supported by data. The ability to transform collected data into value-for-economic benefit/profit is a skill (George et al. 2014). In other words, accurate data are not obtained solely for the creation of practical insight, but also for their implementation in strategic business decision-making. Therefore, this is expected of entrepreneurs due to the significance of making precise decisions under unpredictable conditions, in order to discover business opportunities (Shane and Venkataraman 2000). Entrepreneurs take high-risk decisions (Baron 2004) under highly unpredictable, ambiguous, time-constrained, and emotionally strained contexts.

The efficient exploitation of data has accompanied the growth of information technology architecture, thereby influencing decisions concerning the desirability and viability of entrepreneurial ideas, making entrepreneurial decision-making primarily knowledge-based (Wiklund and Shepherd 2008). Therefore, knowledge-based information systems are valuable tools for entrepreneurs, enabling evidence-based decision-making in complex business situations. Moreover, artificial intelligence (AI) based applications are developing in a wide range of knowledge-based domains (Agrawal et al. 2019). The advancement of artificial intelligence (AI) has altered the dynamics of the business world. AI discussions have centered on its transformational potential for efficiency in pursuing commercial value creation, which helps entrepreneurs evaluate, discover, and exploit opportunities and solutions under business uncertainties (Agrawal et al. 2019). Artificial intelligence comprises building computer systems that can perform tasks that demand human intelligence, for instance, making decisions. A significant application of AI results in improved decision-making and better business performance (Agrawal et al. 2018; Lévesque et al. 2020).

In this paper, artificial intelligence (AI) systems comprising advanced data analysis, data mining, cloud computing, and machine learning technologies are discussed and posited to influence better entrepreneurial decision-making through customer preference and industry benchmark mediation. The study further posits that artificial intelligence (AI) systems directly influence better entrepreneurial decision-making and argues that employee involvement may moderate the direct influence of AI systems on better entrepreneurial decision-making. Employee involvement, encapsulated in the circular economy theory, is considered fundamental to the value delivery process and has consequences for firm performance (Payne et al. 2009; Prahalad and Ramaswamy 2004).

2. Literature Review

2.1. Artificial Intelligence

Artificial intelligence (AI) refers to a software system designed to conduct tasks that require human intelligence (Huang and Rust 2018). In other words, it refers to a system that can imitate human intelligence in the execution of specific tasks, for example, visual insight, speech recognition, recommendation, categorization, and decision-making.

AI has four key elements:

1. Expert systems;
2. Heuristic problem solving;
3. Natural language processing; and
4. Vision.

Natural language processing offers an interaction between people and machines in their natural language. An expert system is a mechanical system where valuable human knowledge is embedded into machine memory to provide intelligent guidance, clarify, and justify its choices or needs. Expert systems handle situations and deliver performance by relying on a vast dataset of precise, specialized knowledge concerning a specific field of interest. Heuristic problem solving is intended to assess a limited scope of solutions and may comprise certain presumptions to find the best solutions. Vision is the capacity to identify shapes and features, to mention a few, automatically (Huang and Rust 2018; Guibao 2016).

Artificial intelligence (AI) is a term propounded by John McCarthy in 1956. It is defined as "the science and engineering of making intelligent machines" (McCarthy 2000). Computer science focuses on the study and design of intelligent agents that notice their environment and take actions that increase their likelihood of success. Therefore, machines programmed to perform decision-making tasks demand artificial intelligence from human intelligence (Syam and Sharma 2018). The scientific goal of AI is to comprehend intelligence by designing computer software programs that display intelligence utilizing symbolic inference or cognition inside the machine. AI systems are designed to work with their own created programming language to employ information more efficiently (Syam and Sharma 2018). These programming languages employ declarative knowledge, particularly with claims whose truth-value is autonomous of the algorithmic context.

Additionally, the AI system can induce, abstract, and occasionally predict data. The AI system can reevaluate decisions using backtracking of solutions. In other words, the system includes a recollection of past experiences in providing good inference power and quick responses to enable better decision-making (Shankar 2018). In essence, the idea of AI is to integrate large volumes of data with rapid procedures and better algorithms. Eventually, this enables the systems to learn from patterns without the need for re-programming (Vasiljeva et al. 2021; Kaplan and Haenlein 2019).

Furthermore, by identifying patterns in data, AI systems can "reason" and efficiently recommend the ideal options for consumers' specified needs. AI gathers information from unstructured data through personality and sentiment analyses (such as facial coding), which enables businesses to measure the affective state of consumers (Shankar 2018). Then, AI generates content through the following methods:

Natural language generation (NLG): Businesses can utilize AI tools, for example, Wordsmith, for creating human-sounding and original content, from tailored messages to news articles or utilize AI for creating marketing content.

Image generation: Creating realistic pictures and animated movies based on text descriptions.

Speech generation: Offering meaningful voiceovers for business promotional campaigns.

The AI system can make decisions based on priorities, and deal with complexity and uncertainty by relying on technologies, such as extensive data analysis, machine learning, data mining, and cloud computing, etc. (Davenport and Ronanki 2018). A study by Sivathanu and Pillai (2020) in India suggests that the technology orientation of entrepreneurs significantly influences sustainable enterprise performance. Additionally, AI depends not only on its fundamental technology, but also on its business use, such as industry benchmarks and consumers' and employees' engagement (Davenport and Ronanki 2018). By utilizing these tools, AI offers a credible approach to the correct interpretation of external data, demonstrates institutional memory, and exhibits better decision-making processes (Kaplan and Haenlein 2019). Adopting artificial intelligence (AI) seems likely to influence better entrepreneurial decision-making through a more efficient business automation process. AI is documented as one of the new technologies that businesses need to adapt in order to reduce costs, as well as increase performance and competitiveness in the market environment (Vasiljeva et al. 2021).

AI has become integral to voice assistants, commonly manifested as Amazon's Echo, Google's Google Assistant, Microsoft's Cortana, Apple's Siri, etc. These have contributed to the changing consumer behavior, and 27% of the global online population regularly use voice assistants (McCue 2018). The use of voice assistants is projected to increase exponentially from 2018 to 2023 (Juniper Research 2018), which necessitates entrepreneurial AI orientation.

This paper discusses Artificial Intelligence (AI), *Big Data Analysis*, *Machine Learning*, *Data Mining*, and *Cloud Computing*.

2.1.1. Big Data Analysis

Data are an essential ingredient of the digital space. The routine capture of digital information through different applications creates massive data streams of customers, and the expected commercial usage of modern technologies has dramatically expanded the volume and scope of the data gathered by businesses (Obschonka and Audretsch 2020). These data contain valuable customer information that can enhance the strategic development of businesses. Additionally, as data increasingly play a central role in business organizations, entrepreneurs aim to harness them for better decision-making (Obschonka and Audretsch 2020). The volume of acquired data enables entrepreneurs to recognize new business opportunities or future markets using, for instance, household consumer profiles. Big Data has evolved as a term that includes both the technical and commercial components of increased data collection activity (Nunan and Di Domenico 2019). Big Data is the fundamental notion of gathering vast amounts of data from consumers. In other words, it refers to the ability to aggregate and separate comprehensive datasets with very little manual labor.

Big Data is the explosive growth of data, which is mainly due to advancements in data storage technology (Nunan and Di Domenico 2019). Big Data refers to vast amounts of data, which traditional data management approaches cannot handle and process due to their complexity and massiveness (Nunan and Di Domenico 2019). Arguably, Big Data has been described to have volume, velocity, and variety as its fundamental features and ensures cost-effectiveness and innovative information processing techniques for improved understanding, decision-making, and process automation (Beyer and Laney 2012). The idea of Big Data has grown to comprise not only the size of datasets, but the dataset characteristics and data management methods (Ohlhorst 2013; Bi and Cochran 2014). Big Data refers to the real-time analysis of all parts of large data sizes. The decision-making process in an organization requires the assessment of large datasets to comprehend trends and developments in business growth. Therefore, Big Data analytics provides solutions for better entrepreneurial decision-making, enabling the achievement of good returns on investments (Ohlhorst 2013).

Big Data analytics is the comprehensive method of gathering, capturing, and analyzing enormous and diverse datasets in order to find concealed patterns, unidentified correlations, market trends, and consumer preferences that can assist firms in making informed and better business decisions (Obschonka and Audretsch 2020). As a framework enhanced for obtaining, shaping, and stacking unstructured data into databases, Big Data analytics can recognize growth opportunities in new and existing businesses, predict customers' behavior, and assist businesses in making better and more strategic business decisions (Obschonka and Audretsch 2020). Big Data analytics can transform data into value, process, and evaluate how the data that can improve decision-making for the benefit of businesses are handled.

Big Data analytics has an enormous potential for creating value for firms, particularly when properly aligned with business cycles and knowledge needs. It can substantially enhance performance and the nature of entrepreneurs' decisions (Obschonka and Audretsch 2020). Big Data analytics offers valuable insights that could improve entrepreneurial decision-making, particularly in recognizing growth patterns and creating growth opportunities for entrepreneurs (Obschonka and Audretsch 2020). Big Data analytics prepares entrepreneurs to capture, evaluate, store, and manage vast volumes of existing data. Business owners utilize Big Data analytics to discover weaknesses in their services and products, suppliers, and customers, as well as consumer intentions and preferences, to design new and improved products (Obschonka and Audretsch 2020).

Big Data analytics can influence improvements in the efficiency of business operations by helping organizations in predicting unpredictable situations and improving their performance process through cost reduction, best operation plan, smaller inventory sizes, productive labor force, and removal of wastage (Hiba et al. 2017). Big Data analytics is fundamental in business decision-making and can help businesses achieve a competitive advantage (Hiba et al. 2017). Additionally, Big Data analytics can affect the operation process effectiveness and organizational performance (Ghasemaghaei et al. 2015). Utilizing Big Data analytics, entrepreneurs can predict customer behavior and design, as well as enhance marketing strategies and sales planning.

Big Data analytics tools can promote innovation and growth that enable the informed decision-making in companies and can aid in offering new and existing companies unparalleled insight (Obschonka et al. 2020). Utilizing Big Data analytics tools makes entrepreneurs more knowledgeable and puts them in a position to make better decisions and invest wisely (Obschonka and Audretsch 2020). Big Data records are extracted from various applications and platforms and can alter development, as well as fast-track social and economic advancement.

2.1.2. Machine Learning

Machine learning studies computational methods for enhancing performance by automating knowledge acquisition from experience (Brynjolfsson et al. 2018). The goal of machine learning is to offer increased levels of automation in the knowledge engineering process, removing laborious human activities and replacing them with automated methods that enhance accuracy or productivity. This is achieved through finding and using the appropriate regulations in data training.

Machine learning addresses the question of how to develop computers that automatically improve through experience. It is at the core of artificial intelligence and data science (Brynjolfsson et al. 2018). Machine learning refers to the use of artificial intelligence (AI) in order to provide machines with the capacity to automatically learn and upgrade without the direct intervention of humans (Brynjolfsson et al. 2018). In general, machine learning also refers to building and utilizing models based on recognized patterns. This enables the retrieval of important information from enormous data repositories. Machine learning platforms can help in recognizing and understanding trends or common conditions, as well as effectively predicting insights and reactions that help businesses understand key factors and the likelihood of recurrence of specific activities (Brynjolfsson et al. 2018).

Machine learning (ML) also refers to a set of algorithms that enhances the performance of AI. The ML algorithms are mechanically produced from data, and the richer the dataset, the better the performance (Jordan and Mitchell 2015). In other words, ML entails the utilization of algorithms to analyze data, learn from it, and make a conclusion or forecast as a result. ML may involve basic learning and deep learning algorithms.

Basic learning algorithms comprise one phase of learning and are appropriate for examining structured data, such as price, size or time, and for predicting results based on a set of inputs or grouping items per their features (Jordan and Mitchell 2015). Several examples include predicting a consumer's churn, the possibility of default (credit scoring), and detecting fraud in financial transactions. However, deep learning algorithms comprise various learning stages that are systematized in a similar manner to the brain's structure. They are appropriate for assessing unstructured data, including pictures, audio recordings or texts, and can be used for facial recognition, speech-to-text transcription or text reconstitution (Jordan and Mitchell 2015). In contrast to basic learning algorithms, deep learning algorithms fundamentally open new approaches for data-driven decision-making, since few alternative methods are available for processing unstructured data. For instance, to forecast whether a client is likely to churn, an ML method will initially train an algorithm to connect customers' churning rates with their qualities on a subset of data (training dataset). After this step, another data subset will be utilized to authenticate the creation of the algorithm (validation dataset). Additional tests include the predicting ability of the final algorithm on another data subset (testing dataset), before predicting the likelihood of the churn. After the process of segmenting unstructured datasets, deep learning algorithms comprise many iterations (Jordan and Mitchell 2015).

In AI, machine learning algorithms (for example, collaborative filtering, deep learning, unsupervised clustering, and k-nearest neighbors) have evolved as the favored technique for designing applications that comprehend consumer preferences (from their reviews, past product procurement, and use) to identify new products or services that they will possibly like (Pollack et al. 2019). Recommendation engines are typical machine learning applications where users are matched with products/services that they previously liked or may like in the future. These recommendations decrease users' mental burden and assume the duty of finding the best options for consumers to search platforms. Similarly, AI can aid in predicting the customer lifetime value and conversion rate (Pollack et al. 2019). Through assessing trends and learning from data about customers' past behavior at the experimental stage of a product, AI can determine how likely a customer is to buy the premium version or forecast the future value of a specific user.

In AI, machine learning has evolved as the preferred approach for designing practical software for computer vision, speech recognition, natural language processing, robot control, and other applications (Pollack et al. 2019). Several developers of AI systems currently acknowledge that, for various applications, it is simpler to train a system by presenting examples of the preferred input-output behavior than to program it manually by predicting the expected reaction for all of the probable inputs. Likewise, the impact of machine learning has been experienced extensively within computer science and various industries regarding data-intensive challenges, for example, consumer services, fault diagnosis in complex systems, and management of logistic chains (Pollack et al. 2019).

2.1.3. Data Mining

Data mining is the study of gathering, cleaning, processing, evaluating, and acquiring valuable knowledge from data (Chung and Gray 1999). Many challenges exist in domains, applications, formulations, and data depictions of real applications. In contemporary times, practically all of the automated systems produce data for diagnostic or analysis purposes, resulting in a massive accumulation of data (Obschonka and Audretsch 2020). The raw data might be arbitrary, unstructured or in a form that is not instantly fit for computer processing. Data mining analysts utilize a processing pipeline in order to extract the existing data for application-specific objectives, where raw data are gathered, cleaned, and refined into a standard form. The data could be kept in a commercial database system and processed for insights using analytical methods. This processing pipeline is theoretically similar to mining from a mineral ore to a polished product (Chung and Gray 1999). The term "mining" stems from this analogy.

Data mining aims to find valid, new, possibly valuable, and clear connections and patterns that are present in data (Chung and Gray 1999). Data mining aids firms in concentrating on the most valuable data present in their current databases.

Data mining has provided value to a wide variety of industries and has been used to boost profits by decreasing costs and increasing revenue. Several firms utilize data mining to facilitate the customer life cycle management, including obtaining new customers, growing profits from existing customers, and keeping good customers (Chung and Gray 1999). When a firm knows the qualities of good customers (profiling), it can focus on potential customers with similar qualities. By profiling customers who purchased a specific product, a company can concentrate on customers with similar qualities who have not purchased that product (cross-selling) (Berry and Linoff 2000). Likewise, profiling helps them keep the customers who are at risk of leaving (decreasing churn or attrition), since it is generally far less expensive to keep a customer than to acquire a new one (Berry and Linoff 2000).

2.1.4. Cloud Computing

Cloud computing uses a vast network of remote servers that are hosted on the Internet to store, manage, and process data. The data-sharing architecture of cloud computing is utilized for AI and non-AI-related purposes (Kumar 2016). AI joins an automated and data-driven learning process. In addition, cloud computing refers to storing and accessing data and programs online rather than on the PC's hard drive (Kumar 2016). The cloud refers to the Internet. Effectively, with an online connection, cloud computing can be performed anywhere, anytime.

Cloud computing is an Internet-based technology, in which data is stored on servers and provided as a service and on-demand to customers. It is defined as a vast pool of easily usable and accessible virtualized resources (for example, hardware, development platforms, and services) that can be dynamically reconfigured to adjust to a variable load (scale), enabling optimum resource use (Mirzayi and Rafe 2015). These resources are usually exploited by a pay-per-use model, in which the infrastructure provider offers guarantees through customized Service Level Agreements (Mirzayi and Rafe 2015).

Companies can rent computing power (hardware and software, usually in their latest versions) and storage from the service provider and pay on-demand. This significantly affects the cost structure of companies (Karthic et al. 2012).

Cloud computing characterizes a crucial change in how information technology (IT) services are designed, developed, deployed, scaled, updated, maintained, and purchased. Cloud computing delivers all the functionality of existing information technology services and drastically decreases the initial costs of computing that prevent several firms from implementing various advanced IT infrastructures (Mirzayi and Rafe 2015). Furthermore, cloud computing characterizes business agility, whereby IT can be utilized as a competitive business tool through fast deployment, parallel batch processing, compute-intensive business analytics, and mobile interactive applications that respond in real-time to user needs (Bharathi and Neelamegam 2012). In effect, cloud computing enables firms to utilize computational tools that can be implemented and scaled quickly.

Cloud computing can be encapsulated from a unique business perspective and its unique features from a technological perspective. It operates as an information technology service model where computing services (both hardware and software) are provided on-demand to users over a network in a self-service model, independent of device and location (Mirzayi and Rafe 2015). The resources needed to offer the necessary quality-of-service levels are shared, dynamically scalable, rapidly provisioned, virtualized, and released with little service provider interaction. Customers pay for the service as an operating cost without experiencing any substantial initial capital expenditure. The cloud services utilize a metering system that splits the computing resource into appropriate blocks (Mirzayi and Rafe 2015).

3. Development of Hypotheses and Conceptual Framework

3.1. Artificial Intelligence and Customer Preference

Marketing comprises all of the activities, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers and all stakeholders, such as clients, partners, and society at large (AMA 2020). In effect, marketing is considered as treating customers well and meeting their needs satisfactorily. This is sufficiently possible when customers' profiles are properly collated and analyzed. Research conducted in Mauritius, an emerging economy (Gungaphul and Boolaky 2009), shows that entrepreneurs regard marketing as an essential function in attaining their business goals.

Customer preference refers to the subjective (individual) tastes, as measured by the utility of various bundles of goods and services (Venkatraman et al. 2012). These preferences enable the customer to rank bundles of products and services according to the levels of utility they deliver. Customer preference assumes that the customer can choose consistently and among the available alternative products or services. Understanding customer preferences and identifying their characteristics is crucial for the management of customers by entrepreneurs (Venkatraman et al. 2012). This knowledge is crucial in developing approaches to satisfying customers' needs.

Artificial intelligence enabled devices, such as mobile devices and social media platforms, enable the efficient generation of rich customer information that helps in discovering customer preferences (Kaplan and Haenlein 2019).

From the preceding information, the following proposition is suggested: *Artificial Intelligence (AI) systems have a direct and positive influence on customer preference*.

3.2. Artificial Intelligence and Industry Benchmarking

Benchmarking is a very general business concept used in many forms by businesses. It is a useful business tool that enables a company to systematically gain new useful business knowledge that can increase the quality of its decision-making. It is conceptualized as a systematic and continuous process involving the comparison of characteristics of the best products, services, and processes in order to improve business performance (Battagello et al. 2016). In other words, benchmarking involves the process of continuous searching for the best practices of competitors and other companies that lead to above-average performance when applied in an enterprise (Raybourn and Coers 2001). The main findings of benchmarking is the generation of business knowledge for the transformation, using comparison and analysis findings, in business decision-making.

Industry benchmarking is more effective when defined by an organized intelligence system, which is crucial for choosing benchmarks and assessing the patterns of important, selected benchmarks. Intelligence systems, such as artificial intelligence (AI), enable benchmarking to be a continuous process requiring regular updates, which is adequately adaptable to incorporate and integrate new approaches of capturing data from the competitive environment (Rai 2019).

Empirical research confirms that benchmarking positively influences the quality of entrepreneurial decision-making based on systematically gained additional knowledge (Lawler et al. 2001).

From the preceding information, the following proposition is suggested: *Artificial Intelligence (AI) systems have a direct and positive influence on the industry benchmarking process*.

3.3. Artificial Intelligence and Entrepreneurial Decision-Making

The term decision-making refers to the process of identifying and choosing a plan to manage or solve specific challenges or exploit opportunities. It is the process where managers respond to opportunities and challenges that they encounter by assessing the available options and making judgments or decisions concerning specific organizational goals and plans (Hellriegel et al. 2005; Stoner et al. 1995). This process includes identifying challenges, collecting data, creating options, and selecting a course of action. Additionally, decision-making refers to the process of defining and selecting options depending on the standards and preferences of the leader (Harris 2009). The approach to making decisions suggests that there are several options to be considered. In these instances, a leader does not solely want to find as many of these options as possible, but to select the one that has the most likelihood of success or effectiveness and best fits the organizational goals, needs, culture, values, etc. Furthermore, the decision-making process is basically an information-gathering function that sufficiently reduces ambiguity and doubt regarding the options that allow a realistic choice be made (Hellriegel et al. 2005).

Decision-making ensures that the best solution or plan is executed by businesses (Hellriegel et al. 2005). Decision-making is the fulcrum of the entrepreneurial process. Entrepreneurial decision-making is vital for a better comprehension of the process employed by persons to create and exploit new business opportunities (Davidsson and Klofsten 2003). Entrepreneurs consistently have to make different decisions co16:20.

Hellriegelncerning the discovery and exploitation of business opportunities, such as creating or identifying a market opportunity, acquiring resources, refining business ideas, resolving technical challenges, recruiting key employees, etc. (Davidsson and Klofsten 2003). Many of these decisions are critical and may have long-lasting consequences on the success and performance of the enterprise (Reuber and Fischer 1997). Entrepreneurs choose to explore opportunities based on their information, knowledge, and experience.

Entrepreneurs pursue novel opportunities to create value for society. They are often involved in the creation of new products, services, and technologies (Levine 2019; Acs and Audretsch 2005), and create jobs and increase standards of living (Åstebro and Tåg 2017; Carter 2011). The idea of creating value for society by improving the decision-making process of entrepreneurs indicates that sustainability issues that affect both consumers and firms in the circular economy must be considered by AI. In effect, the decisions faced by entrepreneurs are one of many options that strategize how and when to enter a market in order to pursue an opportunity for the firm and society. The existing literature emphasizes the identification of opportunities and the decision to explore them as the crux of entrepreneurial activity (Fairlie and Fossen 2018; Shane 2003; Shane and Venkataraman 2000). The specific knowledge base of entrepreneurs can also influence opportunity discovery and exploitation. Discovering and exploiting opportunities is a function of knowledge and experience (Fairlie and Fossen 2018). However, the exploitation of an opportunity must be conducted in the light of society and human dignity.

Entrepreneurial decision-making, to a large extent, varies based on situational contexts (Levine 2019). Entrepreneurs usually deal with new and unclear business concepts whose commercial implementation may not yet be fully explored. This suggests that entrepreneurial activities entail regularly making decisions concerning the opportunities worth pursuing and the available solutions worth exploring, which are influenced by the entrepreneur's knowledge (Fairlie and Fossen 2018). Modern technologies enhance entrepreneurs' knowledge, and artificial intelligence (AI) provides a credible means to correct the interpretation of external data, demonstrate institutional memory, and facilitate better decision-making (Kaplan and Haenlein 2019). The adoption of artificial intelligence (AI) appears likely to influence better entrepreneurial decision-making through a more efficient business automation process. From the preceding information, the following proposition is suggested: *The adoption of artificial intelligence (AI) directly and positively influences better entrepreneurial decision-making and can help entrepreneurs adopt modern circular economy systems that factor sustainable development as part of firms' goals.*

3.4. Customer Preference and Entrepreneurial Decision-Making

Customer preferences have been considered a significant factor influencing entrepreneurial decisions. Understanding customer preference is critical to ensure successful entrepreneurial decision-making to build customers' excitement (Venkatraman et al. 2012). A customer preference construct depicts business entrepreneurs as focusing on customer interactions and relationships for better decision-making and competitive advantage (Baiyere et al. 2020). Entrepreneurs need to identify customers' preferences of products and services offered by an industry or a business. With the increase in the global inventory of small businesses, entrepreneurs do not only provide goods and services, but strive to improve customers' comprehensive experience (Venkatraman et al. 2012). Additionally, entrepreneurs play significant roles in sustaining vibrant economies, providing jobs, and enhancing the standard of life. In other words, entrepreneurship contributes significantly to the development of firms and economies (Levasseur et al. 2019).

From the preceding information, this proposition is suggested: Customer preference provides essential input into better entrepreneurial decision-making. Customer preferences for products or brands develop from a blend of various factors, including features of the product (for instance, price and design) and customer qualities (for example, their goals, behavior, and excess income) (Venkatraman et al. 2012). Customers react to their consumption experience by developing positive or negative attitudes toward the product, establishing trends in their choices (Cullen and Kingston 2009). These trends are essential for entrepreneurial decision-making with artificial intelligence (AI) systems to efficiently analyze the trends.

3.5. Industry Benchmark and Entrepreneurial Decision-Making

Benchmarking is a precise and consistent process that entails comparing the features of the best products, services, and processes in order to boost business performance (Harrington and Harrington 1995; Dahlgaard et al. 1998). Moreover, benchmarking focuses on consistently searching for the best practices of one's rivals and other firms that may result in better performance when applied in a firm (Bogan and English 1994; Raybourn and Coers 2001). In other words, benchmarking is a system of creating business knowledge by comparing and assessing business information concerning other firms in order to improve the quality of decision-making.

Industry benchmarks are reference points usually taken from functioning markets among competitors and other recognized firms for the best practices (Harrington and Harrington 1995). Companies achieve success by creatively adapting the best practices of other companies to fit their needs. Then, these practices can be utilized as examples that lead to better and superior performance (Raybourn and Coers 2001). Benchmark decisions cannot be made without an in-depth analysis of the market and a comprehension of the culture of the decision maker's company. In other words, benchmarking focuses on comparing, adapting, and improving performance by observing and assessing what works well for others (Harrington and Harrington 1995).

Industry benchmarks simplify the entrepreneurial decision-making process. Therefore, entrepreneurs make decisions based on the experiences of others by analyzing the differences between a situation encountered by those firms and the decision-makers from whom the standard was developed (Dahlgaard et al. 1998). The expectation is to select a standard that has been successful for a different firm, assess their differences compared to the other firm, and realistically adjust their analysis based on these differences. This process will ensure that their decisions are, at least, practically successful (Dahlgaard et al. 1998). Benchmarking leads to discovery, advancement, and a continuous learning experience for entrepreneurs.

From the preceding information, this proposition is suggested: Industry benchmarking has a direct potential impact on better entrepreneurial decision-making. Similar to the practice of comparing industry processes and performance to the best in different industries, the industry benchmarking is utilized to assess different parts of an organization's processes regarding the existing best-practice company processes, generally within a peer group defined for comparison (Harrington and Harrington 1995). This process enables firms to create strategies in order to adopt specific best practices, typically to boost their performance. Therefore, the industry benchmark is expected to possibly influence entrepreneurial decision-making.

3.6. Employee Involvement in Entrepreneurial Decision-Making with Artificial Intelligence

Employee involvement in an organization is an environment where all employees are unique (Aliyu 2019). Every employee engages in aiding the organization to attain its goals. The employees' input is all requested and esteemed by their management. The employees and management acknowledge and cherish each other's involvement and contribution to the organization's success (Aliyu 2019).

Moreover, employee involvement entails allowing an organization's employees to participate actively in its affairs and empowering them to attain higher individual and firm performance (Sofijanova and Zabijakin-Chatleska 2013). Involvement is viewed as employees' participation in decision-making and problem-solving, as well as increased independence in work processes (Sofijanova and Zabijakin-Chatleska 2013). Entrepreneurial decision-making may be regarded as a function of the involvement of employees in an organization. Employees' participation in decision-making is crucial to firms as it impacts their quality and competitiveness. Employee involvement motivates workers to volunteer and take responsibility for organizational goals (Sofijanova and Zabijakin-Chatleska 2013).

Engaging an organization's staff in decision-making encourages them to have a sense of workforce membership. In addition, it creates a cozy environment where leaders and managers willingly communicate to ensure a stable industrial relationship (Aliyu 2019). Employee engagement enables workers to engage and inspire each other in order to utilize their actions to attain higher personal and corporate productivity (Sofijanova and Zabijakin-Chatleska 2013). Likewise, employee involvement is usually seen as employees' increased collaboration or contribution in supporting an organization in order to realize its policy document and primary goals by employing their internal ideas, skills, and strategies for critical thinking and decision-making (Aliyu 2019).

Employee involvement in decision-making is a significant driver of organizational excellence. Employee involvement is a cognitive and emotional reproduction for attaining organizational goals and objectives (Aliyu 2019). Therefore, organizations must create an environment where their employees influence the decisions and actions that impact their roles (Aliyu 2019). To this effect, employers make concerted efforts to find participative approaches for managing their workers to enhance organizational efficiency (Macey and Schneider 2008).

Employee involvement in organizations is considered a management and leadership philosophy regarding how workers are empowered in order to contribute to consistent improvement and continuous success. It is a system that enables workers to influence their work and the conditions under which they work (Sofijanova and Zabijakin-Chatleska 2013). Employee involvement is a way to assess democratization in an organization, which reduces the challenges of the operating system. In addition, it is an approach to obtain a communal consensus and pursue the goal of communal benefit (Lin 2006). Employee involvement is a unique type of delegation where the subordinate obtains more control and freedom of choice regarding bridging the communication gap between management and employees (Macey and Schneider 2008). Employee involvement indicates a management agenda regarding the expansion of comprehension and commitment from employees and assurance of an improved contribution to the organization.

Employee participation is viewed as a significant factor in successfully implementing new management strategies and plays a crucial role in defining the level of good organizational citizenship behavior (Harber et al. 1991). As a result, this boosts the commitment of workers and motivates them. The notion of employee participation underscores the importance of collaboration between employers and employees. Moreover, employees must be empowered to share in the organization's decision-making process (Bendix 2010).

Organizations need to foster a cross-functional relationship in order to harness their employees' full potential by engaging them in problem-solving and decision-making (Mullins and Christy 2005). Employees who are highly involved in an organization's efforts toward attaining its objectives do not tend to turnover (Mullins and Christy 2005). In response to competitive pressure, organizations' interest in different types of employee engagement and participation has increased (Frost 2000), resulting in the active participation of employees in organizational decision-making.

Employee participation is regarded as a critical component in successfully introducing unconventional management methods and an essential factor in assessing employees' level of accountability (Aliyu 2019). Employee involvement is essential in adopting modern technology systems in organizations (Aliyu 2019). Therefore, it influences artificial intelligence to moderate better entrepreneurial decision-making. Encouraging employee participation is considered a significant shift from a goods-centered logic to a service-centered logic regarding marketing (Vargo and Lusch 2004). Bendapudi and Leone (2003). In addition, it may be the next frontier for competitive advantage creation and effectiveness. This is due to the fact that workers have become active participants in the value creation process (Grönroos 2006; Gallan et al. 2013). Employee involvement delivers value to both the employee and firm (Auh et al. 2007; Chan et al. 2010). Bendapudi and Leone (2003) discovered that contributing employees are more satisfied than those who do not participate when the service result is better than anticipated.

The circular economy theory (CE) has gained prominence in business and entrepreneurial endeavors. This is due to the fact that CE is an effort to generally reconsider the development that combines social issues, economic activity, and environmental well-being. CE adopts an economic model where planning, resourcing, procurement, production, and reprocessing are creatively developed and adequately managed to enhance processes and outcomes that boost ecosystem activities and people's well-being (Murray et al. 2017). Economic activities in the circular economy revolve around good employees' involvement. Employees' involvement has been seen to be critical in achieving organizational goals. Anning-Dorson (2017) defines employee involvement capability as "the extent of a firm's ability to engage employees in the value creation and delivery process" (p. 2). Employee involvement is considered fundamental to the value delivery process and has consequences for firm performance (Payne et al. 2009; Prahalad and Ramaswamy 2004). Employee involvement is a prerequisite for value creation in a business context, since value is currently co-created (see Grönroos 2008; Vargo and Lusch 2004; Gallan et al. 2013). Therefore, organizations that develop and deploy employee involvement will enjoy a competitive advantage to improve their performance.

From the preceding information, the following proposition is suggested: *Employee involvement influences artificial intelligence to moderate better entrepreneur decision-making*.

3.7. Conceptual Framework

The proposed model is presented in Figure 1 below, illustrating the reviewed literature. The dependent variable is *better entrepreneurial decision-making*, which is the outcome of the model. *Artificial intelligence* (AI) is the independent variable: Four main components constituted AI in the model (big data analysis, data mining, cloud computing, and machine learning). There are two mediating variables (customer preference and industry benchmark) and a moderating variable (employee involvement). The conceptual model explains how entrepreneurs can make better entrepreneurial decisions by effectively using AI and customer preference with the industry benchmark mediating the relationship. The conceptual model also proposes that employee involvement moderates the association between artificial intelligence and better entrepreneurial decision-making.

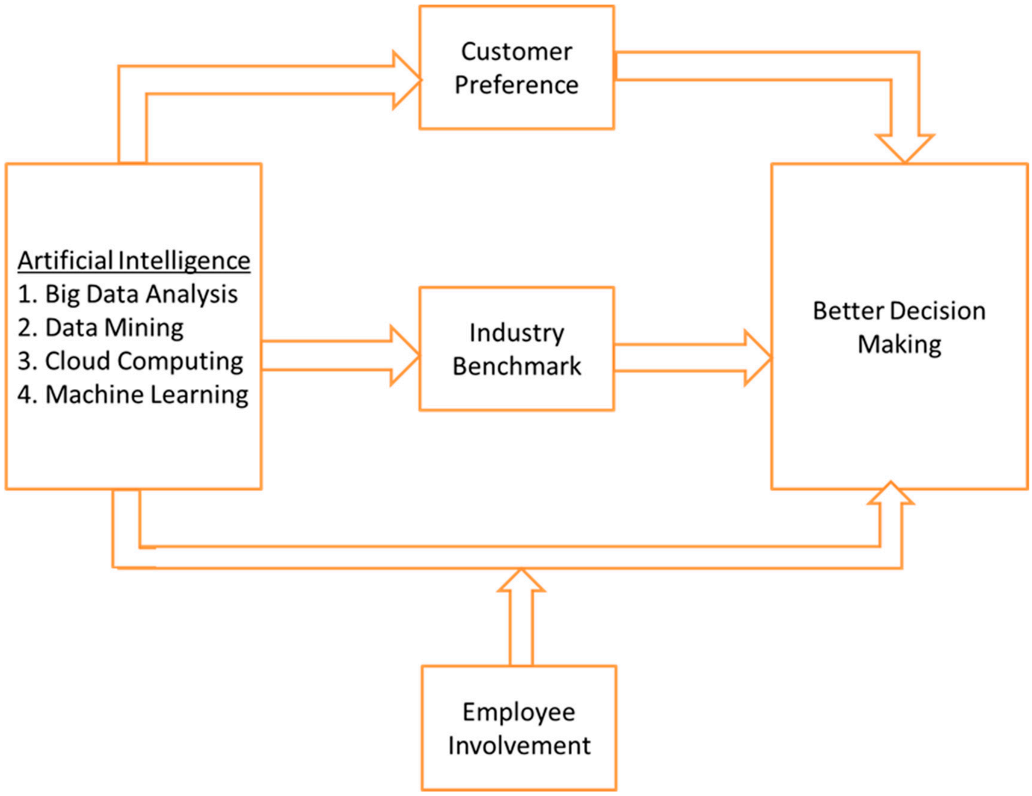

Figure 1. Conceptual model. Source: Authors' conceptualization.

4. Study Context

Entrepreneurial development can invigorate national economies through job creation and this has been recognized as a central pillar in sustainable development in African Union's Agenda 2063 (African Union 2014).

The indigenous private sector in most African countries, including Ghana, consists largely of smaller firms or entrepreneurs (Amankwah-Amoah and Debrah 2010), and the sources of capital of these institutions are typically raised from personal sources of savings, borrowing from friends or family, and retirement funds.

Historically, various trading activities have existed within communities and between various communities in Africa and the West African nation of Ghana. It has been a fertile ground for entrepreneurial development (Bonsu 2009). Entrepreneurship has been at the cornerstone of Ghanaian society.

Ghana covers an area of 238,535 square km and has a population of approximately 30.8 million, with a GDP of USD 68.42 billion and an expected growth rate of 5.7% in 2021 (GSS 2021). Ghana offers unique features of socio-economic and political stability in Africa, providing a suitable context to explore entrepreneurial activities in a developing country setting (Amankwah-Amoah and Debrah 2010). Political stability, viable legal regimes, economic stability, societal wealth, and viable financial systems are some of the factors that contribute to shape entrepreneurial activities within an economy (Bourdieu 2010).

Extant literature indicates that in addition to viable governance systems, as well as legal and regulatory systems, a good infrastructure facilitates entrepreneurship in a country (North 1990; Minniti 2008; Robson et al. 2009; Goedhuys and Sleuwaegen 2010; Lu et al. 2015). Some scholars further posit that entrepreneurship could be a key ingredient in the variation of the levels of development among different societies (Zahra et al. 2005). In other words, the more entrepreneurial a society is, the more prosperous they are. Perhaps the most important factor in entrepreneurial development is the availability of adequate infrastructure, and in the contemporary business environment technological infrastructure is paramount.

The number of persons accessing the technological infrastructure is increasing exponentially. Companies and entrepreneurs are seeking to enrich their operations with digital facilities in order to engage with customers competitively. Recent statistics indicate that there are 4.66 billion active internet users globally from January 2021 (about 59.5% of the global population) out of which 4.32 billion persons (92.6% of internet users) access the internet via mobile devices (Internet World Stats 2021). In Africa, there are about 28.2% of the population that are active internet users. Ghana has 13.7% active internet users and about 40.46 million mobile phone subscribers (over 130% of the population). This rapid growth of popularity of internet and mobile devices has opened a plethora of opportunities for entrepreneurs to leverage digital facilities in order to connect more effectively with stakeholders and make better decisions.

5. Research Design and Methodology

Conventional knowledge suggests that artificial intelligence enabled platforms have a positive impact on better entrepreneurial decision-making. There is broad consensus among different researchers on the impact of artificial intelligence on entrepreneurship development. Moreover, we speculate that the effect of artificial intelligence on entrepreneurial decision-making may be moderated by different factors, such as employee involvement. furthermore, we investigate whether customer preference and industry benchmark mediate the relationships between artificial intelligence-based platforms and entrepreneurial decision-making.

In the above discussion, this study adopted the desk research approach. This secondary research approach involves the summation, collation, and/or synthesis of existing research. This is an accepted and popular analytical research tool that brings various relevant studies under a common conceptual framework.

In order to illuminate our understanding of better entrepreneurial decision-making, we relied on various databases. Moreover, we relied on other secondary materials in other domains, including journals, newspapers, new magazines, books, and electronic resources. In our search, we eliminated studies that did not conform to our broad framework.

Data were collected following this procedure:

(1) We conducted an electronic search with the keywords (artificial intelligence, entrepreneurial decision-making, employee involvement, etc.) on major databases (Emerald Online Journals; Taylor and Francis Online Journals; JSTOR Online Journals; Elsevier Online Journals; IEEE Xplore, Directory of Open Access Journals (DOAJ, etc.) spanning across disciplines, such as marketing, consumer behavior, and computer science engineering.

(2) Further search was conducted in prominent journals (Journal of Marketing; Journal of the Academy of Marketing Science; Journal of Marketing Research; Journal of Consumer Research; Journal of Institute of Electrical and Electronic Engineers, IEEE Xplore, etc.).

These efforts were all complimented with a manual search of the above-mentioned journals, in order to doubly make sure that we did not miss any relevant study. Overall, we believe that we performed an exhaustive search of the literature for the purpose of conducting this study.

6. Theoretical and Managerial Implications

From a theoretical and practical viewpoint, there are many implications that could be gleaned from this paper. Entrepreneurs need to be equipped to identify business opportunities or future markets. In addition, entrepreneurs require the right environment and tools to remain innovative and competitive. This model explores how the structures within firms affect the desirability and viability of exploring new ideas (Wiklund and Shepherd 2008).

The exponential growth in the digital space has been accompanied by the exploitation of the data produced by a progressively technologically linked society (George et al. 2014). Artificial intelligence-based applications are actively created and utilized in different domains. These knowledge-based information systems are advanced tools for entrepreneurs, enabling evidence-based decision-making in complex business situations. With these technological tools, entrepreneurs stand a better chance of understanding their customers, helping them to optimize real practices in their decision-making process. Moreover, the notion of circular economy (CE) can be used to leverage AI to enhance society and human integration. According to Saiz-Alvarez (2020), CE is regarded as an enhanced system that can be used to stop the depletion of resources, close energy, and materials circles, as well as support sustainable development through its adaption at the micro (enterprises and customers), meso (economic agents joined into symbiosis), and macro (city, regions, and governments) levels.

Digital changes in how businesses function are inevitable, and entrepreneurs must incorporate this innovation into the sustainable business environment. The impact of this innovation can be seen in each fragment of the business process. Given that entrepreneurship activities are highly uncertain, ambiguous, time-bound, emotionally intense, and involve high-risk decision-making, digital innovation facilitates better entrepreneurial decision-making and aids entrepreneurs in effectively adjusting their strategies based on shifting market requirements and stimuli.

Although digital innovation is not a new concept, it appears that entrepreneurs do not give full attention to it, although experimentation and risks are integral to their work processes. However, technology systems, such as artificial intelligence can leverage digital innovation for better entrepreneurial decision-making. The research by Nusair et al. (2021) indicated that firms with better organizational capabilities tend to better satisfy their customers. This implies that firms that engage employees with higher capabilities might satisfy their customers better than firms that engage employees with lower capabilities, due to the fact that the higher capability can correspond to better decision-making. The proposed model suggests that employee involvement can influence entrepreneurial decision-making outcomes. This confirms an earlier study by Kassa and Raju (2015), which suggested that when the firm-specific entrepreneurial environment is favorable, workers would respond as innovative. However, entrepreneurs, managers, and policymakers have to note that AI systems have some challenges. According to Dwivedi et al. (2019), these challenges included the possibility for innate bias in AI algorithms and its implications for people who work closely with intelligent machines, and presented substantial issues with regard to trust, security, and ethical considerations. Moreover, entrepreneurs and managers must grasp the most fundamental AI concepts in order to determine when AI is appropriate for their needs.

From a practical standpoint, there is a need for national policy to create entrepreneur-friendly legislations and regulations in order to provide incentives to aspiring entrepreneurs, as well as to provide incentives to existing entrepreneurs in order to expand the scope of their businesses. The conceptual framework clearly indicates a need for government policy toward updating and upgrading the expertise of aspiring and existing entrepreneurs. Furthermore, there is the need for deliberate government policy toward overcoming barriers to entrepreneurial development, such as lack of digital infrastructure, access to finances, and the development of relevant human capital.

This study has significant implications for business practice among entrepreneurs in Ghana and other developing countries with similar circumstances. Its findings will enable entrepreneurs to better understand the changing trends in contemporary business practice, and offer a useful reference point for future empirical studies of entrepreneurship in the developing country context.

7. Conclusions, Limitations, and Directions for Future Research

Understanding and creating better entrepreneurial decision-making is important, since it is widely accepted in the literature that better entrepreneurial decision-making significantly enhances business competitive advantage.

This paper discovered the fact that contemporary entrepreneurs are confronted with numerous stakeholders. This requires the adoption of the appropriate tools and techniques in order to adequately harness these resources for the competitive advantage of the entrepreneur. Multinational companies are increasingly posing a competitive advantage to local entrepreneurs as a result of global attention on emerging markets. This necessitates the adoption and usage of modern technological equipment to remain competitive.

Additionally, this paper discovered that presently businesses are dynamic and largely digital. Therefore, entrepreneurs benefit from this transformation. A contemporary business is established on data, since people are affected by the ability of businesses to collect, analyze, manage, and use data. Several online platforms provide avenues for data collection. Moreover, the ability to transform the collected data into value-for-economic gain is innovative, which is expected of the modern entrepreneur. The real data lie in the ability of entrepreneurs to develop actionable insight and apply it in strategic and better decision-making. Improved decision-making for entrepreneurs should be linked to their desired impact. Therefore, they should consider focusing on the theory of circular economy (CE), since the future of energy production and distribution can be improved with AI systems.

Most businesses consciously gather and store data in large databases. Numerous businesses know the potential value of the data to their decision-making process. The rapidly growing demand for better decision-making can be met by increasing knowledge availability. For instance, from the industrial revolution, the advancement in technical innovation has transformed numerous manual tasks and processes and mechanized or automated them. Artificial intelligence (AI) possesses the same transformative power for growth, and possibly takes over some tasks and activities that are usually performed by people in different industrial, intellectual, and social fields. AI technology changes rapidly, presenting new innovations in algorithmic machine learning and autonomous decision-making, creating new opportunities for advancing innovation. The effect of AI significantly cuts across sectors, including finance, healthcare, manufacturing, retail, supply chain, logistics, and utilities. These sectors have been disrupted by AI technologies (Dwivedi et al. 2019). Industry leaders and entrepreneurs must take advantage of the wide range of artificial intelligence (AI) applications in order to enhance their decision-making process for the benefit of society and firms. However, AI could, in theory, increase the disparity between the developing and developed markets, as well as the poor and wealthy (Bughin et al. 2018).

From the review of extant literature in this paper, it is evident that most of the information on entrepreneurial development was based on data from developed nations. Therefore, there is a need to generate empirical evidence from developing economies to support opinions that might offer fresh insights into the entrepreneurial decision-making process. Moreover, the issue of culture has been known to influence entrepreneurial decision-making, but this was not added in the proposed model. Future studies can discuss culture as a factor in decision-making efforts, especially in Africa. For instance, the study by Liu et al. (2019) of research outcomes indicated that Tanzania's culture affects entrepreneurs' risk-taking behavior, which impacts their decision to exploit opportunities. Furthermore, the limitations of this paper are as follows: It is conceptual in nature and the proposed model has not been tested.

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