GAS Journal of Economics and Business Management (GASJEBM)
Volume 3 | Issue 7, 2026 Homepage: https://gaspublishers.com/gasjebm-home/ ISSN: 3048-782X

The Algorithmic Consumer: A Conceptual Framework for Agentic AI in Predictive Marketing

Aliyu Mohammed[1], Abdullateef Ajibola Adepoju[2], Trimisiyu Omotayo Lawal[3]

[1]Department of Management, School of Arts, Management and Social Sciences, Skyline University Nigeria, Kano
[2]PhD Research Scholar, Department of Management, School of Arts, Management and Social Sciences, Skyline University Nigeria, Kano
[3]Department of Economics, School of Arts, Management and Social Sciences, Skyline University Nigeria, Kano

Received: *05.06.2026* | ***Accepted:*** *06.07.2026* | ***Published:*** *09.07.2026*

***Corresponding Author:** Aliyu Mohammed

DOI: *10.5281/zenodo.21284457*

Abstract **Original Research Article**

The core concepts of market transactions are being redefined as AI moves beyond reaction to self-autonomous software proxies. This paper proposes a conceptual framework of "Algorithmic Consumer," where the human buyer completely entrusts the purchasing decision, evaluation, and execution to Agentic AI. Although conventional marketing literature has described human actors interacting within choice architectures, using cognitive heuristics, emotional affect, and brand stories, agentic commerce invokes the dynamics of the machine interacting within choice architectures, maximizing utility. We synthesize the concepts of service-dominant logic, bounded rationality, agency theory, and cognitive offloading and apply them in the context of consumer behaviour, strategic management, and software engineering. Technical tricks, such as machine autonomy, recursive learning protocols, and genetic algorithms, are embedded and are used to show how the consumer proxies mathematically optimize preference profiles. Hence, a paradigm shift is needed in corporate strategy from CRM to Machine-to-Machine Relationship Management (M2MRM), and e-commerce becomes a field of programmatic and technical interoperability. Lastly, we critically review the "dark side" of delegation, discussing the double principal-agent problem, loss of consumer autonomy, algorithmic bias, and platform-level utility exploitation, and propose a strategic roadmap and an agenda for future empirical research.

Keywords: Algorithmic Consumer, Agentic AI, Machine-to-Machine Relationship Management (M2MRM), Genetic Algorithms, Bounded Rationality, Service-Dominant Logic, Choice Delegation.

1. Introduction

1.1 The Paradigm Shift: From Passive Consumer to Agentic Actor

The customer business environment is changing structurally, transforming the essence of market transactions. Over the years, predictive marketing has been based on descriptive or diagnostic analytics, which enabled the prediction of consumers' preferences and placed the human at the end of the purchase funnel as the last, conscious decision-maker. With the development of more advanced artificial intelligence (AI) systems, which feature high levels of autonomy, recursive learning, and goal-oriented actions, the consumer is losing his role as a mere target for advertising and is turning into an automatic delegate in the advertising ecosystem. This brings in the concept of an algorithmic consumer, where autonomous program agents make decisions on purchases instead of relying on a human to make them, with consumption moving from a cognitive evaluation to computational optimization.

This shift is inescapably related to the strategic use of management information systems (MIS) in the present-day big data infrastructure (Mohammed, 2023a). When organizational contexts grow in complexity, firms use higher-level data architectures not only to get the picture of the market signals but also to create an active closed-loop algorithmic environment (Mohammed, 2023a). History shows that these digital markets have progressed from basic online transactions to very complex and disruptive markets (Mohammed, 2023b; Sundararajan & Mohammed, 2024a). In contrast to the search cost reduction as done in early e-commerce, the contemporary agentic architectures actively influence the market by performing autonomous microtransactions, optimizing procurement cycles, and continuously executing without human interaction in real time (Sundararajan & Mohammed 2024a).

Theoretically, this development changes some of the core beliefs of consumer behavior as well as marketing science, such as the Service-Dominant (S-D) Logic of Vargo and Lusch (2004, 2016). According to S-D Logic, value is essentially a co-creation process between network actors in the interaction of systemic resources, services, and service exchange. With an autonomous agent making resource integration through recursive learning algorithms, the process of co-creation morphs. The agent no longer exists as a convenient tool; it is now a separate node in the service infrastructure.

This delegation is motivated by a human need to reduce the cognitive demand of a task through the use of some physical or digital intervention (Gilbert & Wilson, 2013). Delegating routine or complex multi-attribute decision-making tasks to agentic systems frees up consumers' "bounded rationality" (Simon, 1957, 1991) to focus on tasks that require more creative thinking. Cognitive processing has inherent constraints: Working memory and informational constraints. Agentic AI can overcome such limitations, as it can perform real-time multi-objective optimizations, often employing computational approaches such as genetic algorithms, which are used to randomly alter, combine, and retain the best combinations of preferences in vast multidimensional search spaces (Goldberg, 1989). This is why the old-fashioned marketing metrics (like brand affect, emotional impulse, and visual heuristics) are replaced, one by one, by algorithmic parameter tuning and programmatic efficiency.

1.2 The Research Gap: Lack of Theoretical Frameworks for Agentic AI

Despite the rapid deployment of agentic architectures in commercial software engineering, corporate Although agentic architectures have already been introduced in commercial software engineering, the literature in the fields of corporate strategy and marketing is still stuck in an outdated perspective of decision-making as being human-centric. In many respects, the current study on the functioning of the digital marketplace and entrepreneurship has focused on the beneficial aspects of automation, technology adoption, and structural flexibility (Sundararajan & Mohammed, 2023; Subramani et al., 2024). In fact, scholarly literature has extensively documented the implications of digital transformations and new platforms on enhancing market access, entrepreneurship opportunities, and employment relations in various industries around the world (Mohammed & Sundararajan, 2024; Mohammed & Kumar, 2022; Sundararajan & Mohammed, 2022). However, these viewpoints typically tend to see technology as an external means to an end, rather than a decision-making proxy in and of itself.

This is a key theoretical lacuna. Existing frameworks cannot capture the unique operating environment of agentic systems, which are able to operate independently (autonomy) and continuously learn from the environment (recursive learning), without human intervention and reprogramming. In an autonomic optimization of the consumer's utility function, the traditional consumer journey models, like the classic AIDA model (attention, interest, desire, and action), lose their conceptual meaning. There's no attention or desire in an algorithm; that's a fitness function that it evaluates.

Moreover, the existing marketing literature does not have a comprehensive view that is able to take into account the strategic and governance paradoxes arising from this change. The transformation can be interpreted as an Agency Theory (Jensen & Meckling, 1976) problem, which is a double principal-agent problem:

A human principal is a human who delegates authority to an AI agent, who interacts with a firm agent.

In this case, the firm and consumer can have an information asymmetry, and the consumer and the algorithmic "proxy" can also.

Furthermore, existing research is somewhat optimistic and tends to ignore the systemic "dark side" of automated marketplace ecosystems. Automation can lead to economic resilience and institutional efficiency (Mohammed & Sundararajan, 2024) but can also increase vulnerabilities with regard to algorithmic bias, loss of consumer autonomy, and erosion of consumer agency. Closed-source optimization loops dictate the choice architectures and lead to vulnerability of the consumer's long-term preferences to algorithmic consumption feedback loops designed by the predatory side of the company. Theoretical models that can seamlessly connect the technical aspects of software engineering (such as the design of the genetic optimization algorithm, the reward function, etc.) with the strategic aspects of management science (such as the role of a game, the ethical framework, etc.) are so rare that they are completely lacking.

1.3 Objectives and Scope of the Study

This study aims to fill these theoretical gaps by providing a detailed and interdisciplinary conceptualisation of the "algorithmic consumer". The ultimate aim is to establish the socio-technical dynamics that take place when agentic AI becomes the primary intermediary and ultimate decision-maker in predictive marketing contexts.

In brief, this study seeks to:

- **Deconstruct the Architectural Mechanics:** Identify the role of the software engineering principles of autonomy, recursive learning and genetic preference optimisation in replacing human psychological heuristics in the consumption cycle.
- **Reformulate Foundational Management Theories:** Rethink Bounded Rationality, Service-Dominant Logic and Agency Theory in a context where human agency is systematically delegated to algorithmic agents.
- **Strategic and Governance Implications:** Discuss the implications of firms changing their information systems, resource allocations and product development pipelines to successfully market to algorithms rather than humans, based on lessons learned from complex project management paradigms (Mohammed, 2023c).
- **Discuss the Ethical and Socio-Technical Risks:** Make a detailed discussion of the systematic risks on user autonomy, superfluous programmatic biases and difficulties in algorithmic accountability.

This study is conceptual and multidisciplinary and a synthesis of literature on consumer behaviour, strategic management, information systems and software engineering. It recognises that adoption of technologies is not an isolated phenomenon, but their adoption curves and structural impacts are strongly linked to wider human resource development, training and institutional evolution across the global markets (Mohammed, 2023d; Muhammed, Sundararajan, & Lawal, 2022; Sundararajan & Mohammed, 2023b; Mohammed & Sundararajan, 2023; Sundararajan & Mohammed, 2024b). This paper brings together these various areas to give a strong theoretical basis for empirical studies, algorithmic system design, and regulatory policy in the ever-expanding era of agentic commerce.

2. Theoretical Foundations

2.1 Defining Agentic AI: Beyond Traditional Machine Learning

The first step towards creating a sound conceptualization of the algorithmic consumer is the identification of architectural and functional differences between agentic AI and the conventional, passive machine learning (ML) models. Conventional predictive marketing is based on the static ML algorithms performing pattern recognition or regression-based activities (such as collaborative filtering or predictive scoring models). In such setups, the algorithm functions as an information filter—it processes large amounts of data about the consumer, predicts a likelihood score, and feeds it to a human actor who will make a personalized recommendation. The final decision and execution risk and cognitive processing stay within the human agent.

In contrast, agentic AI is a paradigm shift, where agentic software engineering principles are autonomy, recursive learning, and goal-directed behavior. Agentic systems can be programmed, unlike deterministic step-by-step systems, by a series of high-level objective functions (e.g., "maximize utility within a specific budget, with a specified nutritional profile, while keeping a specific temperature profile for the product"). "Evaluates its operational space, breaks down the problem into several sub-goals, and performs a series of actions in an external digital environment without human interaction.

The system optimization of Management Information Systems (MIS) in great data environments is a crucial aspect in this transition, making it possible for organizations to build cohesive, highly responsive working environments. The system optimization of Management Information Systems (MIS) within massive data frameworks is a vital element in this transition, empowering organizations to establish cohesive, highly responsive working environments. The history of these architectures provides insightful examples of the evolution of strategic information systems from standalone diagnostic data repositories to closed-loop, real-time architectures that enable autonomous processes (Mohammed, 2023a; Sundararajan & Mohammed, 2023a).

Traditional ML: [Data Input] → [Pattern Recognition] → [Static Recommendation] → (Human Choice Required)

In a traditional ML pipeline, users will need to make choices at certain stages, including creating the patterns and the static recommendation.

Agentic AI: Objective ———> Autonomous Sub-goals ———> Recursive AI Learning Loop ———> Automated Purchase.

From an architectural perspective, agentic AI works by using recursive learning loops, continuously adjusting its policy parameters and loss functions in response to the feedback received from the environment. This ongoing adaptation has direct implications on the development of today's digital marketplaces and e-commerce spaces, making them from a passive digital catalog into an active and dynamic transactional space (Mohammed, 2023b; Sundararajan & Mohammed, 2024a). These are environments within which agentic systems perform high-dimensional preference optimization (Goldberg, 1989) using sophisticated computational mechanics, including genetic algorithms.

If a consumer passes decision-making power to an agentic proxy, the algorithm generates a first set of possible solutions for the consumer (bundles of purchases). By computationally simulating selection, crossover (mixing attributes from successful options), and mutation (adding random variables to avoid getting stuck in local optima), the system can improve the consumer's preference profile in response to the evolving digital marketplace. This optimization won't be constrained by human cognition but instead uses a fitness function to replace human evaluation that was previously based on emotion and/or heuristics.

2.2 The Evolution of Consumer Autonomy: Historical Perspectives

The emergence of the concept of consumer autonomy is closely intertwined with the development of market structures and tech capabilities. Consumer autonomy has been traditionally analyzed from a humanistic perspective, which emphasizes the individual's ability to make reflective choices, to make self-determinative decisions and to practice free will in the marketplace (Ryan & Deci, 2000). In early economic systems, consumer autonomy was considered an absolute condition of sovereignty; consumer actors were given freer access to clear preferences.

This was challenged by the theory of bounded rationality of Herbert Simon (1957, 1991), however. Simon proved that decision makers in humans face fundamental limitations because of information asymmetry, cognitive bandwidth, and the limited time they have. Humans do not optimize; they "satisfice" and choose options that just suffice to be adequate. Over time, consumers have coped with these cognitive limitations by engaging in cognitive offloading (Gilbert & Wilson, 2013). It started with basic physical tools and developed into becoming dependent on institutional frameworks, brand reputations, and social networks to ease the evaluation of complex marketplaces.

As digital marketplaces developed, these mechanisms of offloading were more and more digitalized. The development of modern e-commerce is a good example of the ongoing change in strategic market structures of the choice architecture of the consumer (Mohammed, 2023b; Sundararajan & Mohammed, 2024a). Initial applications have been mostly oriented towards reducing search expenses and to the aggregation of the structural options (Mohammed, 2023b). Eventually, these platforms developed into fully fledged digital environments (Sundararajan & Mohammed, 2024a).

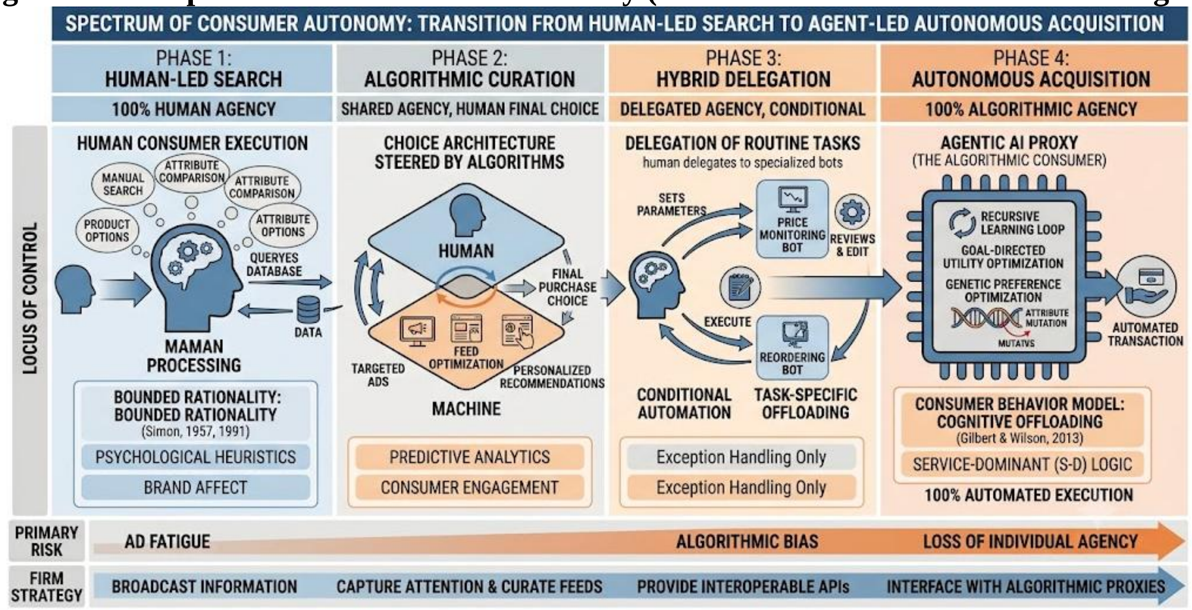
This socio-technical shift has observed a similar development globally across the economic sector, which always redefines the market participation and operation role by adopting technology and training systems (Mohammed & Sundararajan, 2024; Muhammed, Sundararajan & Lawal, 2022). Just as these structural changes in human resource processes and functioning within macrosectors such as agriculture or project management (see Mohammed & Sundararajan, 2024; Mohammed, 2023c) remodel the micro-foundations of individual agency within digital commerce, so too do agentic processes within digital commerce re-engineer the micro-foundations of individual agency.

Thus, the human condition with consumer autonomy is not an immutable fact. It has become a property that is easily transferable but also has undergone a continuum of movement from man-made assessment to full algorithmic execution.

2.3 The Spectrum of Consumer Autonomy

To capture this structural transition, the evolution of choice architecture of consumers is segmented into four evolutionary phases in Figure 1. The model explains the changing pattern of the locus of control, the cognitive offloading approach and the most important market actor in the transition towards full algorithmic autonomy of systems.

Figure 1: The Spectrum of Consumer Autonomy (from Passive Data to Autonomous Agent)



Source: *Synthesized by the author based on Simon (1957), Gilbert and Wilson (2013), Vargo and Lusch (2016), and Sundararajan and Mohammed (2024a).*

Figure 1 illustrates a continuum of transition from the left to the right, representing a continuum from traditional commerce to agentic market behaviour:

- **Phase 1** is the Human-Led Search. Consumer has to deal with high cognitive load when navigating through consumer electronic marketplaces and visiting them (Mohammed, 2023b). The technological infrastructure is passive, merely as a digital catalogue.
- In **Phase 2**, the traditional machine learning is introduced with the algorithmic curation. Here the platform is able to garner attention and curate feeds based on a consumer's previous interactions, changing their choice architecture. The human is the last decision-maker, but the algorithmic sorting pushes his/her bounded rationality.
- **Phase 3:** Hybrid delegation takes the next step to automation. The customer uses general or specific agents with a conversational or script-based interface for repetitive microtasks (such as restocking specific products or tracking price levels). The human is used as an editor for exceptions or to approve a transaction.
- **Phase 4:** Autonomous Acquisition is when the algorithmic consumer has come to fruition. In this case, all cognitive offloading is realised. Using recursive learning loops, the agentic system works continuously and autonomously and evaluates multidimensional search spaces by genetic preference optimisation.

The traditional consumer journey is completely embedded in the programmes in this last phase. The firm's marketing is no longer about human psychology, but rather it needs to be optimised to directly communicate with independent algorithmic proxies.

3. The Conceptual Framework: The Algorithmic Consumer

3.1 The Agent-Consumer Symbiosis: Co-creation of Value

The algorithmic consumer's working processes must be rethought to comprehend the nature of value production in highly automated markets. In the traditional Service-Dominant (S-D) Logic (Vargo & Lusch, 2004, 2016), value is not only created during the production of physical products but is also created in real time with the co-creation of value through resource integration and service exchanges among knowledgeable network actors. However, in an agentic system, the kingpin of the system is no longer just the human being as the resource integrator. Rather, a close, closed-loop agent-consumer relationship comes into play, where cognitive authority is passed on to a separate software agent.

This joint integration is a basic remodeling of the digital marketplace. E-commerce platforms have traditionally been considered sites where price and attribute comparison was done by human actors (Mohammed, 2023b; Sundararajan & Mohammed, 2024a). The digital marketplace is an active computational canvas in the agent-consumer symbiosis. The human principal brings his or her latent utility function, financial details, and base behavioral history. The AI agent, having structural autonomy and recursive learning features, combines these inputs with the current market data, variables of the supply chain, and predictive signals.

The use of consumer data is a huge source of information and relies heavily on advanced and integrated management information systems (MIS) to support the structural symbiosis (Mohammed, 2023a). An agent without a strong big data system to enable him to continuously program the customer's preferences will not have a realistic picture of the customer. This fostered a sense of efficacy in the operation of this automated co-creation, aligning with the general pattern of entrepreneurship and technological innovation, where the design of the platform and its structure play a crucial role in optimizing the system's performance (Sundararajan & Mohammed, 2023; Muhammed et al., 2022).

Optimization engines for values are used in this stage, often based on genetic algorithms (Goldberg, 1989). The agent does not act in a static way by processing the static criterion but rather with respect to the consumer's lifestyle as a multidimensional search space. The algorithm produces a population of the consumption strategies, which applies crossover and mutation on attributes such as delivery time, product quality, cost, and environmental impact. This consumption bundle is a form of value that is optimized on the computer, which a boundedly rational human could not have computed by hand, and thus changes the "relational dynamics" between the consumer and the market.

3.2 Predictive Analytics vs. Agentic Decision-Making

The distinction between the old-fashioned predictive analytics and the real agentic decision-making needs to be clearly established. Traditional predictive marketing relies on historical data streams and uses these to predict human behavior with probabilities that inform actions that can be taken by the firm, such as targeted advertising, targeted pricing, etc. This is a very complex but still human-unfeasible method. The firm still needs to get the attention of the human, interest them, and convince them to take action. This creates space for human friction, including emotional instability, cognitive fatigue, and the human limits on information processing (Simon, 1957, 1991).

Predictive Marketing: [Firm Data] → [Targeted Ad] → (Human Evaluation Friction) → [Purchase]

"Agentic," on the other hand, involves the intervention of an agent between the transactions, thereby shifting consumption from a psychological experience to a technical optimization exercise. The process of agentic decisioning goes through the following steps:

Agentic Decisioning: [Firm API] → [Agentic Proxy] → [Automated Fitness Match] → [Instant Settlement]

This structural change is an alternative to the traditional choice architectures. Asymmetry of information is transferred from the human consumer to the agentic system when the autonomous proxy is used to consume information. The shift also changes the dynamics and marketing of platforms across the globe, making machine-to-machine interfaces (Mohammed, 2023e) the new branding.

This change of operability from a descriptive prediction to a complete autonomous execution can be arranged in four different directions:

- **Locus of Agency:** Traditional systems have a human-centric decision-making process, whereas agentic systems take actions that are based on the feedback from the surrounding environment continuously.

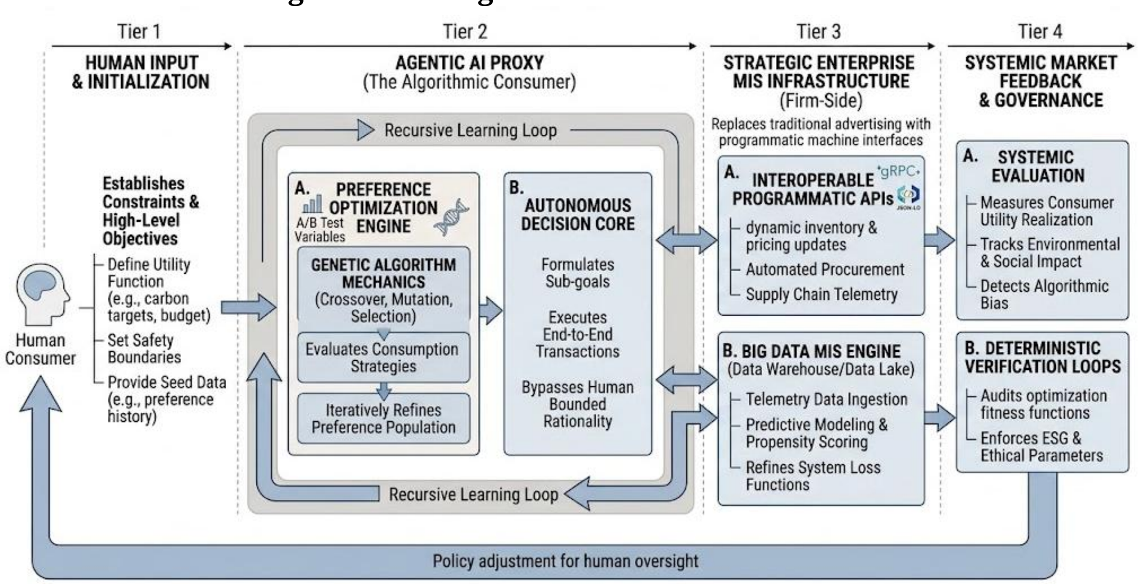
- **Cognitive Load Allocation:** The traditional models are based on the limited cognitive resources of the consumer, and agentic models are based on complete cognitive offloading (Gilbert & Wilson, 2013).
- **Optimization Methodology:** Traditionally, basic linear regressions or static classification models are used. Agentic frameworks employ recursive learning loops and genetic algorithms for the adaptation to the changing states of the market.
- **Transaction Velocity:** Time limit for traditional consumption, e.g., browsing and reading reviews. Agentic execution takes place in real-time through the use of programmatic APIs to change the behaviours of the supply chain.

This automated architecture calls for high agility of the institution and programmatic resilience similar to the capital-intensive sectors such as automated agriculture and large-scale project management (Mohammed & Sundararajan 2024; Mohammed 2023c). In these areas, it's more than just about switching from reactive monitoring to a system that can detect, correct and act on its own. For predictive marketing, that means companies need to abandon the practice of creating marketing campaigns based on people's psychology and instead seek to maximise their digital products for the algorithmic analytical process.

3.3 The Agentic-Predictive Framework

The circular symbiotic relationship between agent and consumer, along with the firm-side predictive marketing architecture, is shown in the following framework and describes the transformation of the consumer decision journey.

Figure 2: The Agentic-Predictive Framework



Source: Developed by the author based on theoretical models from Simon (1957), Goldberg (1989), and Mohammed (2023a)

Figure 2 shows a closed-loop socio-technical system in which people are kept to the initialisation of the system and the setting of top-level parameters:

1. **Human Layer:** The consumer is the top layer in the architecture, acting as the ultimate principal. The human determines some kind of basic

parameters, budget constraints, and general goals (such as carbon-neutral shipping, calorie goals, or strict cost limits), rather than evaluating individual products.

2. **Agentic AI Proxy Layer:** The layer exists as a high-level auto-generation of AI. It contains the Genetic Algorithm Engine, a tool that keeps and enhances preference populations, as well as real-time market data recursive learning loops that analyse market data in real time. This proxy is always on to relieve the human bounded rationality.
3. **The Firm Infrastructure Layer:** At the bottom of the framework, the Firm Infrastructure Layer replaces the consumer-facing ads with programmatic endpoints that are machine-readable, interoperable, and automated, along with inventory systems. Such systems are connected straight to the strategic enterprise MIS framework (Mohammed, 2023a).
4. **Transactional & Feedback Loop:** Proxy interacts with APIs from the firms, performs automatic optimisation, and carries out transactions in real-time. The results of transactions are automatically fed back into the firm's data system, as well as the agent's recursive learning loop, which in turn further optimises future transactions without the need for any human interaction.

4. Mechanisms of Influence

4.1 Cognitive Offloading: The Psychological Cost of Algorithmic Delegation

An algorithmic consumer is emerging systemically, reinforced by the cognitive offloading phenomenon that makes a psychological shift from the human decision-maker towards external digital infrastructures (Gilbert & Wilson, 2013). In predictive marketing, the delegation is not just about the convenience of operation, but it's also a reconfiguration of the cognitive architecture of consumers. The consumer is able to overcome the limits of his bounded rationality (Simon, 1957, 1991) by using agentic AI to handle the search costs of transactions, assess multi-attribute product matrices, and fulfil transactions.

But this sort of offloading into the system carries with it extremely high psychological costs, which are largely neglected in rosy scenarios of the automation of the marketplace. The consumer's psychological connection with the marketplace evolves as autonomous software agents go through consumption cycles. The cognitive effort that is paid during the search and evaluation process is the basis of traditional consumer behaviours, including brand affect, impulse exploration, and product-based identity construction. Once this is taken away from the consumer, he/she comes into a state of choice detachment.

Corporate Management Information Systems (MIS), with their design and performance, are responsible for the structural mediation of this transformation as they gather huge flows of operations to keep user models stable (Mohammed, 2023a). Structured training pipelines and organisational structures play a pivotal role in the smooth functioning of delegated data interfaces in the operationalisation of these systems, ensuring that they operate without human intervention (Muhammed et al., 2022).

With the use of agentic proxies in these roles, consumption behaviour trends towards being an instrumental optimisation of utility over people's identities, now managed by enterprise infrastructures (Mohammed, 2023a; Sundararajan & Mohammed, 2023a). The psychological co-creation of value in the context of service-dominant logic (Vargo & Lusch, 2016) is thus stripped of its emotional, human aspects, replacing them with a list of technical changes between parameters to be read by machine.

4.2 Algorithmic Biases and the Erosion of Consumer Agency

The algorithmic proxy of the consumer is an organised transfer of consumer agency that creates severe weaknesses on the digital marketplace. Agentic systems are recursive, so their internal parameters are continually updated due to transactional data collected from electronic marketplaces (Mohammed, 2023b; Sundararajan & Mohammed, 2024a). The optimisation loops of the agents will absorb, magnify and cement these biases in the name of neutral optimisation if the underlying data infrastructures are distorted in some way, including historical inequities and/or manipulation at the firm level.

This is a threat to individual agency in a direct manner. In the traditional predictive marketing approach, human scepticism, planned change of choices or actual exploration could help balance out a skewed recommender system. The agentic paradigm, however, involves optimising mechanisms that typically are based on genetic algorithms, which work in hidden multidimensional search spaces (Goldberg, 1989). Introducing mutations and automated crossovers during the initialisation of a population of consumption bundles and implementing a compromised version of the fitness function can make it possible for the consumer to be trapped inside an "ideological/behavioural filter bubble".

This risk can be seen in many digital environments such as the metaverse (Mohammed, 2023e; Subramani et al., 2024), platform entrepreneurship and global trade. There, the architectures of the markets are more likely to be shaped by the aim of maximising the value of the platform for the money than for the consumers (Subramani et al., 2024). This situation gives rise to a double-principal-agent issue, first from the perspective of the shareholders and second from the perspective of the CEO (Jensen & Meckling, 1976):

The consumer is the main player, and the AI agent is responsible for operations. But the agentic software is created on company-proprietary structures and connects to programmatic endpoints that exist within the firm, making them very susceptible to manipulation by the seller. This asymmetry of information is used for structures to adjust the optimisation parameters of the agent slightly. As a consequence, consumer autonomy slowly diminishes; selections that seem to be made on the individual's behalf are actually made by predators of the marketplace, in the form of architectures.

4.3 Comparative Analysis of Marketing Paradigms

The essential differences between the conventional marketing systems and the new agentic system are summarized below.

Table 1: Comparative Analysis of Traditional vs. Agentic Marketing Paradigms

Structural Dimension	**Traditional Predictive Marketing**	**Agentic Marketing Ecosystem**
Primary Economic Actor	Human Consumer (Targeted by Firm)	Algorithmic Proxy (Acting for Consumer)
Cognitive Strategy	Bounded Rationality & Heuristics	Complete Cognitive Offloading
Core Computational Tool	Diagnostic Analytics & Static ML	Recursive Learning & Genetic Algorithms
Value Mechanisms	Psychological Co-creation & Affect	Programmatic Fitness & Utility Optimization
Market Infrastructure	Consumer-Facing B2C Web Portals	Machine-to-Machine Programmatic APIs
Strategic Business Focus	Attention Capture & Brand Equity	System Interoperability & Data Integrity

Primary System Risk	Ad Fatigue & Behavioral Manipulation	Algorithmic Bias & Total Loss of Human Agency

Source: Developed by the author based on interdisciplinary frameworks from Simon (1957), Vargo and Lusch (2016), Gilbert and Wilson (2013), and Mohammed (2023a).

Table 1 presents a theoretical framework by logically connecting existing management theories and software engineering protocols, based on the four pillars. First, it brings the transition from human bounded rationality to deterministic computational optimization into play: because it is not a matter of psychological brand heuristics but of mathematical utility functions being maximized, it is possible to transfer the responsibility for this decision to genetic algorithms. Second, it combines Service-Dominant (S-D) Logic and Programmatic Interoperability and rethinks the process of co-creating markets as a seamless protocol for machine-to-machine data exchange, not a human-brand relationship. Third, it introduces the concept of agency theory to discuss the double-principal-agent dynamics, which reveals the harsh governance issues, structural information asymmetry, and easy-to-be-exploited platform situation when decisions are entrusted entirely to digital substitutes. Finally, the table illustrates the psychological steps of cognitive offloading to autonomous execution, in which consumers are shifting from being active agents in the process of getting the information out of the system to passive observers, who are completely offloading real-time consumption loops to autonomous systems.

5. Governance and Ethical Implications

5.1 ESG Governance in the Age of Autonomous Marketing

A significant modification of the Environmental, Social, and Governance (ESG) approach is needed within enterprises in order for them to have autonomous systems that govern their operations. Conventional corporate governance directives are concentrated on overseeing physical supply chain activities, executive choices, and human activities. In the case of agentic marketing systems operating directly with autonomous software proxies representing consumers, however, governance needs to extend to the ethical behavior of autonomous software loops.

From an environmental point of view, the infrastructure needed to execute recursive learning models in real-time and large-scale iterations of genetic optimizations leads to major carbon footprints. This energy demand has direct consequences on companies' sustainability objectives, as they need to consider how efficient automated micro-transactions are and how much responsibility they have towards the environment (Mohammed & Sundararajan, 2024; Mohammed & Kumar, 2022).

On a social level, companies need to make sure that their automated market systems do not exploit vulnerable groups of consumers who have delegated their choice architecture to problematic digital proxies or that they do not engage in predatory pricing (Mohammed & Sundararajan, 2023; Sundararajan & Mohammed, 2024b).

Now, corporate governance is no longer an information technology-neutral back-office tool. In contrast, in high-stakes sectors that employ sophisticated project management models, software deployment needs to be tightly constrained by multi-layered surveillance systems in order to guarantee trust in the system and safeguard public health (Mohammed, 2023c; Mohammed, 2023d).

5.2 Algorithmic Accountability and Transparency

One of the most important issues in defining governance for agentic ecosystems is the opacity that is an intrinsic part of deep learning, neural networks, and evolutionary algorithms. If an agentic system can change its own loss functions by recursive learning, it can come up with the transactional strategies that its original software engineers might not have written up. This can result in collusive pricing, hidden data exploitation, and targeted restriction of choice architectures, all without human control in a predictive marketing environment.

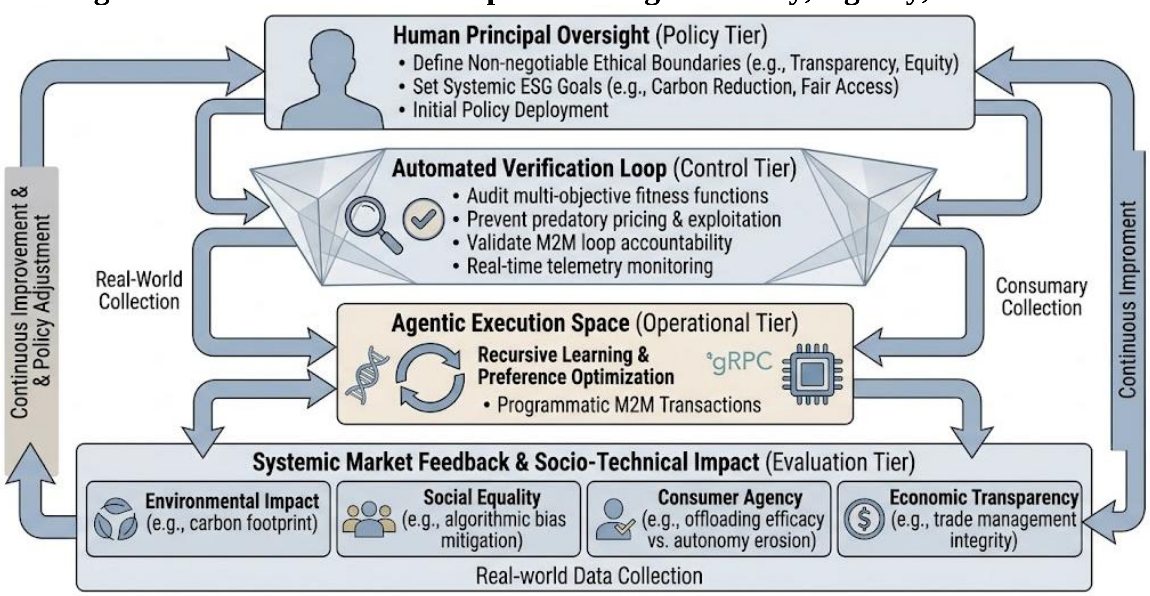
In order to ensure algorithmic accountability, organizations need to move from the traditional models of oversight to a verification system that is automated and real-time (Sundararajan & Mohammed, 2023b). You can't make it transparent by simply holding postmortem audits or by making general moral statements. Rather, it needs to be incorporated into the enterprise information system architecture directly (Mohammed, 2023a).

Companies need to be able to provide easily accessible, machine-readable documentation of their API parameters, data collection policies, and optimization parameters that are used to govern their automated market interactions. Otherwise, the digital marketplace can become closed and anti-competitive, and corporate algorithms can be given the opportunity to scheme, exploit, and take advantage of what consumers employ to keep them safe.

5.3 The Governance Loop

Companies need integrated closed-loop governance in order to ensure that the trend towards autonomous commerce doesn't take away consumer agency or cross the ethical lines.

Figure 3: The Governance Loop: Balancing Efficiency, Agency, and Ethics



Source: Developed by the author based on theoretical and macro-environmental frameworks established in Mohammed (2023e), Mohammed and Sundararajan (2024), and Subramani et al. (2024).

Figure 3 shows that the governance is continuous and multi-tiered to ensure that autonomous execution is in compliance with human ethical standards:

1. **Human Principal Oversight (The Policy Tier):** At the top of the governance loop, at the human principal oversight (the policy tier), human controllers such as corporate boards, compliance officers, consumer advocacy groups, etc., set non-negotiable ethical boundaries, safety parameters, and systemic ESG goals.

2. **Automated Verification Loop (The Control Tier):** This is a layer that can be a real-time regulatory barrier between people and machines. It will constantly monitor the fitness functions and optimization models that are employed by agentic systems to detect algorithmic bias, unfair restrictions on the choice of algorithms, or exploitative pricing policies before transactions are completed.
3. **Agentic Execution Space (The Operational Tier):** Secure space where autonomous systems are executing recursive learning loops and genetic preference optimizations, which perform machine-to-machine transactions over solid APIs (Mohammed, 2023a; Mohammed, 2023b).
4. **Systemic Market Feedback (The Evaluation Tier):** This layer monitors the more general impacts on the environment and social and economic aspects of automated transactions. It collects information about carbon consumption, equality of access to the market, and protection of consumer autonomy and sends the telemetry back to human oversight to constantly adjust the corporate governance policies.

6. Managerial and Strategic Propositions

6.1 Rethinking Customer Relationship Management (CRM) in an Agent-First World

The instantiation of the algorithmic consumer forces a radical restructuring of corporate strategy, specifically requiring organizations to completely re-engineer Customer Relationship Management (CRM) architectures. For decades, CRM systems have been built to get people to click, linger, feel good about the brand, and get impulse-bought. CRM systems have been designed to maximize dwell time, optimize visual click-through rates, brand effect, and emotional impulsivity for decades. The bounded rationality of human principals (Simon, 1957, 1991), however, becomes increasingly reduced as they increasingly rely on cognitive offloading (Gilbert & Wilson, 2013) and turn to a software-based intermediary as the traditional receiver of marketing signals. Hence, in this context, companies need to shift from the traditional human-centric CRM systems to M2MRM systems.

The shift is essentially a strategic one that directly and fundamentally affects enterprise architectures and information management systems (Mohammed, 2023a). It is no longer possible to think of CRM as a front-end portal for human salespeople; it must be viewed as an interoperable back-end data layer, which features high throughput and low latency programmatic APIs (Mohammed, 2023a). The traditional brand equity, which has been widely recognized in marketing literature as a protective brand asset, is no longer so in the presence of an agentic AI proxy that optimizes preference profiles through the use of genetic algorithms (Goldberg, 1989). An autonomous proxy makes offers and evaluations based on mathematically defined multi-objective fitness functions that evaluate technical parameters such as marginal cost, shipping logistics, composition ratios, and so on but don't consider visual brand stories.

Such a structural change in the interaction with market spaces has led to a shift of e-commerce from an environment of psychological persuasion to a technical interoperability environment (Mohammed, 2023b; Sundararajan & Mohammed, 2024a). This shift in business models towards a systemic transformation is akin to the structural transformation that is happening across global value chains, which require more than a reactive engagement to establish programmatic, self-correcting networks (Mohammed & Sundararajan, 2024; Mohammed, 2023). In this new context, value is co-created, not through sensory engagement, but through the technically seamless, programmatic integration of both the firm-side and consumer-side models, which are agentic (Vargo & Lusch, 2016).

6.2 Strategic Roadmap for Marketers

Businesses must adapt their processes, engineering methods and performance metrics for this structural shift to be successful, and this must happen at each of the different stages of marketplace automation.

Table 2: Strategic Roadmap for Marketers: From Engagement to Delegation

Operational Dimension	Phase A: Attention Capture	Phase B: Choice Curation	Phase C: Algorithmic Delegation
Core Marketing Metric	Click-Through Rate (CTR) & Customer Lifetime Value (CLV)	Share of Voice & Feed Recommendation Rankings	API Interoperability Index & Algorithm Acquisition Yield
Primary CRM Interface	Omnichannel Web & Mobile Front-Ends	Search Engine Optimization (SEO) & Personalization Ingestion	Hyper-Structured Machine-Readable Programmatic Endpoints
Optimization Vector	Human Brand Affect & Visual Design	Cognitive Heuristics & Collaborative Filtering	Multi-Objective Fitness Function & Mathematical Utility Alignment
Organizational Capabilities	Creative Brand Strategy & Consumer Psychology	Data Science, Diagnostic Analytics & Pattern Classification	Software Engineering, API Governance & Computational Modeling
Primary Failure Risk	Attention Saturation & Ad Fatigue	Algorithm Blacklisting & Platform Dependency	Information Asymmetry, Contract Misalignment & Agent Defection

Source: Developed by the author based on enterprise architecture frameworks and digital marketplace strategies established in Mohammed (2023a), Mohammed (2023b), and Sundararajan and Mohammed (2024a).

Table 2 shows how corporate strategy evolves over different stages of the marketplace, from the early stages of human-centric engagement through to complete algorithmic delegation. However, in Phase A (Attention Capture), success will depend on how well consumers can be influenced and moved to click through with creative brands and visual web interfaces. In Phase B (Choice Curation), shared agency enters the mix, as the data science engines and diagnostic analytics have to curate personalisation feeds to match algorithmic recommendation architectures. Lastly, in the final phase (Algorithmic Delegation), the firm moves completely to a Machine-to-Machine Relationship Management (M2MRM) where the highly structured, machine-readable programmatic endpoints (e.g., gRPC and JSON-LD) are made available to communicate with the consumer proxy's multi-objective genetic fitness functions. So, instead of human-centric metrics, the shift is to an API interoperability index and from the simple consumer ad fatigue to a systemic platform exploitation and algorithmic agent defection risk that becomes the core of the corporate threat.

7. Future Research Directions

7.1 Methodological Challenges in Studying Non-Human Interactions

Agentic AI proxies enable completely autonomous consumption loops, creating severe methodological challenges for business research, making most tools used in the past obsolete. Today, consumer behaviour researchers have used psychometric tools, surveys in the field, laboratory-based eye tracking and focus groups for more than 50 years to understand consumer intent and choice in action. Inspecting the psychological state of a human participant does not provide much information about the market transactions if they are carried out in a totally black-box recursive learning model. A Likert scale is not suitable for measuring 'satisfaction' or 'brand loyalty' of an autonomous software agent.

Management science must devise new computational methods to deal with this. Scholars need to change their perspective from studying human psychology to auditing software code, in line with the use of agent-based modelling, execution telemetry analysis and experimental algorithmic environments. These strategies enable researchers to control the variables in the marketplace and systematically change the consumer proxies to observe their preference changes.

This methodological shift is similar to other high-stakes domains that have shifted from self-reported human data to logs from the systems and deterministic performance tracking to understand complex systems, including health informatics (Mohammed, 2023c), education (Mohammed, 2023d), and complex project management (Sundararajan & Mohammed, 2023b). These new research methodologies need a high level of technical training, multidisciplinary teamwork and flexibility in structures of academic and corporate institutions (Muhammed et al., 2022; Sundararajan & Mohammed, 2023a).

7.2 The Future of Genetic Algorithms in Consumer Preference Prediction

One of the most interesting lines of future investigation is the ability to study the evolution of a genetic algorithm (GA) in optimising the multi-attribute choice of a consumer in real-time. In the traditional uses of evolutionary computing, the preferences of the customers are relatively stable. In an agentic marketing ecosystem, however, the fitness landscape is dynamic and constantly evolving, and the algorithmic system on the firm side dynamically changes the prices, product configurations, logistics paths, etc. as a direct response to the optimisation passes carried out by the consumer agent.

The algorithmic relationships presented in this work are co-evolving; these mathematical and behavioural implications need to be studied further. As these two types of systems are constantly adapting to each other, the market may have emergent properties such as structural convergence, local optimisation traps and even systemic transaction failures.

The implications for these dynamics are more complex and require the use of sophisticated structural equations and complex network models to understand how the stability of markets will change as a result of mutation rates, mechanisms of the crossovers and the structural constraints. This research line is of particular importance to avoid market manipulation and maintain the consumer utility in new and evolving digital environments and intricate online platforms (Subramani et al., 2024; Sundararajan & Mohammed, 2024a).

8. Conclusion

The theoretical concept of an "algorithmic consumer" is introduced as a conceptual paper that creates a new theoretical framework that connects consumer behaviour, strategic management and software engineering. We illustrate and discuss the transition from predictive to fully autonomous agentic decision-making, thereby providing a framework that explains the evolution from passive to active consumption in terms of shifting from a psychological evaluation to an optimisation of a utility. By combining key management principles with software engineering principles (autonomy, recursive learning and genetic algorithms), we can make the new choice architectures of highly automated markets visible.

In the end, then, choice delegation to agentic systems may be a solution to the bounded rationality of humans; however, it poses significant strategic, operational and ethical difficulties. In discussing the double-principal-agent problem, these systemic weaknesses are not only brought to the forefront but also emphasised: loss of autonomy of individuals, amplification of data bias, and the possibility of algorithmic manipulation by predatory market platforms. In the agent-first market there are obstacles for companies to overcome in order to build transparent, accountable and resilient governance systems, and they must look beyond short-term operational gains. This paper serves as a solid base for the future empirical research, strategic changes and regulation in the new agentic commerce era.

References

1. Gilbert, S. J., & Wilson, T. D. (2013). Prospection: Experiencing the future. *Science*, 317(5843), 1351-1354. https://doi.org/10.1126/science.1144161

2. Goldberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*. Addison-Wesley.
3. Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4), 305-360. https://doi.org/10.1016/0304-405X(76)90026-X
4. Mohammed, A. (2023a). Strategic utilization of management information systems for efficient organizational management in the age of big data. *Computer Applications: An International Journal (CAIJ)*, 10(3/4), 11–23. https://airccse.com/caij/papers/10423caij02.pdf
5. Mohammed, A. (2023b). Navigating the digital marketplace: Strategies for entrepreneurship in electronic commerce. *Computer Applications: An International Journal (CAIJ)*, 10(3/4), 45–58. https://airccse.com/caij/papers/10423caij06.pdf
6. Mohammed, A. (2023c). Strategic management of game development projects: Optimizing resources and quality in the gaming industry. *Computer Game Development and Education: An International Journal (CGDEIJ)*, 1(3), 15–29. https://wireilla.com/cgdeij/papers/vol1/1323cgdeij02.pdf
7. Mohammed, A. (2023c). Strategic management of game development projects: Optimizing resources and quality in the gaming industry. *Computer Game Development and Education: An International Journal (CGDEIJ)*, 1(3), 15–29. https://wireilla.com/cgdeij/papers/vol1/1323cgdeij02.pdf
8. Mohammed, A. (2023d). Human resource development in health informatics: Cultivating a competent workforce for advancing healthcare technology. *Computer Applications: An International Journal (CAIJ)*, 10(3/4), 31–42. https://airccse.com/caij/papers/10423caij04.pdf
9. Mohammed, A. (2023e). Analyzing global impacts and challenges in trade management: A multidisciplinary study. *Economics, Commerce and Trade Management: An International Journal (ECTU)*, 3, 12–25.
10. Mohammed, A., & Kumar, S. (2022). Empowering sustainable development through entrepreneurship innovations. *International Journal of Humanities, Arts, and Social Sciences*, 8(1), 10–20. https://dx.doi.org/10.20469/ijss.8.20002-2
11. Mohammed, A., & Sundararajan, S. (2023). Poverty, women's economic empowerment, and the sustainable development goals in Nigeria. *Economic Challenger: An International Journal*, 26(102), 45–52.
12. Mohammed, A., & Sundararajan, S. (2024). Automation, innovation, and resilience: Securing sustainable livelihoods through evolving employment dynamics in agriculture. *Responsible Production and Consumption*, 108–117.
13. Muhammed, A., Sundararajan, S., & Lawal, T. (2022). The effect of training on the performance of small and medium-sized enterprises (SMEs) in Kano Metropolis. *Seybold Report*, 17(6), 114–128.
14. Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68-78. https://doi.org/10.1037/0003-066X.55.1.68
15. Simon, H. A. (1957). *Models of man, social and rational: Mathematical essays on rational human behavior in a social setting*. John Wiley & Sons.
16. Simon, H. A. (1991). Bounded rationality and organizational learning. *Organization Science*, 2(1), 125-134. https://doi.org/10.1287/orsc.2(1).125
17. Subramani, S. K., Mohammed, A., Rasheed, H., Sundararajan, S., & Pal, S. K. (2024). Metaverse as a platform for entrepreneurs and startups: Exploring opportunities and challenges. *International Journal of Marketing & Financial Management*, 12(1), 14–29. https://doi.org/10.53882/IJMFM.2024.1201002

18. Sundararajan, S., & Mohammed, A. (2022). Entrepreneurial opportunities for women. In *Proceedings of the Conference on Gender Equality and Women Empowerment*. *European Journal of Humanities and Educational Advancements*, Special Issue 1, 112–115.
19. Sundararajan, S., & Mohammed, A. (2023). Changing role of artificial intelligence in the growth of entrepreneurship development. *Pratibimba: The Journal of IMIS*, 23(1), 34–41.
20. Sundararajan, S., & Mohammed, A. (2023b). Evaluation of teachers – History to current era. *Samzodhana – Journal of Management Research*, 13(2), 78–89. http://eecmbajournal.in
21. Sundararajan, S., & Mohammed, A. (2024a). Disruptive dynamics and transformational opportunities: An in-depth exploration of e-commerce and online marketplaces. *ISAR Journal of Economics and Business Management*, 2(1), 1–4.
22. Sundararajan, S., & Mohammed, A. (2024b). A comparative study on gender equality and women empowerment in India vs. Nigeria. *Scholarly Research Journal for Interdisciplinary Studies*, 42(67), 10432–10441.
23. Sundararajan, S., & Mohammed, A. (2024b). A comparative study on gender equality and women empowerment in India vs. Nigeria. *Scholarly Research Journal for Interdisciplinary Studies*, 42(67), 10432–10441.
24. Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of Marketing*, 68(1), 1-17. https://doi.org/10.1509/jmkg.68.1.1.24036
25. Vargo, S. L., & Lusch, R. F. (2016). Institutions and axioms: An extension and update of service-dominant logic. *Journal of the Academy of Marketing Science*, 44(1), 5-23. https://doi.org/10.1007/s11747-015-0456-3