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# Maximizing Mining Operations: Unlocking the Crucial Role of Intelligent Fleet Management Systems in Surface Mining's Value Chain

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**Abstract:** On the one side, the operational expenses of mining enterprises are showing an upward trend; and on the other side, conventional mining fleet management systems (FMSs) are falling short in addressing the high-dimensionality, stochasticity, and autonomy needed in increasingly complex operations. These major drivers for change have convinced researchers to search for alternatives including artificial-intelligence-enabled algorithms recommended by Mining 4.0. The present study endeavors to scrutinize this transition from a business management point of view. In other words, a literature review is carried out to gain insight into the evolutionary trajectory of mining FMSs and the need for intelligent algorithms. Afterward, a holistic supply chain layout and then a detailed value chain diagram are depicted to meticulously inspect the effect of technological advancements on FMSs and subsequently the profit margin. The proposed value-chain diagram is advantageous in explaining the economic justification of such intelligent systems, illustratively, for shareholders in the industry. Moreover, it will show new research directions for mining scholars.

**Keywords:** fleet management system; Mining 4.0; value chain analysis; profit margin; surface mining



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## 1. Introduction

In 2021, the top 40 mining companies generated just below one trillion dollars in total revenue, setting a record year for the industry, while the net profit margin stood at only 17%, i.e., a one-third decline compared to 24% in 2011. This is due to their total staggering operating cost of nearly $600 billion recorded for 2021, a 30% growth relative to the previous year, with a projected 15% increase for 2022 [1]. To maintain their competitive edge in today's intense market, the leading mining companies are left with no choice but to leverage technological advancements in their activities, the most crucial of which is the loading and haulage operation known as the most extravagant part of a surface mining project. Other drivers for change are also contributory to this must transition such as the ever-increasing demand for critical minerals on account of the recent hype in clean energy and net-zero emissions. Dealing with global warming and catering to increasing demands are two contradictory objectives. However, these financial and environmental targets are achievable through an integrated fleet management system (FMS) embedded with the latest disruptive technologies to better adapt itself to the highly dynamic problem of material handling systems. An FMS runs the whole gamut of functions from dispatching to fuel, maintenance, and safety management. Implementing effective mitigating measures in mines significantly enhances safety protocols, promoting a secure working environment [2,3]. The more expectations arise in pillars of sustainable development, the more needs are generated for tapping into multi-objective FMSs, implying the fact that conventional optimization techniques are no longer accountable, and the journey for finding alternatives should begin. However, with artificial intelligence (AI) thrusting itself into every aspect of mankind's daily life, that journey would not be an uncharted territory adventure anymore. A variety of AI-powered techniques have already been employed in a wide range of industries even mining to some extent. One can exemplify autonomous trucks in Australian iron mines, leveraging AI algorithms to navigate, operate, and perform tasks without direct human intervention. Yet, it is not a common practice in other mines in other parts of the world. The harsh fact is that in some mine sites, the at least 30-year-old conventional FMSs are either not applied yet or are being implemented starting just recently. These observations indicate the necessity of further efforts for deeper recognition of intelligent FMSs, particularly in the Mining 4.0 era. To this end, two main viewpoints can be taken: economic or environmental. In this study, the focus is on the first angle via adopting a value-chain-analysis approach. That is to say, the essence of introducing intelligence into FMSs is scrutinized along the exploitation value chain to decipher how this transition contributes to higher margins. A value chain is a conceptual depiction of the sequential steps taken by an organization to conceive, produce, and distribute its offerings to its clientele. The value chain analysis is a tool employed to determine areas that can be modified to enhance efficacy and competitiveness. This analytical approach encompasses both primary activities directly implicated in the creation and delivery of the product or service, and supportive activities facilitating the primary activities. One should distinguish a supply chain from a value chain in that the former focuses on the flow of materials from suppliers to consumers with the aim of cost reduction and efficiency enhancement, whereas the latter is dedicated to the flow of demands (demand chain) from consumers in order to trigger innovation in product development and marketing [4]. The rationale for applying the value chain analysis in the present research work is that it offers the advantage of evaluating load-and-haul systems as a primary activity in relation to technological advancements as a supportive activity to identify opportunities for adding value through improving efficiency and reducing costs. Here, the value-adding activity is the incorporation of Mining 4.0 technologies into the primary activity of the surface mining material handling operation. Taking a value chain perspective on the usability of intelligent FMSs is paramount in the sense that it not only acts as a proof of concept for old-fashioned shareholders but also outlines potential research directions for adding more value and consequently generating higher profit for a mining enterprise. To the best of our knowledge, there is no similar work looking at intelligent FMSs from the value chain viewpoint. The truth of the matter is that research works bridging mining activities to business management suffer in number, causing the think-outside-the-box worldview to elude mining practitioners, while the top-down view gives birth to some innovations that would not be possible with its counterpart. In the ensuing section, a literary analysis is carried out on the interlinked relation of FMSs, logistics, and supply chains to obtain a broad scope of the problem. Then, conventional and intelligent algorithms developed so far are inspected to get acquainted with the evolutionary trajectory of FMSs. Following that, the value chain analysis, the backbone of the article, is expounded and illustrated thoroughly to be as enlightening as possible. Discussion and conclusion will come forth accordingly.

## 2. Literature Review

The history of today's FMSs in the mining industry stems from logistics management in road transportation. This section brings light to the concept of FMSs and related attributes, followed by a glance at the evolution of FMSs from conventional to intelligent units in surface mines.

### *2.1. FMSs: The Concept*

In crude terms, a supply chain is "a structured manufacturing process wherein raw materials are transformed into finished goods, then delivered to end customers" [5]. Thus, the supply chain encompasses a series of interlinked chains (operations) including supplying, manufacturing, logistics, and consuming. The operation embedded with the transportation and storage of materials, parts, and products in a supply chain is defined as logistics [6]. Supply chain management coined by Keith Oliver in 1982 refers to a set of methods used to effectively coordinate suppliers, producers, depots, and stores, to bring about a fast, trustworthy, cost-effective, flexible supply chain sufficient to cater to customers' needs [7–9]. As supply chain management optimizes operations all over the supply chain, logistics management aims similarly to ensure efficient delivery and storage of goods or services between the point of origin and the point of consumption through fleet management, inventory management, materials handling, and order fulfillment [6]. First used probably in the thirteenth century, the word fleet is originally defined as "an organization of ships and aircraft under the command of a flag officer" (Merriam-Webster, 2002). A company's transportation fleet comprises commercial motor vehicles, namely cars, ships, airplanes, boats, shovels, or trucks. Fleet management embraces numerous functions of equipment financing, maintenance, telematics, driver management, speed management, fuel management, and health/safety management [10]. Fleet management under the aegis of logistics management improves scheduling, productivity, quality of service, and effectiveness as well as minimizing costs and risks [11,12]. FMS is described as a wide range of solutions for various operations in the fields of transportation, distribution, and logistics [13]. It owes its existence to computer-integrated vehicles communicating via satellite and terrestrial wireless networks in the 1980s [14]. This achievement would not be possible without the advent of telematics, a combination of telecommunication and informatics. First introduced in 1978 in France, the concept was originally utilized for automobile industries and vehicular tracking in logistical fleets [15]. Telematics is a multidisciplinary area of study incorporating communications, vehicle technologies, road transport, electrical engineering, and computer science. This is a mechanism/tool used for tracking and vehicle communication [16]. It consequently provides fleet managers with numerous benefits including reduction in cost, increase in productivity/profitability, provision of preventive maintenance, extension of equipment life, enhancement of equipment utilization and uptime, improvement of customer service and satisfaction, integration of equipment data with business systems, and reduction of the risk of loss due to theft or unauthorized use [10].

Fleet operational characteristics are categorized into four criteria including size, operating range, routing variability, and the time-sensitivity of deliveries [17]. According to this taxonomy and regarding the first category, four major sizes based on the number of vehicles are discernible small (<20), medium (20–100), large (100–500), and very large (>500). The second criterion indicates the scope of activity as being local, regional, or national. Fixed-route vehicles operating on the same routes during a certain period are distinguishable from variable-route carriers experiencing frequent re-routing and re-scheduling. The urgency of a shipment is described to be of low, medium, or high time sensitivity.

Being treated as a static and deterministic problem in its classical form in the operations research literature, the vehicle routing problem (VRP) is the cornerstone of supply chain and fleet management [18]. A VRP model in an FMS is said to be dynamic if it is influenced by the reciprocal action of parameters with time [19]. All the routing information is available in advance and unchangeable after initial planning in static systems, whereas in the dynamic mode, a fraction of attributes is not only previously unknown but also subject to change after the construction of initial routes [20]. These attributes have been laid out in taxonomy in terms of evolution (updating), quality (certain or uncertain), availability, and processing (centralized or decentralized) [21]. To better differentiate between static and dynamic models, an index called 'Degree of Dynamism' (fluctuates between 0 and 1) has been proposed in various notations considering the number, the request time, or the reaction time of immediate requests [22]. The number of immediate requests has also played a key role in categorizing a variety of dynamic VRPs into a three-echelon framework of weakly, moderately, and strongly dynamic systems [20]. On the one hand, VRP is a stochastic optimization problem on account of dealing with uncertainty-bearing future events. On the other hand, VRP is a dynamic problem since new updates appear during the execution of the routing plan [18]. To cope with unforeseen incidents, a real-time dynamic FMS is essential to re-optimize the initial dispatch plan instantly [13].

Information in FMSs is processed via either the centralized or decentralized approach. In centralized management, the fleet operator (human or automated system) sends low-level globally optimal plans remotely to vehicles after considering all relevant information. Despite guarantying an optimum solution, numerous flaws emerge (1) The requirement for full information of the network and the tasks, (2) Compromising the fleet's response time due to computational and communication constraints in large-fleet systems, (3) Tardy machine-to-machine and center-to-machine data transferring for timely processing by the central unit [23–25]. These aspects together with technological advances in the design and manufacturing of compact mini-computers have drawn attention towards the decentralized approach, in which, faster, less expensive communications, and more autonomy to vehicles, are imaginable.

While first-generation FMSs were assigned the ordinary task of vehicle tracking [26], the second offspring matured into planning tools to undertake more complex roles [27]. However, the third generation is on the verge to be evolving into autonomous cyber-physical systems enjoying digital twin and artificial-intelligence decision-making units in their architecture [28]. The mining industry has witnessed a range of metamorphoses in its fleet management systems ranging from manual to automatic dispatching modes [29]. The ensuing subsection relates a general literature review on conventional and intelligent FMSs in surface mining.

### *2.2. Mining FMSs*

Mine planning involves long-term, medium-term, short-term, and operational horizons. Strategic planning focuses on the long-term and medium-term and involves setting goals that align with the vision and mission of the organization. Tactical planning is concerned with shorter time frames and narrower scopes and looks at the next month or less. Operational planning encompasses the allocation and dispatching of equipment from one second to one hour [30]. Mining operations are responsible for around half of total operating costs, as well as one-tenth of global energy-related greenhouse gas emissions [31,32]. FMSs are essential for optimizing a fleet's performance, as even small changes can lead to significant monetary and environmental gains in a mining operation. Single-stage or multi-stage FMSs have been chiefly applied for the management of operation fleets in mine sites. Single-stage systems do not take production needs into account, and instead, assignments are determined by dispatching criteria. On the other hand, the multistage approach attempts to address shortest path finding, allocation (the upper stage), and dispatching (the lower stage) problems sequentially [33].

#### 2.2.1. Conventional Systems

A small fraction of authors have applied the queuing theory for allocation problems, among them works carried out by Dallaire, et al. [34], Kappas and Yegulalp [35], and Ercelebi and Bascetin [36] are the most noticeable. Nevertheless, the queuing theory can be limited due to its assumption of predictable input data and its narrow scope to specific types of problems, leading to inaccurate results in real-world, uncertain, and complex situations involving multiple interacting variables [37]. Thus, programming-based operations research techniques became the most common fleet optimization tools. White and Olson [38] proposed a linear programming (LP) model for meeting production targets within a specific time horizon using two weakly coupled models. The first segment sought to calculate shovels' digging rates, while the second part focused on allocating a minimum number of trucks to each route to meet the route's flow rate. Ref. [37] employed LP to link FMS to strategic plans via offering shovel assignments. Another research stream belonged to mixed integer linear programming (MILP) used by some authors, namely Ta, et al. [39], Chang, et al. [40], and Moradi Afrapoli and Askari-Nasab [30]. LP-based models are criticized for having to specify an acceptable range for including operational constraints, e.g., stripping ratio and required feed grade [33], wherefore goal programming was highlighted in the upper stage by other efforts like Temeng, et al. [41] and more recently Mohtasham, et al. [42]. Regarding the lower stage, the two chief approaches of assignment and transportation stand out. Accounting for a majority of truck dispatching models developed so far, the assignment approach sends each truck to each shovel in line with an objective such as waiting time minimization like the work published by Soumis, et al. [43]. However, the assignment problem might not perform satisfactorily in the mining context since a shovel may require more than one truck to catch up with its production plan. To tackle this shortfall, Temeng, et al. [44] resorted to the transportation solution by determining a needy shovel and the number of trucks required. Additionally, to these fundamental methods, the trace of evolutionary algorithms is noticeable in the lower stage and observable in works including Dabbagh and Bagherpour [45], Zhang, et al. [46], and Yuan, et al. [47]. While conventional methods have been widely studied, they might be troublesome in large-size optimization problems and stochastic environments like what occurs in real-life mining operations. That is why researchers have been invoking AI-enabled algorithms for the last decade to develop less defective FMSs.

#### 2.2.2. Intelligent FMSs

After two decades of recession due to hardware and big data impediments, machine learning (ML) as a subset of AI staggeringly flourished in 2012 and is forcing its way into every aspect of human life. ML leverages three main strategies including supervised learning, unsupervised learning, and reinforcement learning (RL) to carry out prediction, pattern recognition, classification, and optimization on a variety of input data types such as text, image, voice, or video. With the aim of finding the most efficient solution in mining FMSs, many researchers have applied and compared diverse ML techniques, especially random forests, k-nearest neighbors, linear regression, decision trees, support vector machines, and artificial neural networks [48–55]. Nonetheless, the weakness of supervised learning to accurately address and represent changes occurring in real-time [56] has established a sensational research direction known as the RL-based approach to developing mining FMSs. This stream was initiated by Bastos, et al. [57] and has been pursued by Zhang, et al. [58], De Carvalho and Dimitrakopoulos [59], and Huo, et al. [60]. RL-based FMSs are in the nascent stage now and have a long way to reach the pinnacle of maturity. More precisely, the thus-far developed models are not attentive to multi-aspect goals and requirements of mining operations such as processing plants, in-pit/out-pit ore/waste dumping locations, and alliance with strategic plans. A recent study reveals that nearly two-thirds of dispatching and allocation features are ignored in the intelligent FMSs developed so far in the mining domain [61]. Regardless of these technical shortcomings irrelevant to the scope of this study, here the focus is placed on the economic aspects of employing intelligent FMSs in surface mining operations and how this transition might lead to more profits throughout the exploitation value chain, formulating the hypothesis of this research. Some managers and shareholders are hesitant about the economic justification of such intelligent systems. Thus, expounding on the merits of technological advancements in material handling systems is required for paving the way for more development and application of such systems in the mining sector. The main purpose of this value chain perspective is to provide the general proof needed.

## 3. Materials and Methods

Established initially in 1985 by Michael Porter, the value chain concept is a set of activities interacting within a company to create value for consumers (or profit for the company) in hopes of earning a competitive advantage over rivals [62]. Here, we aim to investigate the interaction between technological advancements and mining FMSs, and their synergy's effect on the profit margin. However, a supply chain analysis is carried out beforehand to obtain a top-down view of the concept.

### 3.1. The Mining Supply Chain

Residing on the operational level of mine planning hierarchy, FMSs show a nested relationship with logistics, and then supply chain management. A typical supply chain is comprised of five elements, namely suppliers, manufacturers, distributors, retailers, and consumers. With that in mind, a holistic mining supply chain diagram is depicted in Figure 1 to better map FMSs along this network. Analogically speaking, each of these five chains can be assumed as a value chain per se. The exploration/exploitation value chain serves as a base supplier for the whole network, accounting for all the activities required to deliver raw materials to the processing plant ranging from exploring potential reserves down to drilling, blasting, materials handling, dumping, and outbound logistics. An FMS consequently copes with materials handling and stockpiling activities to send efficient dispatching and dumping commands to a substantial number of loading and hauling units. A mining FMS also undertakes more diversified tasks including maintenance, fuel management, and provision of required feed for the primary crushing plant; however, the goal sought in this diagram is the positioning of an FMS within the mining supply chain, rather than enumerating all fleet management tasks. One could allocate a separate value chain to preliminary mining phases such as exploration and development each; nonetheless, exploration has been consolidated within exploitation to ensure the availability of new mineral reserves for a continual flow of ores (raw materials). Having been transported and deposited (or warehoused in the business terminology), mined ores undergo a variety of treatments based on their different minerals' properties in a processing plant to yield concentrate before storing and handling to the next value chain named smelting or refinery plant, where the base or precious minerals are extracted from the concentrate, and then stacked in form of bars. Afterward, the distribution chain attempts to deliver the cargo by land, rail, or marine logistics to buyers. Upon being warehoused in the end-user factory, the purified mineral is now readily transformed into a variety of goods, marking the end of this long mining supply chain. The last value chain can also forge another supply chain with downstream industries. As mentioned earlier, the typical supply chain accommodates another chain named 'retailer', which is very common in food and grocery supply chains. Similarly, retailers can exist in the mining network following each value chain, acting as an intermediary occasionally, especially in certain political, economic, legal, technical, or logistical situations. Normally, every enterprise endeavors to sell its commodity directly to the end user unless such obstacles arise.

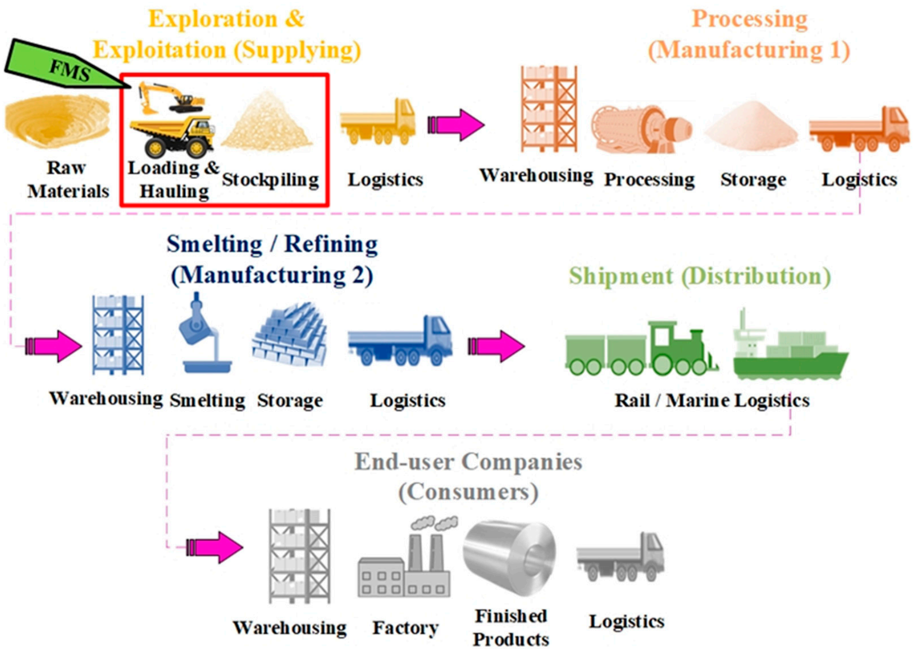


**Figure 1.** A holistic mining supply chain embedded with a fleet management system (FMS).

The mining supply chain comprises five distinct phases—exploration/exploitation, processing, smelting, distribution, and consumer phases—and experiences a significant evolution through the incorporation of intelligent FMSs. The exploration/exploitation phase, as the primary stage for identifying and extracting raw materials from the Earth, undergoes substantial enhancements with these systems. Integrated FMSs in this phase offer real-time monitoring and data-driven decision-making, optimizing vehicle routes and refining resource identification and extraction processes. For example, with GPS technology, these systems precisely track exploration vehicles and equipment within mining sites, ensuring the most efficient paths are taken to reach specific mineral-rich areas. Telematics systems integrated into vehicles during exploitation provide real-time monitoring of equipment performance, fuel usage, and vehicle health, enabling early issue detection and maintenance, thus extending machinery lifespan. Predictive analytics embedded in these systems forecast maintenance needs, reducing downtime by facilitating timely repairs or replacements based on usage patterns. The systems' real-time data sharing and communication capabilities support prompt decision-making, leading to better resource allocation, strategic planning, heightened productivity, and reduced operational costs in mineral resource exploration and exploitation.

### 3.2. The Surface Mining's Value Chain Analysis

The value-chain analysis provides a systematic approach for pinpointing internal value-adding activities, and consequently boosting the organization's profit margin. Porter's approach divides nine activities into two categories primary (inbound logistics, operations, outbound logistics, marketing/sales, and service) and support (procurement, technological development, human resource management, and firm infrastructure) [62]. Primary activities are directly involved in the physical creation and selling of a product, whereas the other category coordinates primary activities to function smoothly. Specifically looking at the first type of activities, inbound logistics encompasses receiving, storing, inventory control, and inspection of inputs. Operations are concerned with all the contributions in transforming raw materials into new products (manufacturing, assembling, packaging, testing, equipment maintenance, quality control, etc.). Associated activities with outbound logistics are known as order processing, warehousing, and shipment. The main tasks assigned to marketing/sales include advertising, promotion, distribution channels, and pricing. Finally, after-sales services bring a huge competitive edge by offering advice, maintenance, parts supply, installation, training, and warranty benefits. At the top of a value chain diagram lie support activities, one of which is procurement referring to the function of negotiating the best prices for the provision of raw materials, machinery, buildings, office supplies, and consumables. Technology development spans all primary activities and even each support activity by offering digitization, telecommunication, automation, artificial intelligence, data mining, research projects, etc. Human resource management is another key area that has a huge impact on the company's efficiency, consisting of recruitment and training resourceful employees. Financial, legal, strategic, planning, and accounting affairs as well as all the primary and support activities go under the umbrella of firm infrastructure. All activities are interlinked with one another (internal linkages), implying that a change in one gives rise to a change in the other positively or negatively. The more optimized and coordinated the activities become, the more profit margin and competitive advantage will accrue.

The combined effect of technology development and an FMS on the efficiency and profitability of a mining unit along its exploitation value chain has been illustrated in Figure 2 and described in Table 1. Despite producing raw materials for downstream industries, mining itself also entails some input items and services known here as inbound logistics including fuel, generators, spare parts, technicians, explosives, and routine errands. With regard to the second primary activity, typical mining operations are characterized by preparing new benches and ramps, implementation of drilling and blasting, loading, hauling, dumping, and feeding the crushing plant. The orderly superintendence of a large set of giant vehicles together with an enormous volume of materials necessitates a consistent FMS operating continuously to enhance productivity. Thus, an FMS is deemed as the cornerstone of the transport stage within an exploitation operation. Outbound logistics deals with the control and monitoring of dumping sites in terms of tonnage and grade; additionally, blending practices on an ad hoc basis, and ultimately, shipping the crushed or uncrushed ores. Multimedia advertising, attending fairs for product promotion, branding, and sales analysis strategies are usually followed in the marketing section. Being heterogeneous, ores are occasionally susceptible to grade volatility, posing trouble in the succeeding value chain. The last main activity copes with such circumstances to build client satisfaction.

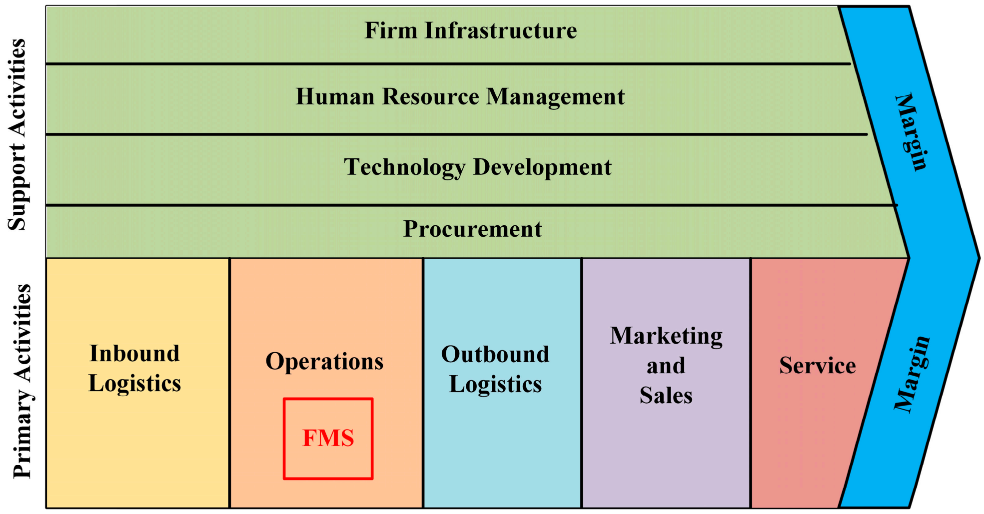


**Figure 2.** The combined effect of technology and a fleet management system (FMS) on profitability along the exploitation value chain.

**Table 1.** Description of various activities along the exploitation value chain.

| Type | Activities | Description |
|---|---|---|
| Support activities | Firm infrastructure | Finance, accounting, legal permits, buildings, equipment. |
| | Human Resource Management | Recruiting, training, career development, fringe benefits, retention, compensation, safety and health assessment. |
| | Technology Development | Mining 4.0 enablers (Data mining, robots, simulation, system integration, Internet of Things, cyber security, cloud computing, augmented reality, artificial intelligence, digital twin, cyber-physical systems, quantum computing, 3D printing, research and development, autonomous vehicles, drones, etc.). |
| | Procurement | Supplier management, negotiation, and subcontracting of equipment and services. |
| Primary activities | Inbound logistics | Utilities (e.g., fuel, electricity), spare parts, explosives, errands (e.g., food, office affairs). |
| | Operations | Development of new working faces, drilling, blasting, loading, hauling, stockpiling, crushers' feeding. |
| | Outbound logistics | Ore dumps management, grade control, blending, order handling, invoicing, and shipment. |
| | Marketing and sales | Multimedia advertisement, domestic and international exhibitions, branding, sales analysis, and market research. |
| | Services | After-sales services in case of grade fluctuations, consulting. |

Support activities were generally and sufficiently explained earlier. Specifically looking at technology development, one could imagine how the fast pace of scientific advancements is reshaping the traditional shop-floor concept beyond recognition. The fourth industrial revolution initiated in 2015 is founded on nine main pillars, namely big data and analytics, robots, simulation, system integration, Internet of Things, cyber security, cloud computing, additive manufacturing, and augmented reality [63,64]. The list can go on with more enablers, especially with artificial intelligence and digital twins taking center stage in the last decade. Mining 4.0 attempts to increase profitability by leveraging these disruptive technologies [65]. The grasp of internal linkages among value chain activities is essential for a more insightful appraisal of the diagram. Support activities are stretched over all the primary activities, indicating that activities on the bottom shelf are directly influenced by alterations in each activity at the top and vice versa. Therefore, mutual communication (a circular linkage) is discernible between these two types of activities so that coordination and optimization are realized throughout the value chain. A probe into Figure 2 highlights the fact that technological advancement in the FMS of a mining operation leads to, for example, fuel conservation in inbound logistics, and this will bring benefits for the company (Firm Infrastructure) by diminishing the fund for fuel purchasing. In another case, upgrading the FMS to state-of-the-art technology enhances the ore production tonnage, which entails the marketing unit making efforts to absorb more customers. To this end, the human resource unit feels the necessity to employ more dexterous marketers. The advantages of an intelligent FMS continue when fleet maintenance practices are accurately scheduled, resulting in fewer spare parts needed, and consequently, fewer negotiation efforts made by the procurement department. All these improvements propel a mining enterprise toward a higher profit margin, emphasizing the point that an FMS, particularly an intelligent one can strengthen the value chain.

## 4. Discussion and Conclusions

The mining sector has historically served as a cornerstone of the worldwide economy, contributing significantly to the production of vital commodities and resources utilized by numerous downstream industries. This industry encompasses a multifaceted and intricate series of value chains typically commencing with prospecting and exploration, proceeding to exploitation, processing, and refining, and concluding with marketing and sales. Throughout the various stages, AI technologies offer opportunities for optimizing operations and cutting costs. For instance, in surveying systems for facilitating the discovery of ores, automating material handling systems through robotics and autonomous equipment, or analyzing the data produced during processing and refining to improve treatments accordingly. In 2021, the global smart mining industry was estimated to be worth around $9 billion, with projections indicating that this figure could escalate threefold by 2027. Consequently, automation in this sector is expected to witness a substantial expansion over the next decade, with analyses predicting that the market value of automation solutions will grow from nearly $2 million in 2017 to just above $4 million by 2026 [1]. However, these forecasts are hinged on a certain group of known mining companies already familiarized with the essence of technological embedment within their systems. The main challenge is acquiring underdeveloped mining companies around the world with the principles of Mining 4.0 and the underpinning technologies accompanied by this novel paradigm. Thus, research works shedding light on this blind spot make a substantial contribution to promulgating profitable mining all over the world, especially with operational expenses following an ascending trend as mentioned at the beginning of the article. To this end, the present work looked at intelligent FMSs from the value chain point of view to illuminate the multilateral linkages within the triangle of technology, transportation, and margin. The more technology is leveraged, the more efficient FMSs will be developed, and the higher profit is believed to accrue from streamlining maintenance, dispatching, production scheduling, fuel consumption, and generally the whole operation. However, a generalized methodology that can be included in the article to guide research using intelligent systems for management during ore exploitation in a mining complex seems necessary to follow. This methodology consists of the following steps:

Step 1: Problem Identification and Scope Definition:

- Define the specific challenges and inefficiencies in mineral extraction processes within the mining complex.
- Identify areas where intelligent FMSs could potentially enhance efficiency, safety, and productivity.

Step 2: Literature Review and Technology Assessment:

- Conduct an extensive literature review to understand existing methodologies and technologies used in mining and FMSs.
- Assess various intelligent systems, such as GPS tracking, telematics, predictive analytics, and the Internet of Things, to determine their applicability in mineral extraction processes.

Step 3: Data Collection and System Integration:

- Gather relevant data from the mining complex, including equipment performance, operational data, geospatial information, and historical records.
- Integrate FMSs with the existing infrastructure, ensuring compatibility and seamless data flow.

Step 4: System Implementation and Testing:

- Implement the selected intelligent systems within the extraction phase of the mining complex.
- Conduct comprehensive testing and validation to assess the functionality and performance of these systems in real-time mining operations.

Step 5: Performance Evaluation and Analysis:

- Monitor and evaluate the performance metrics, including equipment uptime, fuel efficiency, maintenance schedules, and safety records.
- Analyze the collected data to quantify the impact of intelligent systems on productivity, cost-effectiveness, and safety protocols during mineral extraction.

Step 6: Feedback Incorporation and Optimization:

- Gather feedback from stakeholders, operators, and system users regarding the effectiveness and usability of the implemented intelligent systems.
- Incorporate feedback to refine and optimize the systems for better integration and operational efficiency within the mining complex.

Step 7: Documentation and Reporting:

- Document the entire research process, including methodologies, findings, challenges faced, and recommendations for future implementations.
- Prepare a detailed report outlining the outcomes, insights, and potential areas for further research using intelligent systems in mineral extraction processes.

This methodology aims to provide a structured framework for researchers and practitioners interested in deploying intelligent FMSs within mining operations for enhanced efficiency, safety, and productivity during mineral extraction. These improvements have been showcased with several research works conducted on the incorporation of intelligent algorithms such as reinforcement learning into FMSs. Zhang et al. (2020) concentrated on utilizing multi-agent deep reinforcement learning algorithms to tackle the dynamic allocation of truck-shovel resources. Their proposed method demonstrates a remarkable performance improvement of 5.56% in productivity compared to traditional approaches [58]. De Carvalho and Dimitrakopoulos (2021) aimed to optimize the delivery of supply material extracted by shovels to the processing plant using a variant of reinforcement learning algorithms. The results show that their framework outperforms the baseline policies in terms of producing 12 to 16% more copper and 20 to 23% more gold [59]. Hue et al. (2023) successfully reduced greenhouse gas emissions in mining by over 30% through intelligent real-time dispatching. Their solution adeptly balanced fleet efficiency, operational uncertainties, and emissions, showcasing promising environmental impact reduction in mining operations [60]. These practical applications of intelligent solutions for fleet management in open pit mines highlight the potential benefits of integrating technology into mining operations.

The diagram developed in Figure 2 explicitly depicts these links in the graphical tongue, simplifying the process of justification and explanation for old-fashioned mining shareholders dubious about equipping their mine sites with advanced methods. The existence of such enlightening studies is beneficial not only industrially but also academically since it establishes a broader scope for mining students. It contributes to the enrichment of their knowledge about the mining supply chain as well as pinpointing potential improvement opportunities to seize. Therefore, the authors encourage more illuminating works in the mining sector, especially in this AI-powered world of nowadays, with the aim of not only briefing the mining community about the latest trends but also mapping possible research directions for keeping up with the fast pace of technology. To recapitulate, the present research proved the profound effect of introducing intelligence within FMSs on the profit margin, which per se opens an opportunity for more incorporation of Mining 4.0 technologies both in loading/hauling equipment monitoring and along the exploitation value chain activities. The literature review showed that a holistic multi-objective intelligent FMS is still missing in mining texts, drawing a research roadmap for more efforts on this subject for years to come.

Expanding further research in the realm of intelligent FMSs in mines from a value chain perspective could significantly contribute to advancing the field. Here are some recommendations for further research in this area: (1) Comprehensive case studies: Conducting more extensive and in-depth case studies across various mining operations, encompassing different minerals, geographical locations, and operational scales. This could help in understanding the nuanced impacts and challenges faced when implementing these systems in diverse mining settings, (2) Long-term impact analysis: Analyzing how these systems evolve, adapt, and continue to affect efficiency, safety, and productivity in mining operations over several years, (3) Integration of emerging technologies: Investigating the potential synergies between intelligent FMSs and emerging technologies like AI, Internet of Things, and advanced data analytics, (4) Cost-benefit analysis: Conducting rigorous cost-benefit analyses to provide a clearer understanding of the economic implications of adopting intelligent FMSs. It would be helpful to assess the initial investment, ongoing maintenance costs, and the resultant cost savings, efficiency gains, and safety improvements achieved, (5) Human factors and training: The role of training programs, workforce readiness, and behavioral aspects in maximizing the effectiveness of fleet management technologies needs to be investigated, (6) Environmental impact assessment: Studying how these systems contribute to reducing carbon footprint, optimizing fuel consumption, and minimizing environmental risks associated with mining activities, and (7) Regulatory and policy implications: Assessing how existing regulations influence these systems' implementation, and suggesting policy frameworks that could facilitate their adoption more effectively.

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