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Strategic Application of Industry 4.0 Technologies in Enhancing Intermodal Transport Terminal Efficiency

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Abstract: In the realm of contemporary logistics, the criticality of intermodal terminals as central nodes for seamless cargo transitions between various transportation modes is well-recognized. This study focuses on the strategic integration of Industry 4.0 (I4.0) technologies to advance the operational efficiency of these terminals. A hybrid Multiple Criteria Decision Making (MCDM) methodology, amalgamating the Best-Worst Method (BWM) and Axial Distance based Aggregated Measurement (ADAM), is employed for a systematic evaluation. This approach facilitates the identification and prioritization of key I4.0 technologies. Findings of this study underscore the paramount importance of the Internet of Things (IoT), Artificial and Ambient Intelligence, and Autonomous and Automated Guided Vehicles in revolutionizing terminal efficiency. The efficacy of the proposed hybrid model is demonstrated in its capacity to generate practical, insightful recommendations for technology selection, thereby guiding stakeholders in making informed investments. These investments are projected to significantly enhance the operational capabilities of intermodal terminals and, by extension, the efficiency of the overall supply chain. The contribution of this study lies in its addressal of the existing research gap concerning the applicability and selection of I4.0 technologies in intermodal transport terminals (ITTs). It offers a novel, pragmatic framework for stakeholders within the logistics sector, aimed at facilitating the modernization and optimization of terminal operations. The insights and strategic directions provided herein are anticipated to be of substantial value to those endeavoring to navigate the complexities of terminal modernization in the era of I4.0.

Keywords: Intermodal terminals; Industry 4.0 (I4.0) technologies; Multiple Criteria Decision Making (MCDM); Best-Worst Method (BWM); Axial Distance based Aggregated Measurement (ADAM)

1. Introduction

Intermodal transport, recognized as a cornerstone in the fabric of contemporary logistics, offers a versatile and efficient mechanism for the uninterrupted flow of goods through varied transportation modes (Acero et al., 2021). Central to this complex network are the intermodal terminals, serving as critical junctures where cargo seamlessly transitions across road, rail, and sea modalities. The value of these terminals is primarily in their function as dynamic hubs, orchestrating the smooth transfer of shipments between disparate transport methods, thus enhancing the overall supply chain efficiency (Bouchery et al., 2014). The provision of centralized points for cargo consolidation and deconsolidation, coupled with the facilitation of modal shifts at these terminals, contributes significantly to reduced transit times, increased flexibility, and cost efficiencies. As integral components of the intermodal network, the role of these terminals in fostering operational efficiency and supply chain fluidity is indispensable.

The imperative of modernizing intermodal terminals is underscored in the context of advancing the efficiency and resilience of current supply chain networks (Makarova et al., 2019). This modernization encompasses the adoption of cutting-edge technologies and methodologies, tailored to meet the evolving requisites of logistics operations. The implementation of I4.0 technologies, characterized by their emphasis on connectivity, automation, and data-centric decision-making, emerges as a pivotal strategy in this transformation. The integration of these technologies within intermodal terminals is instrumental in streamlining operations, optimizing resource allocation, and facilitating a dynamic response to fluctuating demands (Vida et al., 2023). Such advancements yield marked improvements in throughput, minimize delays, and amplify overall operational efficacy. The assimilation of I4.0 technologies in the modernization of intermodal terminals is congruent with the broader objective of cultivating agile, responsive, and technologically sophisticated logistics ecosystems, adept at navigating the complexities of modern supply chain dynamics.

The primary objective of this research is the systematic identification and assessment of I4.0 technologies, focusing on those with the potential to significantly enhance the operational efficiency of intermodal terminals. This entails a meticulous process to discern and evaluate technologies that not only promise substantial operational improvements but are also critically relevant for these terminals. By employing a structured methodology, the study seeks to isolate I4.0 technologies that demonstrate the highest potential in optimizing terminal operations, alleviating bottlenecks, and contributing markedly to overall terminal efficiency. Consequently, the research endeavors to furnish logistics industry stakeholders with insightful, strategic guidance for modernizing intermodal terminals and augmenting their operational effectiveness.

The adopted methodology in this study is a robust, hybrid MCDM model, which incorporates the BWM and the ADAM. The BWM is utilized to derive criteria weights essential for the evaluation of I4.0 technologies, while the ADAM method is instrumental in ranking these technologies based on their suitability for intermodal terminal application. The principal findings suggest that technologies such as the IoT, Artificial and Ambient Intelligence, and Autonomous and Automated Guided Vehicles are most efficacious in enhancing terminal efficiency. The derived conclusions from this hybrid model highlight its capability in offering concrete, actionable insights for technology selection. This provides a practical and strategic framework for stakeholders, enabling them to make informed investments in technologies poised to significantly influence terminal operations and, by extension, the efficiency of the broader supply chain.

The remaining sections of the paper are structured to present an exhaustive overview of the study. An extensive literature review delves into the existing body of knowledge regarding the application of I4.0 technologies in intermodal terminals. The methodology section delineates the hybrid MCDM model, explicating the BWM and ADAM methods. This is followed by a succinct description of the problem, setting the groundwork for the results section. Here, the findings of the technology evaluation are disclosed, accompanied by a sensitivity analysis. The discussion section offers an analytical interpretation of these results, and the paper culminates in a conclusion that summarizes the key discoveries, underlining their practical significance and proposing avenues for future research.

2. Literature Review

The body of existing literature pertaining to intermodal transport and terminal efficiency is characterized by a diversity of research domains. Investigations in the field of intermodal transport predominantly focus on operational dynamics, as highlighted by Priemus & Konings (2017), with a particular emphasis on the crucial role of terminals in facilitating efficient cargo movement across various modes, as delineated by Tadić et al. (2019). The exploration of terminal optimization strategies is extensively covered (Muravev et al., 2021), alongside analyses of the impacts arising from modal shift initiatives on supply chain performance (Colicchia et al., 2017) and the economic ramifications of enhanced logistics operations within these terminals (Protic et al., 2019).

A significant facet of the literature concentrates on the modernization of intermodal terminals. Winkelhaus & Grosse (2019) underscore the necessity of adopting advanced technologies and methodologies in response to the evolving demands of logistics operations. The discourse extensively deliberates on the implementation of I4.0 technologies, including the IoT, Artificial and Ambient Intelligence, and Autonomous and Automated Guided Vehicles (Barreto et al., 2017). These technologies are examined for their capacity to revolutionize operations, optimize resource utilization, and dynamically adapt to changing requirements. The outcome of I4.0 implementation, as evidenced by improved throughput, diminished delays, and enhanced overall operational efficiency, is scrutinized (Cañas et al., 2021).

Furthermore, research underscores the strategic imperative of modernizing intermodal terminals to align with overarching logistics goals (Hu et al., 2019). The literature advocates for the creation of agile, responsive, and technologically advanced logistics ecosystems, equipped to navigate the complexities of contemporary supply chain dynamics (Chowdhary, 2022). This research contributes to this scholarly conversation by systematically identifying and evaluating potential I4.0 technologies, thereby providing stakeholders with practical insights for enhancing intermodal terminal efficacy. The employment of MCDM methods is pivotal in this context, facilitating the ranking and selection of I4.0 technologies. This study utilizes a hybrid model, integrating the BWM and ADAM, to ensure a comprehensive and efficacious evaluation.

The BWM, conceptualized by Rezaei (2015), serves as an evaluative tool for comparing alternatives across a variety of criteria. As a pairwise comparison technique, BWM involves a systematic assessment process wherein a decision maker evaluates each alternative against each criterion, identifying the best and worst options for each. Criteria are then assigned weights according to their significance, and scores for alternatives are calculated accordingly. Despite the subjective nature of judgments inherent in this method, BWM is noted for its flexibility, suitability for handling multiple criteria with a reduced need for pairwise comparisons, and ease of use (Rezaei, 2015). It has been recognized for its superior consistency, accuracy, and compliance in comparison to other MCDM methods (Guo & Zhao, 2017). Recent applications of BWM include the classification and ranking of key factors and external influences in I4.0 technology adoption (El Baz et al., 2022), site selection for power stations (Besharati Fard et al., 2022), prioritization of key success factors in sustainable Lean Six Sigma implementation (Swarnakar et al., 2022), sustainability assessments in urban transportation (Yucesan et al., 2024), and supply chain disruption evaluations (Ali et al., 2023). This study employs BWM for determining criteria weights, leveraging these advantages.

Conversely, the ADAM method, introduced by Krstić et al. (2023a), facilitates alternative rankings by quantifying the aggregate dimensions of complex polyhedra, offering an intuitive graphical representation. ADAM is known for minimizing rank reversal risks, maintaining stability across a range of criteria, and aligning with other MCDM methods (Krstić et al., 2023b). Despite its relative novelty, both the conventional and fuzzy versions of ADAM have proven effective in various contexts, such as in selecting city logistics concepts (Kovač et al., 2023), ranking circularity-enhancing strategies (Agnusdei et al., 2023), and choosing logistics service providers (Krstić & Tadić, 2023).

A significant research gap exists in the identification and selection of the most suitable I4.0 technologies for intermodal terminals. There is a notable absence of a tailored MCDM model specifically designed for their systematic ranking. The literature lacks a comprehensive framework for the evaluation and prioritization of these technologies within the context of intermodal terminals. This gap impedes the formulation of strategic modernization plans. Bridging this gap is pivotal for establishing an effective approach to select and implement I4.0 technologies, thereby enhancing the overall efficacy of intermodal terminals in the realm of contemporary logistics.

3. Methodology

The methodology of this study encompasses the utilization of a MCDM model, which entails the delineation of the problem structure through the specification of sets of alternatives and criteria. Integral to this process is the establishment of an evaluation scale, typically a nine-point scale, for the assessment of alternatives, as detailed in Table 1.

Table 1. Evaluation scale

Linguistic Evaluation	Abbreviation	Numerical Value
“None”	“N”	1
“Very Low”	“VL”	2
“Low”	“L”	3
“Fairly Low”	“FL”	4
“Medium”	“M”	5
“Fairly High”	“FH”	6
“High”	“H”	7
“Very High”	“VH”	8
“Extremely High”	“EH”	9

The BWM is employed to obtain criteria weights. This process includes identifying the best and worst criteria, determining preferences, and calculating weights to ensure consistency. It implies the following optimization problem:

$$\min \xi \tag{1}$$

$$\left| w_b - u_{bj} w_j \right| \leq \xi, \forall j = 1, \ldots, m \tag{2}$$

$$\left| w_j - u_{jw} w_w \right| \leq \xi, \forall j = 1, \ldots, m \tag{3}$$

$$\sum_{j=1}^{m} w_j = 1 \tag{4}$$

$$w_j \geq 0, \forall j = 1, \ldots, m \tag{5}$$

where ξ serves as a measure of the consistency in the comparison (the lower the better), w_j indicates the weight of criterion j, m is the total number of criteria, w_b and w_w are the weights of the best and the worst criteria, respectively; u_{bj} is the preference of the best criterion over criterion j, and u_{jw} is the preference of criterion j over the worst criterion.

The ADAM method is then applied to evaluate and rank alternatives. This involves creating a decision matrix based on evaluations of alternatives (e_{ij}) for each criterion.

$$E = \left[e_{ij} \right]_{n \times m} \tag{6}$$

where, i indicates the alternative and n is the total number of alternatives.

The matrix is sorted by the importance of criteria, and normalized values are derived based on benefit (B) and cost (C) criteria.

$$S = \left[s_{ij} \right]_{m \times n} \tag{7}$$

$$n_{ij} = \begin{cases} \dfrac{s_{ij}}{\max_i s_{ij}}, & \text{for } j \in B \\ \dfrac{\min_i s_{ij}}{s_{ij}}, & \text{for } j \in C \end{cases} \tag{8}$$

Reference (R_{ij}) and weighted reference points (P_{ij}) in a three-dimensional space are calculated, forming a complex polyhedron. Coordinates of these points are obtained as follows:

$$x_{ij} = n_{ij} \times \sin \alpha_i, \forall j = 1, \ldots, n; \forall i = 1, \ldots, m \tag{9}$$

$$y_{ij} = n_{ij} \times \cos \alpha_j, \forall j = 1, \ldots, n; \forall i = 1, \ldots, m \tag{10}$$

$$z_{ij} = \begin{cases} 0, \text{ for } R_{ij} \\ w_j, \text{ for } P_{ij} \end{cases}, \forall j = 1, \ldots, n; \forall i = 1, \ldots, m \tag{11}$$

$$\alpha_j = (j-1) \frac{90^\circ}{n-1}, \forall j = 1, \ldots, n \tag{12}$$

Volumes of these polyhedra, computed using pyramid volumes, are used to rank alternatives. The higher the volume, the better the alternative is considered.

$$V_i^C = \sum_{k=1}^{n-1} V_k, \forall i = 1, \ldots, m \tag{13}$$

$$V_k = \frac{1}{3} B_k \times h_k, \forall k = 1, \ldots, n-1 \tag{14}$$

$$B_k = c_k \times a_k + \frac{a_k \times \left(b_k - c_k \right)}{2} \tag{15}$$

$$a_k = \sqrt{\left(x_{j+1} - x_j \right)^2 + \left(y_{j+1} - y_j \right)^2} \tag{16}$$

$$b_k = z_j \tag{17}$$

$$c_k = z_{j+1} \tag{18}$$

$$h_k = \frac{2\sqrt{s_k\left(s_k - a_k\right)\left(s_k - d_k\right)\left(s_k - e_k\right)}}{a_k} \tag{19}$$

$$s_k = \frac{a_k + d_k + e_k}{2} \tag{20}$$

$$d_k = \sqrt{x_j^2 + y_j^2} \tag{21}$$

$$e_k = \sqrt{x_{j+1}^2 + y_{j+1}^2} \tag{22}$$

4. Evaluation of the I4.0 Technologies Applicability in ITTs

This section offers an in-depth exploration of the diverse applications of I4.0 technologies within ITTs, highlighting their transformative potential in the management and movement of goods across various transportation modes.

4.1 I4.0 Technologies Applicable in ITTs

This section offers an in-depth exploration of the diverse applications of I4.0 technologies within ITTs, highlighting their transformative potential in the management and movement of goods across various transportation modes.

The integration of ***IoT*** technology, referred to as T_1, serves as a paradigm shift in operational efficiency within intermodal terminals. The deployment of sensors across containers significantly enhances the monitoring and tracking capabilities, thereby optimizing the movement of goods. These sensors provide critical updates on the location, condition, and status of the cargo. In addition, equipment sensors yield valuable data on usage, performance, and maintenance requirements, which is pivotal for the implementation of predictive maintenance strategies. This not only augments operational efficiency but also prolongs equipment lifespan. For cargoes that are sensitive to environmental conditions, the application of temperature, humidity, and vibration sensors plays a vital role in mitigating the risk of damage by generating timely alerts should any deviations from optimal conditions occur. The use of predictive maintenance algorithms, which analyze data from both equipment and vehicles, contributes to a reduction in unforeseen breakdowns. Furthermore, the employment of RFID-enabled smart containers revolutionizes inventory management processes by automating them and ensuring the accuracy of real-time data. The implementation of IoT sensors extends beyond cargo handling to traffic optimization within the terminal vicinity. Surveillance cameras bolster security measures, while smart energy systems monitor and regulate energy consumption, aligning with sustainability objectives. The analysis of data collected from IoT devices is instrumental in identifying operational bottlenecks, streamlining workflows, and enhancing overall efficiency. This results in a more responsive supply chain, underpinned by informed decision-making. The seamless communication facilitated between devices within the terminal not only improves coordination but also fosters collaboration, culminating in a service that is both reliable and efficient.

The adoption of ***Autonomous and Automated Guided Vehicles*** (***AV&AGV***), denoted as T_2, within intermodal terminal operations, marks a significant leap towards enhanced efficiency and automation. These vehicles, outfitted with advanced sensors and navigation systems, are capable of autonomously traversing the terminal environment. This capability is pivotal in the seamless transfer of containers and goods across different transportation modes. AGVs are employed in a variety of tasks including container handling, loading and unloading operations, and internal goods transportation within the terminal. The automation of these processes notably diminishes the reliance on human intervention, thereby increasing precision and optimizing the utilization of both time and resources. Furthermore, autonomous vehicles contribute to heightened safety standards by adhering to predetermined routes and proficiently avoiding obstacles. An additional advantage of AGVs lies in their ability to integrate seamlessly into the overarching terminal management system. This integration enables the provision of real-time data, which in turn enhances the terminal's capacity to respond promptly and effectively to operational changes. The implementation of AV&AGV technologies in intermodal terminals is in alignment with the industry's ongoing endeavors to boost efficiency, curtail operational costs, and foster a supply chain that is both more streamlined and interconnected.

The integration of ***Artificial and Ambient Intelligence*** (***AI&AmI***), identified as T_3, within intermodal terminal operations, signifies a substantial advancement in decision-making capabilities and operational efficiency. AI, with its potent data processing and analysis capabilities, plays a crucial role in enabling predictive maintenance. This is achieved by identifying patterns and optimizing resource allocation through advanced machine learning algorithms. Concurrently, AmI contributes to creating a more responsive terminal environment by dynamically adjusting ambient factors such as lighting, temperature, and energy consumption, in accordance with real-time conditions. The combined application of AI&AmI unfolds across various domains within terminal operations. This includes the development of predictive maintenance strategies tailored for terminal equipment, the implementation of intelligent traffic management systems aimed at optimizing vehicle flow, and the deployment of AI-enhanced surveillance systems for real-time security monitoring. Additionally, AI significantly enhances inventory management practices by analyzing historical data to forecast demand patterns, thereby ensuring optimal stock levels and reducing potential delays. The seamless integration of these intelligent technologies propels intermodal terminals into a new paradigm of operation. By leveraging AI&AmI, terminals not only witness an escalation in efficiency but also an augmentation in their adaptability and sustainability. This integration heralds a new era in terminal operations, characterized by responsive and user-centric approaches, fundamentally reshaping how intermodal terminals function within the logistics ecosystem.

The adoption of ***Augmented and Virtual Reality*** (***AR&VR***), denoted as T_4, within intermodal terminals, marks a transformative development, bringing a myriad of advantages. AR, by overlaying real-time data onto the physical terminal environment, significantly empowers operators. It enhances their decision-making capabilities and operational efficiency, particularly in areas like container status evaluation and maintenance assessments. VR, through its immersive simulations, not only accelerates skill acquisition in hands-on training but also promotes a heightened awareness of safety protocols among operators. In addition to training applications, these technologies profoundly impact maintenance procedures. AR assists technicians in navigating through repair processes, thereby reducing equipment downtime. In the realm of logistics planning, AR is instrumental in optimizing container positioning for efficient loading and unloading operations. This is complemented by VR's immersive capabilities, which are utilized in the design and refinement of terminal layouts. The collaborative potential of AR and VR also plays a pivotal role in enhancing communication among various stakeholders within the terminal. Remote experts leverage AR for providing real-time guidance and support, while VR facilitates the creation of collaborative environments that enable seamless interaction among geographically dispersed teams. In summary, the integration of AR and VR technologies within intermodal terminals is revolutionizing not only the efficiency and safety of operational procedures but also the methodologies of training and stakeholder collaboration. This integration is ushering in a new era of advanced, efficient, and interconnected terminal operations, significantly enhancing the efficacy of intermodal transport systems.

The integration of ***Big Data and Data Mining*** (***BD&DM***), referred to as T_5, within intermodal terminals, constitutes a pivotal transformation, revolutionizing the operational framework to achieve enhanced efficiency. The application of Big Data analytics plays a critical role in providing real-time insights, encompassing the tracking of container movements, optimization of traffic flows, and prediction of equipment maintenance requirements. This data-centric approach promotes proactive decision-making, enabling the development of predictive models that are essential for the optimization of resource allocation and the enhancement of terminal efficiency. Data Mining, with its capability to delve deep into large datasets, uncovers patterns that are instrumental in implementing predictive maintenance and streamlining inventory management. The combined power of Big Data and Data Mining not only significantly reduces equipment downtime but also ensures the maintenance of optimal stock levels, thereby minimizing operational delays. This integration of BD&DM within intermodal terminals fosters a remarkable degree of adaptability. It empowers terminals to anticipate and swiftly respond to emerging trends, marking a substantial progression towards a more agile and efficient intermodal terminal ecosystem. In essence, this data-driven evolution lays the groundwork for a responsive and proactive operational landscape, which is crucial in the dynamic and ever-evolving logistics sector.

The incorporation of ***Data Security measures and Blockchain technology*** (***DS&BC***), identified as T_6, within intermodal terminals, marks a significant advancement toward bolstering operational integrity. The implementation of Data Security protocols plays a crucial role in safeguarding sensitive information, encompassing container movements, traffic optimization strategies, and equipment maintenance forecasts. The protection of this data is instrumental not only in building trust among stakeholders but also in laying a resilient foundation for secure and reliable decision-making processes. In parallel, the introduction of Blockchain technology brings forth a decentralized ledger system, characterized by its resistance to tampering and its transparency. This technology ensures the immutability of data transactions, thereby enhancing the credibility and integrity of information within the supply chain. In the context of intermodal terminals, the application of Blockchain technology significantly mitigates risks associated with fraud and unauthorized data access. The synergistic combination of robust Data Security measures and Blockchain technology fortifies the terminal ecosystem against an array of cyber threats. This approach is pivotal in maintaining the confidentiality and integrity of critical operational data. The adoption of this data-centric security model heralds a new era in intermodal terminal operations, characterized by reinforced trust, transparency, and resilience. This is particularly vital in an increasingly digitalized world, where the challenges posed by the digital landscape are continually evolving.

The implementation of ***Management and Control Support Systems and Cloud Computing*** (***MCSS&CC***), denoted as T_7, within intermodal terminals, represents a significant advancement towards enhancing operational efficiency. Management and Control Support Systems, encompassing a range of sophisticated software and hardware solutions, play a vital role in refining terminal management processes. These systems are instrumental in improving decision-making capabilities and overall operational efficiency. In tandem, Cloud Computing introduces a paradigm shift in the way data is stored and accessed, enabling centralized storage and facilitating real-time collaboration across intermodal terminals. The amalgamation of MCSS with Cloud Computing creates a dynamic and synergistic environment. This environment empowers terminals to quickly adapt to changing operational demands, ensuring capabilities such as remote monitoring, instantaneous updates, and secure data storage. The integration of MCSS and Cloud Computing lays the groundwork for a technologically advanced operational framework within intermodal transportation systems. This integrated approach ensures that terminals remain adaptable and responsive, qualities that are essential in navigating the ever-evolving challenges of the logistics sector. It signifies a step towards a more sophisticated, efficient, and agile operational landscape, essential in the context of modern intermodal transport dynamics.

The incorporation of ***Modern Robotic Systems*** (***MRS***), identified as T_8, in intermodal terminals marks a significant shift towards heightened operational efficiency across various functions. Robots, integrated with advanced sensors and bolstered by artificial intelligence, are strategically utilized for a multitude of tasks, including predictive maintenance, inventory management, and security surveillance. In the realm of predictive maintenance, robotic systems play a crucial role in analyzing the condition of equipment. They are adept at identifying potential issues preemptively, effectively reducing the likelihood of breakdowns and consequently minimizing operational downtime. In terms of inventory management, robots are employed for their capability to perform real-time tracking. This ensures precise monitoring and efficient handling of container contents, enhancing the accuracy and reliability of inventory operations. Furthermore, robots significantly augment the security framework of intermodal terminals. They utilize IoT-connected cameras and sensors to establish a comprehensive surveillance network. This network is instrumental in promptly detecting and responding to security breaches, thereby bolstering the safety and integrity of the terminal operations.

The integration of ***Digital Twins*** (***DT***), denoted as T_9, within intermodal terminals, signifies a significant advancement in operational efficiency. Digital Twins are virtual models that employ advanced technologies to create real-time, dynamic simulations accurately reflecting the real-world conditions and behaviors of the actual terminal. These simulations provide a comprehensive visual representation of the terminal's operations, thus empowering operators with an intuitive understanding of the entire terminal layout and aiding informed decision-making. Beyond mere visualization, Digital Twins utilize predictive analytics to process both historical and real-time data. This capability enables terminals to proactively identify potential bottlenecks, predict equipment failures, and preempt delays. Such predictive insights are crucial for optimizing workflows and enhancing overall operational efficiency. In the context of asset management, Digital Twins offer an in-depth view of the terminal's equipment and infrastructure. This includes monitoring their condition, performance, and maintenance requirements. This level of insight is pivotal for implementing predictive maintenance strategies, effectively reducing downtime and prolonging the lifespan of essential assets. Furthermore, Digital Twins have a far-reaching impact that extends to areas such as traffic optimization, workflow simulation, energy management, and collaborative planning among various stakeholders. The continuous monitoring and analytical capabilities of Digital Twins foster a culture of ongoing improvement within intermodal terminals. This approach is instrumental in identifying optimization opportunities and contributes significantly to the development of a resilient, technologically advanced, and efficient supply chain ecosystem.

4.2 Criteria for the I4.0 Technologies Applicability Evaluation

In assessing the applicability of I4.0 technologies for ITTs, the following eight criteria are critical:

Integration Capabilities (C_1): This criterion evaluates the technology's ability to seamlessly integrate with the existing infrastructure and systems of the terminal. It focuses on ensuring compatibility with current databases, communication protocols, and other software or hardware components. A well-integrated technology should align smoothly with the operational setup, minimizing disruptions during its implementation.

Scalability (C_2): Scalability assesses the technology's capacity to accommodate growth and increasing complexity in the terminal. It examines whether the solution can effectively handle growing operational demands, larger data volumes, and additional functionalities, essential for maintaining long-term viability and effectiveness.

Data Security and Privacy (C_3): Given the sensitive nature of logistics data, this criterion underscores the necessity of robust data security and privacy standards. Technologies should prioritize safeguarding information confidentiality and integrity, employing measures such as encryption, access controls, and other security protocols to prevent unauthorized access and data breaches.

Operational Efficiency Impact (C_4): This assesses the technology's effect on enhancing the efficiency of terminal operations. Technologies that streamline processes, reduce downtime, optimize resource use, and contribute to overall efficiency gains are favored. The aim is to boost the terminal's effectiveness and productivity.

Financial Sustainability (C_5): This criterion evaluates the technology's contribution to the terminal's long-term financial health. Consideration includes ongoing operational costs, maintenance expenses, and adaptability to future economic conditions. Financially sustainable technologies should offer long-term value without imposing excessive financial burdens.

Adaptability and Flexibility (C_6): This involves assessing the technology's capacity to evolve with changing industry standards, regulations, and emerging technologies. Technologies that can adapt to dynamic environments are essential for future-proofing the terminal, enabling it to remain current and responsive.

Environmental Impact (C_7): This criterion considers the environmental implications of the technology's implementation. Technologies promoting sustainability, energy efficiency, and a reduced carbon footprint are preferable, aiming to minimize adverse environmental effects and foster responsible operational practices.

Reliability and Resilience (C_8): This evaluates the technology's consistent performance under various operational conditions, including adverse weather and unexpected disruptions. Technologies showcasing high reliability and resilience contribute to the terminal's robustness, ensuring uninterrupted and dependable operations.

These criteria provide a comprehensive framework for making informed decisions regarding the adoption of I4.0 technologies in ITTs, ensuring alignment with the terminal's specific requirements, objectives, and operational context.

4.3 Results

In this section, the findings derived from the evaluation of I4.0 technologies' applicability in ITTs are presented. Experts in the field were engaged to identify the most and least important criteria essential for this assessment. Utilizing a linguistic scale, as outlined in Table 1, these experts compared all other criteria against these identified benchmarks. The majority opinions formed the basis for representative evaluations, and subsequent calculations were performed using Eqs. (1)-(5) to determine the weights of the criteria. The outcomes of this exercise, encompassing both evaluations and finalized criteria weights, are succinctly captured in Table 2.

Table 2. Evaluations and final weights of criteria

Criterion	Best/Worst	Best over Other	e_{Bj}	Other over Worst	e_{jW}	w_j
C_1		"M"	5	"FL"	4	0.079
C_2		"FL"	4	"M"	5	0.099
C_3		"L"	3	"FH"	6	0.132
C_4		"VL"	2	"H"	7	0.198
C_5	BC	/	/	"EH"	9	0.338
C_6		"H"	7	"VL"	2	0.057
C_7		"FH"	6	"L"	3	0.066
C_8	WC	"EH"	9	/	/	0.031

Table 3. I4.0 technologies applicability evaluations and final ranking

	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9
C_1	“VH”	“FH”	“M”	“FH”	“N”	“VH”	“FL”	“L”	“M”
C_2	“H”	“FH”	“FH”	“VL”	“VH”	“L”	“L”	“FH”	“M”
C_3	“EH”	“VH”	“FH”	“H”	“FH”	“M”	“FH”	“FL”	“FL”
C_4	“EH”	“H”	“H”	“L”	“EH”	“M”	“M”	“M”	“H”
C_5	“VH”	“FH”	“EH”	“FH”	“VL”	“FH”	“H”	“M”	“FH”
C_6	“H”	“H”	“EH”	“FL”	“L”	“VH”	“H”	“VL”	“FL”
C_7	“M”	“EH”	“VH”	“H”	“N”	“H”	“FH”	“VL”	“M”
C_8	“VH”	“FH”	“VH”	“L”	“M”	“VL”	“VL”	“FL”	“FH”
V_i^C	0.051	0.038	0.039	0.016	0.02	0.023	0.021	0.015	0.024
Rank	1	3	2	8	7	5	6	9	4

Subsequent to the determination of criteria weights, the same panel of experts proceeded to evaluate the applicability of various I4.0 technologies. This assessment was guided by the previously established evaluations detailed in Table 1. The analytical process involved the application of Eqs. (6)-(22) to calculate the volumes of the polyhedra representing each technology. The final ranking of these alternatives, based on the derived polyhedra volumes, is systematically documented in Table 3. For an enhanced understanding and visual representation of these findings, Figure 1 illustrates the graphical depiction of the calculated polyhedra. This methodical evaluation process yields a comprehensive insight into the relative strengths and limitations of each technology in the context of ITTs. It serves as a crucial aid in the decision-making process for the adoption of I4.0 technologies. The results underscore that among the various I4.0 technologies evaluated, the IoT, AI&AmI, and AV&AGV emerge as the most applicable and beneficial for ITTs. These technologies are highlighted for their significant potential to revolutionize operational efficiency and adaptability in the dynamic realm of intermodal logistics.

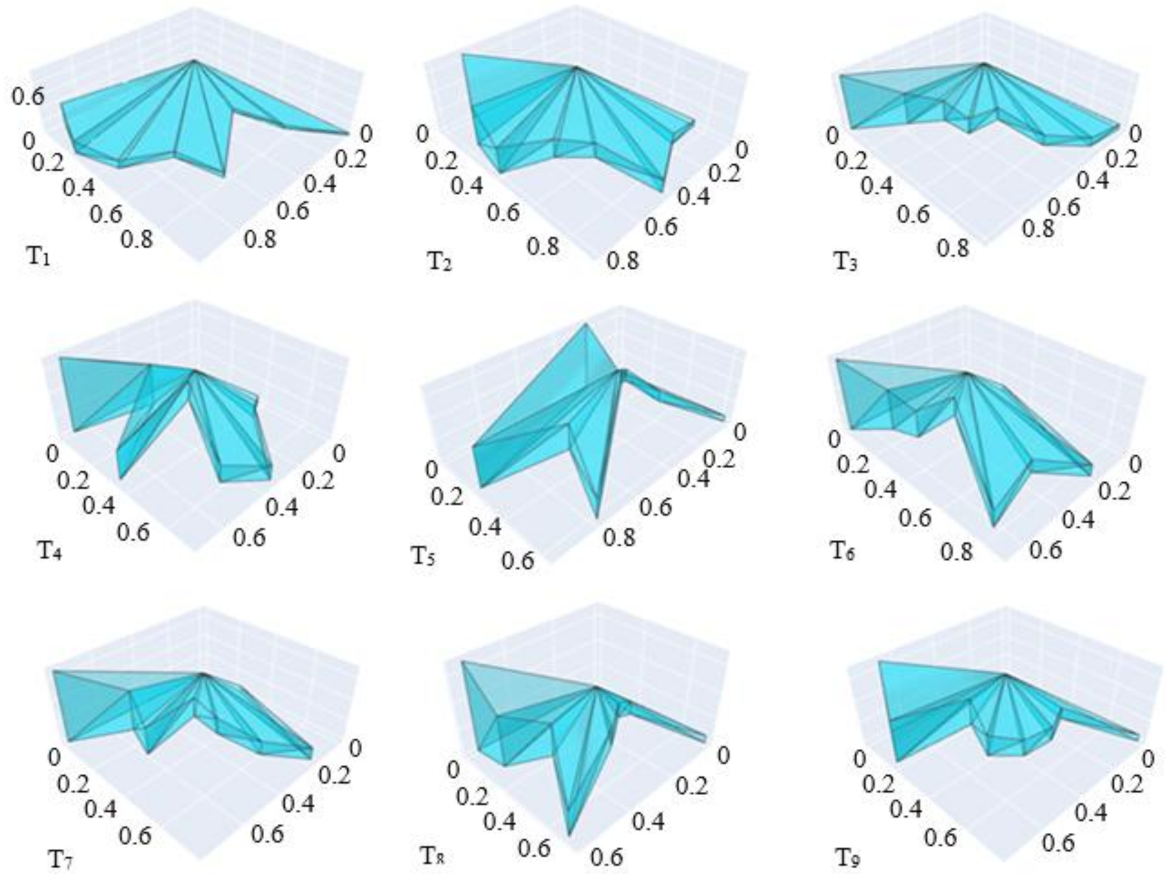

Figure 1. Polyhedra volumes

4.4 Sensitivity Analysis

This section delves into the sensitivity analysis performed to evaluate the stability and reliability of the final rankings assigned to I4.0 technologies in their applicability to ITTs. The analysis comprised twelve distinct scenarios, labeled Sc.1-12. Each of these scenarios involved altering the weights of the three most critical criteria, implementing reductions by 25%, 50%, 75%, and 100%, respectively. For each scenario, the ADAM method was utilized anew to recalculate the rankings of the technologies. The results derived from these adjusted scenarios were then meticulously compared with those of the initial scenario, designated as Sc.0, with the comparative data presented in Table 4. To further ascertain the consistency and robustness of the rankings across these varied scenarios, Spearman correlation coefficients were computed. These coefficients provided a statistical measure of the rank correlation, thereby offering insights into the degree of similarity between the rankings under different weighting conditions. The analysis yielded an average Spearman correlation coefficient of 0.985. This high coefficient value signifies a strong level of conformity and consistency in the rankings across all scenarios when juxtaposed with the initial scenario. Additionally, a graphical representation of the sensitivity analysis results is illustrated in Figure 2. This visual aid complements the tabular data and aids in better understanding the impact of weight variations on the technology rankings. The comprehensive nature of this sensitivity analysis underlines the robustness of the study's findings. The high degree of stability observed in the results, even under varied weighting scenarios, underscores their reliability. This analysis reinforces the validity of the final rankings determined for the applicability of I4.0 technologies in ITTs, advocating their consideration and potential implementation in the field.

Table 4. Sensitivity analysis results

	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	SCC
Sc.0	1	3	2	8	7	5	6	9	4	/
Sc.1	1	3	2	8	7	4	6	9	5	0.983
Sc.2	1	3	2	8	7	4	6	9	5	0.983
Sc.3	1	3	2	8	7	4	6	9	5	0.983
Sc.4	1	3	2	8	7	5	6	9	4	1.000
Sc.5	1	3	2	8	7	4	6	9	5	0.983
Sc.6	1	3	2	8	7	4	6	9	5	0.983
Sc.7	1	3	2	8	6	4	7	9	5	0.966
Sc.8	1	2	3	8	6	4	7	9	5	0.950
Sc.9	1	3	2	8	7	4	6	9	5	0.983
Sc.10	1	3	2	8	7	5	6	9	4	1.000
Sc.11	1	3	2	8	7	5	6	9	4	1.000
Sc.12	1	3	2	8	7	5	6	9	4	1.000

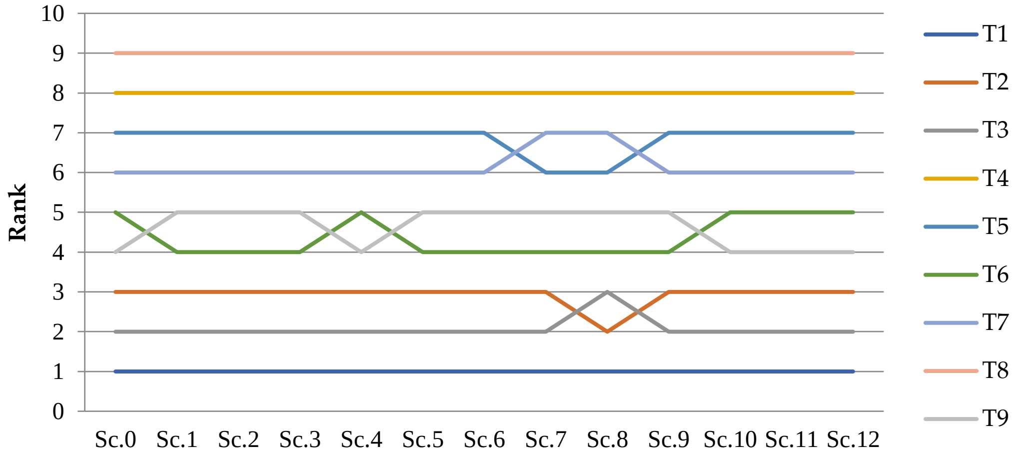

Figure 2. Comparison of rankings obtained in sensitivity analysis scenarios

5. Discussion

The findings from this study underscore the integral role of I4.0 technologies in augmenting the operational framework of ITTs. The comprehensive evaluation process, encompassing a diverse range of criteria, has identified the IoT, AI&AmI, and AV&AGV as technologies of paramount applicability. This identification reflects a keen industry insight into the value of real-time connectivity, intelligent decision-making, and automated systems in optimizing terminal operations. Moreover, the application of a hybrid model combining the BWM and ADAM, followed by a rigorous sensitivity analysis, has affirmed the robustness and stability of the resultant rankings. These outcomes instill confidence in the reliability of the conclusions and provide valuable directional insights for stakeholders in intermodal transport, offering a strategic roadmap for technological integration in pursuit of sustained efficiency, resilience, and adaptability amidst the dynamic landscape of intermodal logistics.

This research contributes significantly to the field of intermodal transport and technology selection. Primarily, it elucidates applicable I4.0 technologies, highlighting IoT, AI&AmI, and AV&AGV as notably suitable for intermodal terminals. The establishment of a comprehensive evaluation framework with a well-defined set of criteria presents a structured approach to assess these technologies within the complex environment of terminals. Additionally, the innovative use of a hybrid model, merging BWM and ADAM methodologies, showcases an effective strategy for technology selection. This approach, which accounts for linguistic variables, enhances the evaluation's reliability through robust and stable rankings.

However, the study is not without limitations. The reliance on expert opinions in determining evaluation criteria and weights introduces an element of subjectivity and potential variations in interpretation due to the linguistic scale employed. The focus on expert perspectives may also bring biases based on individual experiences. Furthermore, the rapid evolution of technology necessitates continuous updates to the identified technologies, as they may become outdated over time. The study's concentration on ITTs limits the generalizability of its findings to other areas within the broader supply chain, where distinct requirements may not be fully addressed. Additional criteria, potentially overlooked in this study, might influence the technology selection process.

Future research should aim to mitigate these limitations, refining the methodology for more comprehensive and universally applicable insights. This could involve broadening the scope to include diverse logistics segments, updating the technology list regularly, and exploring methods to reduce subjectivity and bias in expert opinions. Such advancements will further enrich the understanding of technology applicability in intermodal terminals and beyond, contributing to the field's ongoing development.

6. Conclusions

This research was embarked upon with the objective of systematically evaluating the applicability of I4.0 technologies in ITTs. Employing a hybrid methodology that integrates the BWM and ADAM, key technologies were identified. Notably, the IoT, AI&AmI, and AV&AGV emerged as the most applicable technologies. The primary contributions of this study are threefold: the establishment of a comprehensive evaluation framework, the discernment of critical technologies, and the pioneering implementation of the hybrid BWM-ADAM model for technology selection.

These findings present crucial insights for stakeholders aiming to bolster operational efficiency in intermodal terminals. However, given the rapidly evolving nature of technological trends, it is imperative for future research to continuously adapt to these changes, ensuring ongoing relevance and applicability. Further research should also broaden its scope to encompass a more expansive range of supply chain contexts, offering a more inclusive understanding of technology integration across logistics networks.

Additionally, it is recommended that future studies delve into the long-term effects and implications of implementing the identified technologies in intermodal terminals. Such investigations would shed light on the enduring benefits and potential challenges posed by these integrations. Another promising avenue for exploration is the augmentation of real-time data analytics, which aligns well with the dynamic evolution of I4.0 technologies. This approach could significantly enhance decision-making processes within the logistics industry, contributing to its continuous advancement.

In summary, while this study offers substantial contributions to the field of intermodal transport and technology assessment, its findings should be considered as part of an ongoing dialogue in a rapidly advancing technological landscape. Continuous updates, broadened scope, and deeper investigations into long-term impacts and new technological innovations will be crucial for maintaining the relevance and practicality of these insights.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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