The Impact of Extended Warehouse Management System Implementation on Warehouse Operational Performance: A Case Study of Fast Moving Consumer Goods Industry

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INTRODUCTION

Warehousing is becoming increasingly important in the supply chain to secure a competitive advantage in terms of better customer service, reduced lead times, and costs in the mass customization age (Minashkina et al., 2021). And in today's mass customization environment, optimizing the operational performance of warehousing enriches competitive advantage (Faber et al., 2002). Warehouse Management Information System (WMS) implementation is considered a critical tool to efficiently accomplish a higher warehouse operational performance (Faber et al., 2002). Higher levels of flexibility, support for automation, advanced capabilities are becoming more demanded by customers over traditional or basic WMS (Faber et al., 2002). In response, vendors of WMSs strive to offer additional advanced features improving the capabilities of the systems.

In the global context, though there are a number of researches carried out in the broad aspect of the impact of Enterprise Resource Planning (ERP) systems or narrowed down to traditional warehouse management module of ERP systems or stand-alone systems, a handful of researches were found which are in-depth on advanced features of extended warehouse management systems and its impact on warehouse operational performance in the supply chain. Gupta et al. (2018) use a contingent resource-based theory perspective in studying the impact of cloud ERP systems on organizational performance. Further, early literature discusses different metrics that are context-specific to measure warehousing operational performance (Staudt et al., 2015). However, it is challenging to generalize performance measures. In addition, early research uses a macro approach to study the WMS impact to supply chain performance and organizational performance. Nonetheless, empirical investigation into the before and after implementation impacts of Extended Warehouse Management System (EWMS) on specific factors such as the throughput, average receiving rate, average allocation and picking rate, average loading rate, average last truck dispatch time, and average on-time delivery lacks in literature. Therefore, the problem statement of the research is indicated below;

"What is the impact of Extended Warehouse Management System implementation on Warehouse Operational Performance?"

Research objectives

The objectives of the research are mentioned below;

1. Examine the advanced features of the Extended Warehouse Management System
2. Examine the impacts of Extended Warehouse Management System implementation on Warehouse Operational Performance.

LITERATURE REVIEW

Introduction to the Warehouse management systems (WMS)

Warehouses play a critical role in linking upstream and downstream entities of the supply chains affecting their costs, customer service levels, and lead times (Minbo et al., 2011; Faber, 2012). The basic purpose can be identified as consolidating products to reduce transportation costs, providing value-added services, shortening response time, or achieving "economies of scale" in manufacturing/purchasing (Ramaa et al., 2012, Zunic et al., 2018). In today's intensified competition, companies strive to customize their value proposition to serve their customers with increased customer service, which leads to changing the traditional role of warehouses (Ramaa et al., 2012). Therefore, the role of the warehouse is not only for keeping large stocks in storage but to fulfill increasingly complex customer orders with a wide variety of products, in small quantities, with requirements for customized value-added services, on-time delivery, and reliably shorter response time (Chow et al., 2006, Chiang et al., 2013, Lam et al., 2015). Such changes to order patterns make it increasingly challenging to enhance warehouses' efficiency and service level, demanding more storage capacity, labor, real-time information, and data accuracy (Lee et al., 2017, Baruffaldi et al., 2018; Gils et al., 2019). Moreover, it becomes complex to plan and direct warehouse facilities and systems. Lack of timely and quality data from precise monitoring and measuring mechanisms results in bias decisions, leading to the need for a systematic approach (Chow et al., 2006). Warehouse management systems have a critical role in addressing the above scenarios.

Advanced features of Extended Warehouse Management Systems (EWMS)

Extant literature has defined WMS as, "A warehouse management system is a database-driven computer application, to improve the efficiency of the warehouse by directing cutaways and maintaining accurate inventory by recording warehouse transactions" (Shiau et al., 2010, Ramaa et al., 2012).

The challenges and limitations associated with traditional WMSs lead to the evolution of advanced and complex WMSs. According to Faber et al. (2002), WMSs can be classified into three types: basic WMS, advanced WMS, & complex WMS. Basic WMSs support stock and location control, use scanning systems to identify goods, determine storage locations and register that information, generate instructions for storing and pick processes, simple information mainly focusing on throughput. Advanced WMSs include the ability to plan resources. Complex WMSs can optimize a group of warehouses using diverse, complex storage, replenishment, picking, and cycle counting strategies, Availability of information on the location (through tracking and tracing), and movement (through planning, execution, and control). Baruffaldi (2018) highlighted advanced features of Complex WMS over Basic WMS as; ability to manage a group of warehouses, implement combined inventory management, and pick policies. More value-added capabilities include data-driven planning, dock allocation, traceability, automated process supervision, and control (Baruffaldi et al., 2018).

Pulungan et al. (2013) proposed an intelligent WMS (i-WMS), which comprises five subsystems, and the design integrates advanced intelligent system applications such as neural network, fuzzy control, bee colony optimization. And a decision support system and technologies such as RFID and Android-based handheld devices (Binos et al., 2021, Pulungan et al., 2013).

Minbo et al. (2011) suggested RFID-based Intelligent WMS (RFID-IWMS), addressing critical limitations of the traditional bar-code base system, such as lack of integration with the WMS and difficulty to get Key Performance Indicator (KPI) data of the operation. In the proposed system, pallets and shelves are fixed with RFID tags, facilitating scanning data automatically. And checking the location of storage, the forklifts are furnished with an RFID reader, intelligent terminal, and antenna, communication between the WMS, forklift, and portable terminals, are supported by middle-layer software over wireless Local Area Network and Forklift scheduling, 3D shelves monitoring, and picking sequence management are the added functions supported by the system (Minbo et al., 2011). The proposed design enhances the ability to manage the warehouse, tightly integrating with background WMS. The efficiency and accuracy of the warehouse operation improved incredibly due to automation of the manual process, tight coordination with WMS, support from forklift task scheduling, and 3D shelf monitoring (Minbo et al., 2011). The study highlighted the value of RFID-IWMS as an improvement in warehouse service level, the accuracy of stock control, inventory turnover and visibility, and reduced warehouse operation cost (Minbo et al., 2011).

Andiyappillai (2020) and Wang et al. (2010) addressed the RFID-based Digital WMS (DWMS), which comprises of three modules, Digital Warehouse Management System (DWMS), Forklift Guided System (FGS), and Back-End Module. By implementing FGS on forklifts, appropriate commands are given to forklifts, and drivers perform them as indicated by the automated guided map, which reduces labor consumption and misoperation. At loading, it is eliminated the requirement for scanning the barcode of items, one after another, to confirm the picking accuracy. With RFID-DWMS, it is just needed to drive the forklift, which carries the digital pallets, through the scanner, where the system automatically collects and verifies the data. It generates notifications to FGS, warning the driver if the orders are picked erroneously (Wang et al., 2010).

Smart WMS utilizes artificial intelligence, optimization algorithms, and advanced data mining techniques to improve warehouse processes (Li et al., 2021, Zunic et al., 2018). Smart WMS saves resources by optimizing the operations and making those efficient.

Mostafa et al. (2018) proposed a smart WMS framework based on the Internet of Things (IoT). The system supports accomplishing more control and monitoring of the operations in real-time. Moreover, an IoT-based WMS ensures real-time visibility within the warehouse, increases speed and efficiency, and prevents inventory shortage and counterfeiting (Mostafa et al., 2018). Also, Lee et al. (2017) suggested IoT-based WMS stated that the system enhances warehouse productivity, picking accuracy, and efficiency being robust to order variability.

The focus of this research is Extended WMSs allow deploying Automatic Identification and Data Capture (AIDC) technologies like RFID, Pick-to-Light, Voice Picking, and robotized systems. All required data could be input to the system without data entry operators, reducing data entry errors, freeing up human resources for performing more value-added tasks, and increasing efficiency (Garcia et al., 2006).

Implementation of WMS

WMS may be implemented as a stand-alone system or as a module of an ERP system (Ramaa et al., 2012, Atieh et al., 2016). It may deploy as a paper-based, RF/wireless-based, or amalgamation of the two (Ramaa et al., 2012). Decades ago, almost all WMSs implementations were tailor-made, addressing specific requirements and issues of a warehouse. However, with the changing role of warehouses, many standard WMSs implementations are growing rapidly with increased functionalities (Faber et al., 2002). Standard WMSs have various advantages such as being proven software solutions, less costly in acquiring, implementing, maintaining and having shorter implementation time, but largely compromise the way a warehouse wants to work and how the system allows the warehouse to work (Faber et al., 2002). Further, the implementation of WMSs is usually associated with Automatic Identification and Data Capture (AIDC) technology, Bar-coding, Electronic Data Interchange (EDI), wireless Local Area Networks (LAN), mobile computers, and Radio Frequency Identification (RFID) (Huang, 2021, Ramaa et al., 2012, Autry et al., 2005).

Warehouse Operational Performance Measures

Early research addresses warehouse operational performance measures in different industries. Nonetheless, it isn't easy to generalize these measures to all warehouse operations due to the complexity and context-specific nature. Establishing proper metrics enables auditing warehouse performance and assessing the WMS potential as a base for justifying investment. Ramaa et al. (2012) classified metrics to measure the performance of a warehouse under three categories: Order fulfillment, Inventory management measures, and Warehouse productivity. Fattah et al. (2016) used the “Supply Chain Operations Reference (SCOR) model” and “Batch Deterministic and Stochastic Petri Nets”; a modeling tool for modeling, evaluating, and analyzing the performance of warehouse inventory management systems.

Moreover, Ramaa et al. (2012) used warehouse performance measures to assess the impact of WMS implementation in the Supply Chain, focusing a case on India's retail industry. When supply chains become complex, more indicators and tools were introduced to measure various aspects but not address the issue (Staudt et al., 2015). Using the content analysis method, Staudt et al. (2015) conducted a literature review to identify operational warehouse performance measures and classify them under the dimensions of time, cost, quality, and productivity.

Impact of WMS implementation on Warehouse Operational Performance

Hendrick et al. (2007) found the financial benefits of enterprise resource planning (ERP) system implementations. Financial benefits are measured in terms of profitability and stock returns. And early adopters of ERP systems are able to gain higher profitability (Hendrick et al., 2007). The profitability and publicly available stock return do not address the internal operational performance of an ERP implementation. And also unable to estimate the long-run impact of ERP implementation due to lack of pre and post-implementation data. Chatterjee et al. (2002) positive stock market reactions to IT investment announcements. Stock market reaction is an unbiased estimate of the financial impact of positively perceived performance enhancement derived from IT investments. Therefore, early researchers address macro-level performance improvements of IT investments. Warehousing operations involve context-specific complex

processes. Few studies focus on the impact of the specific ERP systems on context-specific pre and post operational performance.

Practitioners and researchers acknowledge that WMSs are capable of enhancing warehouse performance (Baruffaldi et al., 2018). WMSs are widely implemented for handling resources and monitoring operations of warehouses (Minbo et al., 2011). The right application of WMS helps organize the functioning of a warehouse in online mode, improving the state of warehouses (Fomina et al., 2017). A large number of resources can be saved by improving processes by using provided business analysis (Zunic et al., 2018). WMSs ensure that warehouse employees never have to re-enter the data, as it can be accessed through a centralized database once entered or captured automatically (Ramaa et al., 2012). By sharing data through WMSs among companies in the Supply Chain, the impacts of the bullwhip effect can be minimized while making companies more responsive to changing customer demand (Baruffaldi et al., 2018).

Ramaa et al. (2012) stated some intangible benefits apart from above mentioned tangible benefits. However, firms with traditional WMSs face challenges and limitations due to their systems' inherent features. Early literature addresses the benefits of WMS implementation as increased productivity, better space utilization, reducing cost, reducing errors, reducing inventory, enhanced service quality, and time savings (Baruffaldi et al., 2018; Atieh et al., 2016).

According to Ramaa et al. (2012), WMS implementation unaccompanied by process changes doesn't immediate efficiency improvements or cost savings but only reduces errors because of human factors. Thus, process reengineering is essential to harness the most benefits from WMS implementation. Pulungan et al. (2013) highlighted that most of the traditional WMSs mainly focus on inputting and processing data and generating reports, but not on utilizing the results of intelligent systems in processes of WMSs. Also, traditional WMSs largely depend on data entry operators for inputting operational data manually or using a bar-code system, which leads to inaccuracy.

Measuring the impact of EWMS implementation on Warehouse Operational Performance

According to Wang et al. (2010), the performance comparison results of warehouse operation before and after the system implementation are identified as improvement of warehouse capacity by 52.5%, workers of loading task turned down by half, average time for loading is lessened from 50 to 18 minutes; which is a 64% improvement. This was mainly due to employing digital pallets, which significantly lower the time to collect barcode data and carry manually and inventory accuracy: an increase from 80% to 99% mainly due to the reduction of misplacements and transaction errors (Wang et al., 2010). Reduced human resources and time in loading tasks improved its efficiency.

Achieving visualized inventory management, high inventory accuracy, and automatic storage/retrieval assignment are significant impacts of RFID-WMS implementation (Wang et al., 2010).

According to the research done by Zunic et al. (2018), A module in Smart WMS provides pickers a sorted list of items, and their positions, considering the earliest expiration date first. The algorithm decides the optimal order picking path, even, the warehouse is according to an arbitrary or non-standard design. The improvements were over 90% ordered items accounts to be picked from picking zone, reduced Stock to Pick zone transfers by 16.2 times, and a total number of transactions over 4%.

Lee et al. (2017) identified using IoT-based WMS, and the process can be streamlined, as data is automatically captured and inputted into the system. As a result, the average receiving time is reduced from 2.54 min to 0.96 min, showing a 62% improvement. Further, it enhances the order fulfill performance as the position of inventories is distinctly indicated in the system; time spent on completing the order can be saved, which is otherwise spent for finding inventory locations. Thus, the result shows a 96% to 99% improvement in order fill rate (Lee et al., 2017).

Regarding order accuracy, many Stock Keeping Unit (SKU) numbers, which are remarkably similar, lead to product misidentification and mistaken products for the customer. IoT-based WMS automatically generates a notification if the goods do not have a shipment and inform the workers that incorrect products have been picked. The result shows the order accuracy has improved from 99% to 100% (Lee et al., 2017). And IoT-based WMS can reduce the chance of inaccuracy in records due to poor handwriting or data integrity. The technology helps automatically record inventory information, requiring the worker to scan the goods using the handheld device. Thus, a mistake due to manual recording can be reduced. Moreover, the record of the items can be updated over the Wi-Fi connection in a real-time manner, which helps monitor the warehouse more effectively. The result shows inventory accuracy has improved from 92% to 100% (Lee et al., 2017).

Furthermore, the most appropriate method for order picking can be generated using the “fuzzy logic engine” of IoT-based WMS. It helps to pick the orders in lesser travel time, improving order picking efficiency. Also, redesigned floor plan reduces the travel distance to the picker and reduces the time for the order picking process (Lee et al., 2017).

In terms of human resource management in manual operation, workers place products arbitrarily, and after that, the picking process depends on the worker’s memory, as well as experience, which leads to very time-consuming operation and a comparatively higher workload for the worker than a highly automated warehouse. Hence, the morale of the worker is deceased, resulting in a high labor turnover. With IoT-based WMS, unnecessary manual processes are eliminated so that the reduced workload enhances job satisfaction (Lee et al., 2017).

Extant research studied the impact of diverse WMS on context-specific warehouse operational performance. The different researchers used context-specific operational performance improvements and various measurement methods. Therefore, developing a standard metric to measure warehouse operational performance in the EWMS implementation context is challenging. Additionally, there is a lack of empirical studies comparing the pre and post-operational performance due to EWMS implementation in Sri Lanka.

METHODOLOGY

Case study research method

The previous research used the survey method to evaluate the impact of traditional WMSs in the Sri Lankan context. Moreover, the methodology used is subjective, as the respondents were asked to rate the developed constructs using a scale based on their judgment. Nonetheless, the case study method was used rarely except in a few international pieces of research, rare in the Sri Lankan context, primarily focusing on Extended WMSs.

Heterogeneous systems or versions are used by companies, even though they are in the same industry. Thus, the responses are depended on the WMS and its unique features implemented by each company. In some companies, as the WMSs were implemented years ago, the employees there before the system implementation and continue in the company are few in numbers. That is, a limited number of knowledgeable respondents are available. Moreover, some companies are reluctant to share information or lack longitudinal data before the system implementation.

However, the case study method allows the researcher to select suitable cases considering data and respondents' availability. Further, the method has the opportunity for an in-depth analysis, answering the questions of What & How; in this research, what are the impacts of Extended WMS implementation. Since the case study method gathers data from multiple sources, the richness of data is ensured. Therefore, the study uses the case study research method, collecting data from various sources and analyzing quantitative and qualitative data.

The study uses the case study research method, collecting data from multiple sources and using quantitative and qualitative data and analysis techniques. The selected case was an example of EWMS implementation in Sri Lanka, which has taken place in a food product Distribution Center. The case study can be identified as “an immensely powerful research method in questioning accepted theory, as it is essentially an inductive research method. Rooted in the observation of empirical ‘data’ and then can be used, within limits, to evaluate the efficacy of particular theoretical frameworks” (Adams et al., 2007). Data collection in case studies is generally a combined approach, using observation, surveys, and interviews. Kotzab et al. (2005) stated five criteria; a case selection can be done under one or a few. A particular case is considered as a critical example if it satisfies at least one criterion.

Accordingly, the study selected a case, which forms an extreme/unique case being an EWMS implementation in Sri Lanka and a representative case as an example of Extended WMS with additional advanced features. Table 1 shows a method of achieving each objective of the study.

Table 1: Method of achieving Research Objective

RESEARCH OBJECTIVE	**METHOD**
EXAMINE WHAT ARE THE IMPACTS OF EXTENDED WMS IMPLEMENTATION ON WAREHOUSE OPERATIONAL PERFORMANCE	Review literature to identify relevant performance measures, Develop an instrument to collect relevant data, Analyze using quantitative techniques Face-to-face in-depth interviews comparing process changes, improvements, complexities before and after system implementation Site visits (observational)

Population and Sample

Between Probability and Non-Probability sampling techniques, the study selected Non-Probability sampling as in the absence of a sampling frame (Kotzab et al., 2005). Among the few techniques under non-probability sampling, weighing their advantages and disadvantages, Judgement sampling was selected as the most suitable sampling technique for the study as it is used for choosing a group for screening purposes that confirm defined criteria.

Hypothesis development

The literature review chapter critically reviewed extant literature. It is used as the basis for developing the hypotheses of the study, as indicated below.

Overall performance: The experimental results of all Minbo et al. (2011), Wang et al. (2010), Lee et al. (2017), and Zunic et al. (2018) stated that the Extended WMS improved the efficiency and accuracy of the processes, resulting in the increased overall performance of the firm. Minbo et al. (2011) mentioned that, since RFID-EWMS captures data automatically, it reduces the data entry errors and frees up human resources for performing more value-added tasks. Thus, it offers outstanding improvements in the service level of the warehouse, accuracy of stock control, visibility, productivity, efficiency, and reduced warehouse operation cost (Minbo et al., 2011). The statistics of the experimental results of Minbo et al. (2011) showed that the stock-taking efficiency is improved by 40%, the warehouse condition becomes more visible, resulting in decreased average out-of-stock situations.

Zunic et al. (2018) argued that Smart WMS utilizes artificial intelligence, optimization algorithms, and advanced data mining techniques to improve warehouse processes. Smart WMS saves resources by optimizing the processes and making those efficient (Zunic et al., 2018). In their studies, Mostafa et al. (2018) also proposed that a smart WMS provides warehouse managers with more control and real-time monitoring of operations. Tracking real-time information about inventory helps manage inventory accurately, improving the visibility of demand and preventing stock-outs and inventory shrinkage (Mostafa et al., 2018).

Statistics of Lee et al. (2017) showed that by implementing IoT-based WMS, the order accuracy has improved from 99% to 100%. Further, inventory accuracy has been improved from 92% to 100% by implementing the WMS (Lee et al., 2017). Moreover, Wang et al. (2010) mentioned that the RFID-DWMS implementation improved storage and retrieval operation, reduced labor consumption and misoperation. The statistics showed the warehouse capacity improved by 52.5%, and inventory accuracy increased from 80% to 99% (Wang et al., 2010). In other words, overall firm performance or warehouse capacity improvement can be showcased with the increased throughput of the warehouse. This leads to the first hypothesis of the study as follows.

$H1_a$:	Average Throughput after EWMS implementation is improved (increased) from average Throughput before EWMS implementation

Process-wise performance:

Receiving

Zunic et al. (2018) argued that the set of SQL procedures of the system recommend positions to place every product to be received, hence improving the efficiency of receiving process. Lee et al. (2017) also mentioned that the process could be streamlined by using IoT-based WMS, and required data is captured and entered into the system automatically. Thus, the average receiving time is reduced from 2.54 min to 0.96 min, showing a 62% improvement (Lee et al., 2017).

Furthermore, Minbo et al. (2011), through their experimental studies on a distribution center of the retail industry in China, stated that their proposed RFID-IWMS achieved an accuracy of the rate of receiving as well as shelf storage above 99.9%, and time-saving by 71% when compared with the barcode-based system. This leads to the second hypothesis of the study as follows.

$H2_a$:	Average Receiving rate after EWMS implementation is improved (increased) from

average Receiving rate before EWMS implementation

Allocation & Picking

Wang et al. (2010) stated that the RFID-WMS implementation eliminates workers' requirement to walk around and decide storage/retrieval assignment and scan barcode data, which improves the allocation and picking process efficiency. Minbo et al. (2011) stated that, due to forklift scheduling and picking sequence management, the improvement of order picking rate is 195%.

Zunic et al. (2018) argued that the algorithms implemented using historical transaction data could predict future order requirements so that the workers can arrange the picking zone with enough product quantities (Zunic et al., 2018). Further, the algorithm provides a sorted list of items, and their positions, considering the earliest expiration date first, the optimal order picking path, improving the efficiency of allocation, and picking process. Zunic et al. (2018) mentioned the improvements as; over 90% of ordered items accounts to be picked from picking zone, and reduced Stock to Pick zone transfers by 16.2 times, using the optimal order picking path decided by the algorithm.

The statistics of Lee et al. (2017) showed that 96% to 99% improvement in order fill rate since time spent on completing the orders had been saved, as the position of inventories is distinctly indicated in the system. Lee et al. (2017) also argued that using the fuzzy logic engine of IoT-based WMS, the most appropriate method of the order picking policy can be generated, which leads to picking the order in less travel time, improving the efficiency of order picking. This leads to the third hypothesis of the study as follows.

$H3_a$:	Average Allocation & Picking rate after EWMS implementation is improved (increased) from average Allocation & Picking rate before EWMS implementation

Loading

Wang et al. (2010) stated that deploying RFID-WMS drives the forklift, which carries the digital pallets through the scanner. The system automatically collects and verifies the data generates notifications the orders are picked erroneously. This eliminates the requirement to scan barcodes of items, one by one, at loading, which improves the efficiency of the process. Statistics showed that the average time for loading tasks had been reduced from 50 to 18 minutes, showing a 64% improvement (Wang et al., 2010). This leads to the fourth hypothesis of the study as follows.

$H4_a$:	Average Loading rate after EWMS implementation is improved (increased) from average Loading rate before EWMS implementation

Moreover, the distribution center of the case study considers 'Last truck dispatch time' and 'On-time delivery %' as their major KPIs. This is due to; the two performance indicators are shown the final output or success of the operation. Therefore, the study develops the fifth and sixth hypotheses as follows, considering their importance.

Last truck dispatch time

The KPI measures the dispatch time of the last truck of the daily operation, which indicates the end time of the whole operation of the distribution center. The improvement of overall process efficiency leads to the fifth hypothesis of the study as follows.

$H5_a$:	Average Last truck dispatch time after EWMS implementation is improved (decreased) from average Last truck dispatch time before EWMS implementation

On-time delivery %

The KPI measures the number of deliveries made to the customer points on or before the target time, 7.30 a.m. The improvement of overall process efficiency leads to the fifth hypothesis of the study as follows.

$H6_a$:	Average On-time delivery after EWMS implementation is improved (increased) from average On-time delivery before EWMS implementation

Data collection

The process of data collection used in the study is shown in Figure 1.

Figure 1: The process of data collection of the study

Figure 2 illustrates the summary of data used in the study according to their type.

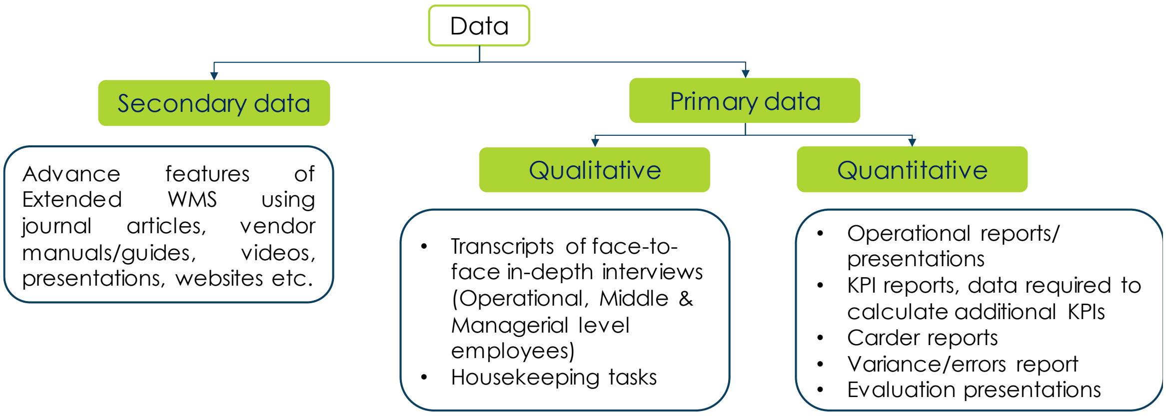

Figure 2: Data used in the study according to their type

Secondary data collection: The study uses secondary data as a supplement. For instance, international context literature, journal articles, ERP vendor manuals/guides, videos, presentations, websites, etc., were referred to collect relevant data to examine the advanced features of Extended WMS. Those can be used as evidence for triangulation of findings to ensure construct validity of the study.

Primary data collection: The study mainly utilizes Primary data using both quantitative and qualitative data.

Qualitative: The data are mainly gathered by conducting Face-to-Face, In-depth interviews. According to a semi-structured questionnaire, these interviews aim to conduct an exploratory, in-depth study on the impact of Extended Warehouse Management System implementation on Warehouse Operational Performance. The respondents will be operational, middle, and top-level users and consultants from warehouse operation and information technology mainstreams. The sample size is designed based on judgmental sampling. The study also gathered relevant operational documents such as consultant reports, housekeeping tasks reports, and field notes.

Quantitative: Relevant documents such as Weekly operational meeting reports/presentations, existing KPI reports, Reports containing required data to calculate additional KPIs, Evaluation reports, carder, and Variance & errors reports are gathered.

DATA ANALYSIS

Qualitative data analysis

The study gathered mass and in-depth qualitative data from interviews, site visits, and relevant documents. It used a more structured, Framework Approach to analyze qualitative data, following the five stages; Familiarization with data, Creating a thematic framework, Coding, and Indexing of data, Charting and Mapping and interpretation, as presented by Adams et al. (2007).

Quantitative data analysis

The study mainly uses quantitative data analysis techniques to analyze the research objectives. A more flexible and user-friendly statistical analysis software package, Statistical Package for Social Sciences (SPSS) 21, was used to analyze descriptive Statistics and Comparing Means using Paired t-test, the most suitable mean comparison test.

Quantitative data analysis results

Descriptive Statistics: The study has conducted descriptive statistics analysis for KPIs as indicated next section. The scope of the main variables of the study is indicated below.

- Throughput: the KPI measures the volume the distribution center manages daily. The unit of the measure is kilograms.

- Receiving: the KPI measures the efficiency of the receiving process. Time for Receiving is calculated using the time difference between Receiving start and finish time and deducting the idle time. Then, kgs' inbound volume is divided from the time for receiving and the number of workers in the process. The unit of the measure is kilograms per user per hour.
- Allocation & Picking: the KPI is calculated the same as the Receiving KPI. The picked volume in kgs is divided from the time for Allocation & Picking and the number of workers of the process. The unit of the measure is kilograms per user per hour.
- Loading: In the same way, the outbound volume in kgs is divided from the time for Loading. The unit of the measure is kilograms per hour.
- Last dispatch: the KPI measures the dispatch time of the previous truck, which indicates the end time of the whole operation of the distribution center. The unit of the measure is the time in AM.

The target time is 6.15 a.m. In contrast to the other KPIs, the KPI indicates lesser value and better performance, as dispatches were made early.

- On-time delivery (%): the KPI measures the number of deliveries made to the customer points on or before the target time, 7.30 a.m. The unit of the measure is the time in AM.

Table 2 shows the common descriptive statistics of the selected performance indicators.

Table 2: Descriptive Statistics

	No. of weeks	Minimum	Maximum	Mean	Std. Deviation
Throughput (Before)	16	92784.00	123952.00	104210.5625	7617.34490
Throughput (After)	16	115932.00	138029.00	124577.6875	6741.85123
Receiving (Before)	16	800.00	2375.00	1929.3750	429.31680
Receiving (After)	16	3809.00	5518.00	4783.5625	469.56802
Allocation & Picking (Before)	16	267.00	1042.00	632.5000	201.66837
Allocation & Picking (After)	16	1812.00	2473.00	2193.0625	215.87604
Loading (Before)	16	5675.00	11950.00	9037.5000	1545.36943
Loading (After)	16	19820.00	26746.00	23501.8125	2045.55369

Last dispatch (Before)	16	5.87	10.25	7.1419	1.40144
Last dispatch (After)	16	5.31	6.49	5.6138	.28364
On time delivery % (Before)	16	50.01	91.00	80.2356	10.56574
On time delivery % (After)	16	80.00	100.00	97.5625	4.80234

It shows the variability of the KPIs before and after the system implementation using the minimum, maximum, and standard deviation. The Standard deviation of Receiving, Allocation & Picking, and Loading rates are increased compared to before the system implementation. In contrast, the Standard deviation of the Last dispatch and On-time delivery is reduced. This indicates that the variability of the first three KPIs is widened while the last two KPIs' variability is narrowed with the system implementation.

Table 3: Comparison of Means before and after the implementation

Performance Indicator	Before implementation	After implementation	Impact
Throughput	104210.5625	124577.6875	19.54%
Receiving	1929.3750	4783.5625	147.93%
Allocation & Picking	632.5000	2193.0625	246.73%
Loading	9037.5000	23501.8125	160.05%
Last dispatch	7.1419	5.6138	21.40%
On time delivery %	80.2356	97.5625	21.60%

Table 3 illustrates a comparison of Means before and after the implementation. All the performance indicators except the Last dispatch showed an increased Means, showing improvements. However, the reduced Mean of the Last dispatch indicates that the average last truck dispatch time is 6.37 a.m. compared to its previous value of 8.08 a.m., which indirectly depicts an improvement.

Comparing Means:

Tables 4, 5 and 6 show the SPSS output of Paired t-test.\

SPSS output of Paired t-test

Table 4: Paired Samples Statistics					
		Mean	No. of weeks	Std. Deviation	Std. Error Mean
1 Throughput	Before	104210.5625	16	7617.34490	1904.33623
	After	124577.6875	16	6741.85123	1685.46281
2 Receiving	Before	1929.3750	16	429.31680	107.32920
	After	4783.5625	16	469.56802	117.39201
3 Alloc. & Pick	Before	632.5000	16	201.66837	50.41709
	After	2193.0625	16	215.87604	53.96901
4 Loading	Before	9037.5000	16	1545.36943	386.34236
	After	23501.8125	16	2045.55369	511.38842
5 Last dispatch	Before	7.1419	16	1.40144	.35036
	After	5.6138	16	.28364	.07091
6 Ontime Deliv.	Before	80.2356	16	10.56574	2.64144
	After	97.5625	16	4.80234	1.20059

Table 5: Paired Samples Correlations				
		No. of weeks	Correlation	Sig.
1 Throughput	Before & After	16	.024	.928
2 Receiving	Before & After	16	-.481	.059

3 Alloc. & Pick	Before & After	16	-.444	.085
4 Loading	Before & After	16	.409	.116
5 Last dispatch	Before & After	16	.721	.002
6 Ontime Deliv.	Before & After	16	.765	.001

Table 6: Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
1 Throughput	Before - After	-20367.12500	10047.92978	2511.98244	-25721.28884	-15012.96116	-8.108	15	.000
2 Receiving	Before - After	-2854.18750	773.83566	168.76330	-3266.53542	-2441.83958	-14.753	15	.000
3 Alloc. & Pick	Before - After	-1560.56250	354.90336	77.27296	-1749.67715	-1371.44785	-17.589	15	.000
4 Loading	Before - After	-14464.31250	1996.41301	471.68750	-15528.12590	-13400.49910	-28.981	15	.000
5 Last dispatch	Before - After	1.52813	1.21301	.30325	.88176	2.17449	5.039	15	.000
6 Ontime Deliv.	Before - After	-17.32688	7.55126	1.88782	-21.35066	-13.30309	-9.178	15	.000

Table 4 illustrates Paired Sample Statistics; Mean and Standard deviation statistics are the same as in Table 2: Descriptive Statistics and Standard Error Mean. The results of the Pared t-test are illustrated in Table 6. It shows that all two-tailed paired t-tests are significant (0.000) at a 95% confidence interval.

However, since the study's hypothesis is defined for one-tailed (directional), paired t-tests, significance levels of two-tailed tests should be divided by two to adjust those for the significance level of one-tailed tests. The 0.000 significance level for all the tests at 95% confidence interval. Therefore, all the null hypotheses are rejected, accepting all alternative hypotheses.

Qualitative data analysis results

The study used the Framework Approach to analyze qualitative data following the stages of Coding, Charting and Mapping, and interpretation. Accordingly, the impacts on processes and overall firm performance were identified.

Process Flowcharts: The study created Process Flowcharts to map and graphically interpret the impacts of Extended WMS implementation on each process, comparing and highlighting the improvements and drawbacks.

(Note: The acronyms used in the process flow chart includes; IBD: In-Bound Document, OBD: Outbound Document, STO: Stock Transfer Order, WC: Work Center, TU: Transport Unit, PBL: Pick By Line, DEO: Data Entry Operator, WHA: Warehouse Assistant, GRN: Good Receiving Note, HU: Handling Unit, PGI: Post-Good Issue).

Planning

Before	After
Customer email the IBD and STO numbers	Customer email the IBD and STO numbers
STO: Call all the suppliers to verify item wise quantities to be deliver against quantities in IBD	STO: Received STO numbers are run in ERP to create warehouse tasks in EWM
IBD: From the excel document sort items for WC & numbers separately, VLOOKUP the quantities to be received and get a printout before start receiving	IBD: Use to create TU for trucks before start receiving

Receiving

Before

- Supplier arrival time – Note on Guard room book
- Arrival to the dock
- Unloading of goods – stack on dollies
- Quality checks
- Input good received to the system
  - Manually writing item, Qty, invoice no. in supplier-wise maintained ~35 books
  - Manually calculate the exact weight of each dolly (scale reading – weight of crates & dolly)
  - Enter the summation of exact weight of each item to the system
- Print GRN & handover to supplier

After

- Supplier arrival time – Note on Guard room book
- Create TU (Transport Unit - barcode) – Assignment of dock
- Arrival to the dock – Scan TU: verify right dock, show items to be received with Qty
- Unloading of goods - stack on dollies
- Quality checks (visual, detailed, random)
- Input good received to the system – through RF device
  - For number items – enter the #crates
  - For weighing items – enter the #crates, scale reading of weight
  - Update the system (EWM)
- Print Source HU (Handling Unit - barcode) & paste on each dolly
- Print GRN & handover to supplier

Put-away & Allocation

Before

- Items are moved from receiving area to WCs / numbers storage area
- Based on supplier confirmation, & receiving Qty.s, manually allocate item wise quantities for outlets based on the demand (STO)

After

- **System:**
  WC items: automatically transferred to WC storage location
  PBL items: transferred to PBL storage location by completing put-away transaction
  Physically:
  items are moved from receiving area to WCs / PBL storage area
- System using an algorithm allocates (in PBL this is named as 'Wave release', in WCs this is named as 'Execution') GRN quantities to outlets based on demand

Picking

Before

Item wise allocated quantities are given to pickers on a paper

Accordingly, picked quantities are put on outlet / destination bins

After picking, the paper is handed over to DEO to manually enter the quantities to the system

After

WC

Weighed quantities are stacked on a dolly which is pasted a second source HU barcode

The HU is entered under both outlets

Manually written outlet code is put on each side of the dolly

By scanning the HU / looking at manually written outlet code, picker is informed the destination bins the items should be put on

PBL

After Wave release, when scanned the source HUs, picker is informed the destination bins the items should be put on

When arrive to destination bin, scan the barcode of the destination bin – verify whether the destination bin is correct

Scan the barcode of the destination bin, put items on destination HUs (dollies) & scan the bin barcode for each item – can verify which items in which quantities at which destination HUs

Loading

Before	After
DEO manually enters the picked quantities to an excel document	OBD and outlet bin numbers are download separately, VLOOKUP to route plan excel sheet, Filter OBD numbers and Copy paste to EWM
Sort outlet codes of a route and verify whether picking is completed	Verify through the system whether all the outlets of a transport route are picked
Copy paste from excel to ERP and save to PGI	Quantity adjustment: quantities were adjusted from STO quantities to Picked quantities
Trans-out Note is printed and handover to loading supervisor to start loading	TU is created, printed and handed over to loading supervisor with a loading sheet to start loading
WHA gets the items from destination bins to loading area	WHA gets the items from destination bins to loading area
	Scan the destination HU Arrange the crates according to the crate type outlet wise Note down the number of each crate type, outlet wise on loading sheet and enter the same to the system through RF device
Load crate by crate doing 100% inspection	Load dolly wise according to the unloading sequence and get the signature of driver as a confirmation
	Do PGI using TU
Put on security seal and dispatch with shipping document (two ply)	Print shipping document and dispatch

DISCUSSION AND IMPLICATIONS

The findings and implications in line with each research objective of the study are discussed. The study's objectives are achieved by discussing the impact of the implementation on each process and operational performance, highlighting the improvements and drawbacks.

Process wise impact

Planning: The implementation could eliminate the burden of calling suppliers and noting the confirmed quantities to be delivered against the In Bound Document (IBD). This saves warehouse resources such as labor, facilities, and other consumables, eliminating the associated costs. The implementation only requires running the IBD numbers in the system, where the system automatically creates warehouse tasks to RF device level, even before the commencement of receiving process. This eliminates the human interventions mostly, thus, reducing the errors and improving the accuracy of the process.

Receiving: In the results of quantitative analysis, the graph for the receiving rate shows a steep increase, where the Mean value shows 1.5 times increment, and the Paired t-test results in accepting the alternative hypothesis that, average receiving rate after Extended WMS implementation is improved (increased) from before the implementation.

With the introduction of the Transport Unit (TU) concept, it is possible to verify the right dock arrival of the trucks, and the receiving supervisor is provided with the information (though the RF device) of item-wise quantities to be received before the commencement of receiving process. After the implementation, verifying the receiving quantities against IBD quantities is not necessary, as there is no manual allocation in the next stage. When the amounts received are input into the system, it automatically adjusts against the IBD. The quality checks become more organized by introducing three types of quality checks under 21 well-defined reasons, where a quality reject can happen. Thus, it becomes more streamlined and effective with system implementation. With the introduction of the source Handling Unit (HU) concept, information of each handling unit (item, quantity the HU carries) is available by just one scan, which improves the visibility of the whole operation.

Eliminating manual writing, calculations, data entering, and bookkeeping immensely improved the process. Supervisors only have to enter a number of crates &/ scale-reading through RF devices now, which saves a lot of time improving the efficiency of the process. Moreover, it drastically reduces the workload for the workers. It creates an automated working environment with new devices rather than the manual paper base, which increases workers' job satisfaction, thus their productivity.

However, the study suggests that the process can be improved if the system can automatically capture the scale-reading without requiring the worker to enter it through the RF device. Thus, the efficiency and accuracy of the process can be further improved.

When comparing the study results versus literature, by using IoT-based WMS, the average receiving time was decreased by 62%, as required data is captured and inputted into the system automatically (Lee et al., 2017). Further, RFID-IWMS achieved time-saving by 71% compared with the barcode-based system (Minbo et al., 2011). The study shows a comparatively more significant improvement since it was an entirely paper-based manual operation before the system implementation.

Put-away & allocation: The physical put-away process is more or less the same as before. However, a great positive impact can be seen in allocation, with the deployment of advanced algorithms over manual allocation. When allocating manually, it consumes human resource, their experience, and a lot of time. Thus, heavily inefficient. The system uses advanced algorithms considering several bases and allocates automatically within seconds, making the process more efficient and precise.

Picking: In the results of quantitative analysis, the Mean value of the picking rate shows 2.5 times increase, and the Paired t-test results in accepting the alternative hypothesis that, average picking rate after Extended WMS implementation is improved (increased) from before the implementation.

Eliminating paper-based operation and manual data entry on item-wise picked quantities to the system improves the efficiency and accuracy of the process compared to before. More than efficiency, it could achieve a higher level of accuracy as, though there was no controlling mechanism preventing errors before and after the implementation, picking errors could be prevented through scanning and confirmation mechanisms. For instance, when scanning a wrong destination bin, an error is shown in the RF device, and the picking task can be completed only when scanning the correct destination bin.

With the system implementation, picking errors can be identified user-wise. For instance, even though the correct bin was scanned, items were put on the wrong bin; since the RF devices are assigned for username, the user-wise errors can be captured with quantities, though they picked the same item. Thus, a monitoring mechanism is available to monitor and take corrective actions. Further, as pickers were informed of the destination bins with respective quantities, guidance from the systems supports pickers to perform their role.

Moreover, the resulted improvement is the highest compared to the other processes. This may mainly be due to before the implementation. There was only one department, Work Center (WC), and after the implementation, another department was introduced; Pick By Line (PBL). The additional resource commitment, such as labor and facilities, improves the overall picking rate.

However, the RF device’s inability / requiring more steps to sort outlet-wise item quantities when a Handling Unit (HU) carries items of more than one outlet requires manually writing and pasting the outlet code. It prevents utilizing a HU for more than two outlets, though the quantities are small. This can be improved with system upgradation.

When comparing the study results versus literature, Minbo et al. (2011) stated that the order picking rate showed a 195% improvement with forklift scheduling and picking sequence management. The study shows a comparatively greater improvement, mainly due to increased resource commitment with an additional department.

Loading: In the results of quantitative analysis, the graph for the loading rate shows approximately two times improvement soon after the system implementation, where the Mean value shows 1.6 times increment, and the Paired t-test results in accepting the alternative hypothesis that, average loading rate after Extended WMS implementation is improved (increased) from before the implementation.

Despite loading one by one, doing 100% inspection, as performed before the implementation, it is performed lot wise, after the implementation only requiring scanning the destination HU. This saves a lot of time and human resource requirements, incredibly improving the efficiency of the process. However, the improvement is only possible due to properly controlling and monitoring mechanisms implemented in the picking stage.

The requirement of using a paper base (loading sheet) in this stage is directly due to the inability of the system / RF device to show the outlet-wise HU breakdown according to the unloading sequence at once. Currently, it requires several more steps back and forth, which is difficult to perform within the limited time available. Resolving the issue with a system up-gradation may further improve the efficiency of the process.

When comparing the results of the study versus literature, Wang et al. (2010) stated that employing digital pallets could reduce the time to collect barcode data and carry it manually. Thus, the average time for the loading task was reduced, showing a 64% improvement. Despite additional resource commitment in the picking task, the study shows the highest improvement in the loading task, mainly due to the proper controlling and monitoring mechanism implemented in the picking stage.

Overall impact

The overall impact of the Extended WMS implementation can be discussed below;

Throughput: In the results of quantitative analysis, a graph for the throughput KPI shows a slightly decreasing trendline before the implementation, while it is slightly increasing after the implementation, indicating the system implementation positively impacts throughput, converting it from diminishing to a boost. Further, the Mean value shows a 19.54% increment, and the Paired t-test results accept the alternative hypothesis that the average throughput after Extended WMS implementation is improved (increased) from before the implementation.

Space utilization: Before implementation, the warehouse was fully occupied for 80 outlets' operation. However, after the system implementation, with the HU concept and Data management techniques, the same facility can be utilized for 117 outlets, though it currently operates 99 outlets. Thus, the implementation opens up opportunities to grow with better utilization of existing resources.

Carder: In the results of quantitative analysis, a graph for the carder KPI shows the reduction of required carder against the planned carder after the system implementation. It is highlighted that the improvements shown in other KPIs were achieved with a lower available carder than the planned carder. The progress of the overall operation was realized with a reduction from 119 to 98 total staff.

Last truck dispatch time: This performance indicator is considered as one of the two indicators which the warehouse considered as most critical. In the results of quantitative analysis, a graph for the last truck dispatch time KPI shows before the implementation, most of the last truck dispatches (avg. last truck dispatch time was 7.30 am) were after the target time; 6.15 a.m. However, after the implementation, almost all the last truck dispatches were completed before the target time.

Further, the Mean value shows a 21.4% increment. The Paired t-test results accept the alternative hypothesis that the average last truck dispatch time after Extended WMS implementation is improved (decreased) from before the implementation. Further, with the introduction of dispatch waves, a greater number of dispatches shifted from last waves to first waves, indicating that the trucks were dispatched earlier due to overall efficiency improvement of the processes.

On-time delivery: This is the other indicator that the warehouse considered as most critical. Before system implementation, the average percentage of on-time deliveries was below 90%, and none were made on time. However, it could achieve more than 98% after the implementation, having 100% on-time deliveries in four to five days of a week.

Further, the Mean value shows a 21.6% increment, and the Paired t-test results accept the alternative hypothesis that the average on-time delivery after Extended WMS implementation is improved (increased) from before the implementation.

Other: Even though the overall operation was streamlined and improved after the Extended WMS implementation, it created some housekeeping tasks in the system for the SuperUser or Admin of the distribution center to work on daily, to maintain the operation smoothly. This can be identified as a non-value-added activity, which can be solved with a system upgradation.

CONCLUSION

Original contribution

This paper is among the very few evaluating Extended WMS, specifically, EWM system implementation. Using empirical quantitative and qualitative data and analysis techniques, the unique methodology deployed a case study approach addressing what and how. The study's findings reveal that implementation of EWMS increases the throughput, average receiving rate, average allocation and picking rate, average loading rate, average last truck dispatch time, and average on-time delivery. The scope of the research is limited to evaluating the EWMS implementation impact on warehouse operational performance in a selected FMCG warehouse. The in-depth analysis of performance improvements in the extent of the throughput, average receiving rate, average allocation and picking rate, average loading rate, average last truck dispatch time, and average on-time delivery signals warehouse managers in decision making on effective utilization EWMS implementation. This paper is among the very few evaluating Extended WMS, specifically, empirical investigation of the impact of EWMS system implementation on FMCG warehouse operational performance.

Limitations

The study is more focused on the impact of the implementation on warehouse operational performance. Therefore, the findings and implications are limited to the focus area rather than its impact on firm financial performance, human resources, or supply chain partners. Further, though the system automatically captures and calculates the number of KPIs, there were limited KPIs measured before the system implementation since they had to be captured and calculated manually. Thus, the ability to do more comparative, quantitative analysis was restricted, though the data is available after the system implementation.

Future research

Future researchers can use multiple case studies to evaluate the impact of the same system in the same industry, generalizing the findings and implications more effectively. Moreover, Future researchers can focus on the impact of EWMS on supply chain capability enhancements and the strategic performance of supply chain partners.

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