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Developing an Efficient Model for Online Grocery Order Fulfillment

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Abstract: Due to the convenience of online grocery apps and home delivery, online grocery shopping has become popular in recent years. Globally, consumer behavior has significantly changed the consumption and purchase patterns of online grocery shopping. This study aimed to develop an efficient model for online grocery order fulfillment that both reduces costs and increases supply chain efficiency and sustainability. This study first aimed to develop the current picking model by adopting real-world data from a store in Riyadh, Saudi Arabia. Subsequently, four proposed models were developed to improve the efficiency and sustainability of the online grocery order fulfillment process. The results show a significant improvement in all models over the current picking model. The percentage improvements in fulfillment time per product are as follows: single order picking—8.33%; batch order picking—6.78%; zone order picking—3.08%; and hybrid order picking—13.20%, which combines zone and batch order picking. Retailers and online grocery apps could adopt these models to increase efficiency and sustainability. Also, these models have great potential for future research and improvement by optimizing product placement, in addition to picking methods and picking routes, which are the focus of this study.

Keywords: e-commerce; online grocery shopping; optimization; simulation; routing; order fulfillment; order picking models; logistics and supply chain; sustainable development

Citation: Alrasheed, M.A.; Rehman, A.U.; Alharkan, I.M. Developing an Efficient Model for Online Grocery Order Fulfillment. *Sustainability* **2024**, *16*, 4270. https://doi.org/10.3390/su16104270

Received: 13 April 2024
Revised: 13 May 2024
Accepted: 14 May 2024
Published: 19 May 2024

1. Introduction

Online grocery shopping has become popular in recent years due to the convenience of online grocery apps and home delivery, as well as the outbreak of the COVID-19 pandemic [1]. This trend was evident before the pandemic and, in 2018 alone, there was a 13% increase in online grocery orders. These customers also spent 20% more than their in-store counterparts [2]. The practice of online grocery shopping saves customers' time, making it popular with the urban demographic. It is expected that the demand for online groceries will grow more than fivefold in the coming decade [3].

In Saudi Arabia, grocery retail is a developing industry with intense competition. Retailers and grocery apps that provide an efficient customer experience can develop a competitive advantage in any market space [4]. The role of online grocery shopping is likely to be more relevant in Gulf Cooperation Council (GCC) countries, given their relatively young population with an average age of 27. Studies have shown that millennial shoppers are more inclined to buy online, highlighting the huge potential for online grocery services in Saudi Arabia [5]. Similarly, the majority of online grocery shoppers in the United States are between the ages of 27 and 42, with 65 percent of them doing so on a monthly basis in 2023 [6].

Online grocery stores commonly use one or multiple models from among four digital grocery business models. The first business model is "Store to Home", where orders are picked from an existing grocery store and then delivered to the consumer. Similarly, orders in the "Click-and-Collect" model are picked in an existing grocery store but are not delivered. Instead, customers collect their complete orders from the store. The other two models, the "Warehouse to Home" and "Drive-through" business models, are similar to the models mentioned above. However, these orders are fulfilled from a warehouse designed for online grocery orders [4]. This research deals with the first two business models, "Store to Home" and "Click-and-Collect", since it focuses on online grocery order fulfillment from an existing store. These two business models were chosen because they address the emerging research topic of order fulfillment from an existing store, whereas the other two models, the "Warehouse to Home" and "Drive-through" business models, are covered by warehousing management studies.

These days, most hypermarkets and grocery chain stores have to incorporate order picking and home delivery into their selling channels. These functions were previously carried out by consumers and, therefore, the complexity and number of processes that are performed by stores have increased [7]. Unlike other types of online shopping, the picking process for online grocery is far slower because of the complexity, variety, and large product selection. An online grocery order can contain products that need special preparations, such as fresh dry food, frozen products, and products that require specific care. In addition, the complexity is further increased by the need for the small response time window that consumers require and transportation logistics [8].

It has been recognized that the order picking process is one of the major bottlenecks of the supply chain, and any improvement in the process would lead to time and cost reductions [8]. Furthermore, improving the efficiency would not only increase company profits but also picker wages, which, in turn, would increase the Saudization of pickers. In addition, increasing order picking efficiency would mean faster responses and the flexibility to increase throughput in times of crisis. This study aims to propose an efficient model for online grocery order fulfillment that reduces costs and waste, and that increases the supply chain's efficiency and sustainability.

This research focuses on the order fulfillment phase of online grocery shopping and specifically on the order picking process. Furthermore, this study focuses on order fulfillment from an existing store (supermarket/hypermarket), as this is the most representative of the industry, and on the ability to implement the model in different countries and companies with minimal changes.

Since few studies model both order picking methods and order routing, this research aims to develop an efficient online grocery order fulfillment model that works by selecting the order picking method and routing. Furthermore, while there are multiple studies on online grocery order fulfillment, there are no models that combine different picking methods and routing for each order. Therefore, the proposed hybrid model combines different picking methods: batch and zone order picking. Considering the above research gap, research objectives were set, the details of which can be found below.

This research's main objective was to propose an efficient model for online grocery order fulfillment that reduces costs and waste, while increasing supply chain efficiency and utilization. These proposed models would improve the supply chain's sustainability because they eliminate the need to build special warehouses for grocery fulfillment, by improving fulfillment from existing supermarkets around the world. Retailers and online grocery apps could use this model to increase efficiency and utilization. Furthermore, this model has high potential for future research and improvement by optimizing product placement, in addition to picking methods and picking routes, which are the focus of this study.

The basic terms adopted in this research are as follows:

- Online grocery shopping: a system in which shoppers can buy grocery products online and receive them at their doorstep.
- Order: a list of products ordered by the customer.
- Picking efficiency: the time it takes to pick up products from an order in the store [9].

2. Literature Review

After reviewing and studying the literature, we ascertained the complete online grocery supply chain from manufacturing to the final consumer, which is presented in Figure 1. A sub-value chain for order fulfillment is also presented in the same figure. This research focuses on the order fulfillment phase of online grocery shopping, as shown in Figure 1, and specifically on the order picking process.

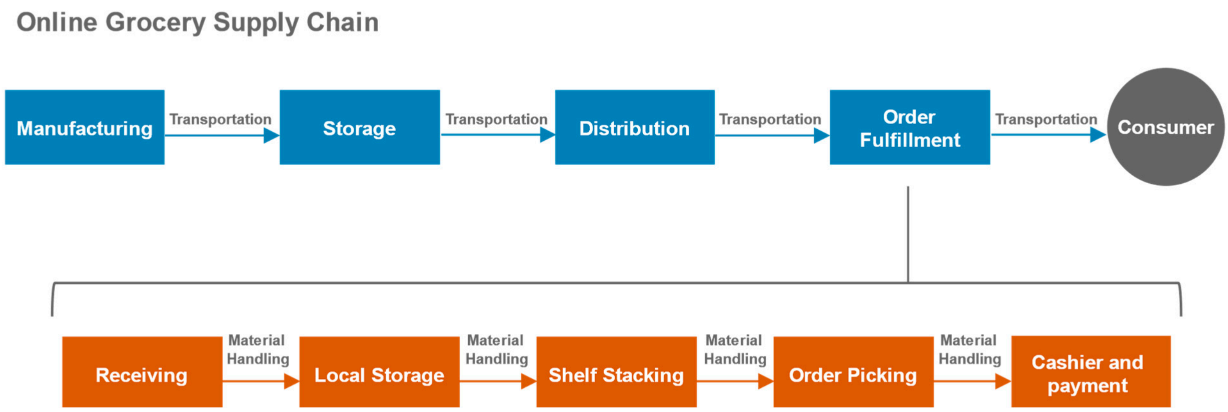

Figure 1. Online grocery supply chain.

In the literature, many strategies for optimizing order picking have been proposed. Researchers have categorized order picking into two main parts. The first part is order picking methods, where the critical focus is the strategy for consolidating customer orders, so that orders are picked as quickly as possible with minimum effort. The second part is order routing, which is concerned with the sequence in which items are picked, in order to minimize the distance traveled by the picker [9].

In the literature, common order picking approaches are single order picking [6], batch order picking [10], and zone order picking [10]. Details of each approach are presented below. Researchers adopted these order picking approaches individually and selected the best routing approach for each case. In this research, the objective was to focus on all three types of order picking, as well as their combination (hybrid approach), and to suggest the best routing for each order.

2.1. Single Order Picking

Single order picking is where each order is picked individually. In other words, a single order is picked in each picking tour. This picking method is suitable for reasonably large orders. Sometimes, this way of picking is referred to as pick-by-order or discrete picking [10]. Vazquez- Noguerol et al., (2020) studied single order optimization in grocery stores. However, the main objective was to schedule order picking within the same day to increase efficiency [7].

2.2. Batch Order Picking

Batch order picking is the policy of combining multiple orders into a picking tour performed by a single picker. This picking method is suitable for small orders, as it results in a reduction in routing times [10]. Valle et al., (2017) focused on the exact algorithm for order picking and batching. However, their study only addressed batching as a picking method [11]. Another study by Yadav et al., (2019) used a two-phase heuristic approach. However, the authors' focus was on batch order picking as a consolidation policy [9].

2.3. Zone Order Picking

Zone order picking is where the picking area is divided into multiple zones, and each picker is assigned to one zone. This means each picker only picks the part of the order in their designated zone. Compared to other picking methods, the zoning method has received little attention in order picking research, despite its significant impact on order-picking fulfillment efficiency. One of the advantages of adopting zone order picking is the short amount of travel required by each picker, since they are assigned to a specific area. Another advantage is traffic congestion reduction.

Furthermore, on the one hand, assigning a picker to one area is considered an advantage since it increases the picker's familiarity with different items in their zone. On the other hand, zone order picking's main disadvantage is the added process of consolidating orders from each zone before shipping to the customer [10]. Eriksson et al., (2019) studied zone order picking for groceries, but from a warehouse and not directly from a store [12]. Table 1 below summarizes order picking strategies, the research problem, and optimization objectives for related studies [13].

Table 1. Summary of related studies of order picking strategies.

Article	Order Picking Strategy	Research Problem	Optimization Objectives
[14]	Batch order picking	The optimization of order batch picking in multi-location storage systems, which involves developing models and algorithms to address the correspondence relationship between location and SKU, while also reducing travel distance during picking.	Minimize the total travel distance during order picking.
[15]	Batch order picking	The challenges that Logistics Service Providers (LSPs) face when handling B2B e-commerce orders due to structural changes in B2B logistics orders, the inadequacy of existing logistics facilities and internal order handling procedures, and the complexities that arise from fluctuating customer demand, delivery requirements, and distribution center capacity availability.	Minimize the total travel distance of all B2B e-commerce order picking routes in distribution centers.
[16]	Batch order picking	The integrated order batching and delivery planning problem in online retailing systems, with a focus on order arrival dynamics and the need to meet specific order due dates.	Minimize the total cost, which includes transportation and picking costs, while maximizing the number of orders delivered on time.
[17]	Batch order picking Zone order picking	The development of a CPS-enabled synchronization mechanism for two-stage picking and sorting ecommerce order fulfillment, which includes addressing the lack of integrated order picking research from a synchronization perspective, proposing a next-generation solution, and understanding the performance trade-offs between picking simultaneity and sorting punctuality.	Minimize the waiting duration of total batch picking and the mean earliness and tardiness of each customer order.
[18]	Batch order picking Zone order picking	The operational workload balancing problem (OWBP) in the context of order picking in warehouses, with the goal of developing a method for scheduling and balancing workloads to avoid peaks.	Minimize the difference between the maximum and minimum scheduled workload.
[19]	Batch order picking	The integration of picking and transport activities in the context of e-grocery, taking into account the unique challenges of the online food channel, with the goal of presenting a mathematical model for planning picking and transport activities that minimizes associated costs.	Minimize the total e-fulfillment costs, which include order picking and delivery costs.
[20]	Zone order picking	Solving the storage assignment problem (SAP) for order picking operations in an e-commerce-based warehouse, with a focus on balancing workload between picking activities and managing emergency replenishment.	Minimize the wait time among pick-and-pass operations resulting from emergency replenishment and imbalance of workload among picking cells.
[21]	Batch order picking	Deep reinforcement learning is used to solve the online order batching and sequencing problem (OBSP) in a warehouse setting, with the goal of reducing the number of late orders.	Minimize the number of tardy orders.
[22]	Batch order picking	Investigating the impact of splitting customer orders on the picking process in e-commerce warehouses and proposing a heuristic solution to this generalized problem.	Minimize the total order picking time.

Table 1. *Cont.*

Article	Order Picking Strategy	Research Problem	Optimization Objectives
[23]	Batch order picking	The optimization of wave picking systems, specifically addressing the joint problem of order batching, batch assignment, and picker routing (BAR) in a warehouse that uses the Mixed-Shelves Storage Strategy (MSSS), with the goal of developing a method that minimizes the makespan and workforce level, while analyzing the trade-offs between these two objectives.	Minimize the makespan and workforce level.
[24]	Batch order picking	Improving the efficiency of order picking in smart warehouses by developing a novel picking strategy that includes order splitting and batching, with the objective of minimizing total tardiness under an order splitting policy.	Minimize the total picking distance in the first stage and the total tardiness of orders in the second stage.

3. Research Methodology

Based on the above research objective, the following research methodology was developed.

3.1. Data Collection

Data were collected from actual practice in the online grocery shopping industry. The first set of data contains historical order fulfillment records from one major hypermarket. The second set is the hypermarket layout and the placement of different items inside the store. Data were obtained from a major Saudi online grocery app that operates in multiple cities across the Kingdom. Additionally, we collected further data on the products' placement and hypermarket layout because the online grocery app did not have these data.

In order to develop efficient order picking models, actual data were obtained from a major Saudi online grocery app (denoted as XYZ because its management declined to disclose its identity), which operates in multiple cities across the Kingdom.

The set of data contains historical order fulfillment records from one major hypermarket in Riyadh that cover a 6-month period, starting on 17 April and ending on 17 October 2021. The hypermarket's location was selected considering multiple factors, including the availability of data, the ability to visit the hypermarket, and the ability to collect more quantitative and qualitative data regarding the layout of the hypermarket and its product placements. As the online grocery app does not have these data, additional data were collected. This process was performed manually by drawing the hypermarket layout and taking measurements using a Laser Measuring Device (Bosch GLM 120 C Professional purchased from Riyadh, Saudi Arabia). Then, the final layout of the hypermarket was drawn using AutoCAD software (version 23.1). Also, product placement was noted on the layout for each aisle of the hypermarket. Table 2 shows general stats for the collected data.

Table 2. General stats for collected data.

Type	Count
Store	1 hypermarket
No. of orders	47,442 orders
No. of picked items	1,039,419 items
No. of pickers	288 pickers

Table 3 shows the data structure requested from XYZ needed to develop the current order picking model.

Figure 2 shows the hypermarket layout drawn using AutoCAD software (version 23.1). The figure also shows aisle numbers corresponding to the product categories in Table 4.

Table 3. Data structure for order fulfillment.

Data Code	Title	Description	Unit
oID	Order ID	Identification for each order	Code
OR	Order Received	Time of receiving orders from customers	Date and time
OA	Order Accepted	Time of accepting orders from customers	Date and time
ST	Picking Start Time	Time of starting the picking process by a picker	Date and time
FT	Picking Finish Time	Time of finishing the picking process by a picker	Date and time
PT	Payment Time	Time of processing the payment for the order	Date and time
DT	Delivered Time	Time of delivering the order to the customer	Date and time
NP	No. of Products	Number of products in each order	Count
prID	Product ID	Identification of the product	Code
GS	General Section	The section where the product belongs (baked goods, vegetables, meat, . . .)	Section
Q	Quantity	Quantity of the product for each order	Count
PPT	Product Picking Time	Time of picking each product	Date and time
pID	Picker ID	Identification of the picker for each order	Code

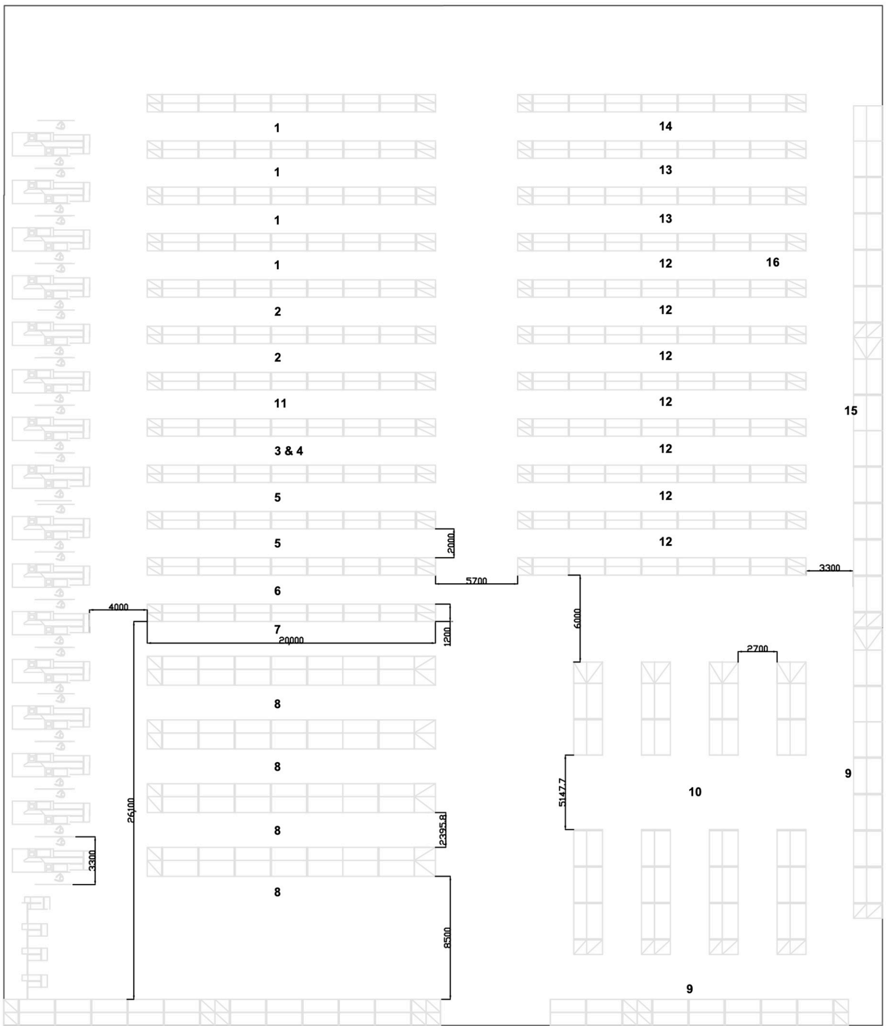

Figure 2. Hypermarket layout with aisle numbers drawn using AutoCAD software (version 23.1).

Table 4. Placement of different categories inside the store and corresponding aisle numbers.

Aisle Number	Product Category Code	Product Category
1	PC01	Personal Care
2	PC02	Snacks
3	PC03	Bakery
4	PC04	Breakfast Cereals
5	PC05	Organic and Healthy
6	PC06	Dairy Products
7	PC07	Beverages
8	PC08	Frozen Food
9	PC09	Fresh Food (meats)
10	PC10	Fruits and Vegetables
11	PC11	Breakfast Goods
12	PC12	Cooking Supplies
13	PC13	Home Cleaning
14	PC14	Baby Products
15	PC15	Water
16	PC16	Pet Supplies

3.2. Data Cleansing

After the data were received from XYZ, a full evaluation was performed to assess their quality and usability. There were apparent issues with incomplete and duplicate data points. Also, some inconsistencies were observed regarding the data format. Additionally, after analyzing current data, low efficient picking was observed. These low efficiencies are due to the lack of experience of some pickers. These orders were removed to increase the accuracy of the current order picking model and, subsequently, the proposed models. Low efficient orders are defined as any order that has a more than 10 min to pick one item. That means the picker spent over 10 min picking one product. Due to the dimensions of the hypermarket, taking this time to pick one product means the picker is inexperienced or was interrupted for some reason. The data cleansing process included removing incomplete data, removing duplicate orders, removing orders with an inconsistent format, and removing low-efficient order fulfillments. After following the cleansing process, the data set was decreased from 47,442 orders to 14,815 orders, and the number of picked items was decreased from 1,039,419 items to 193,364 items. Although the cleansing process removed over 50% of the data, this was necessary in order to improve the validity and accuracy of the model.

3.3. Current System Modeling

In this phase, a simulation model of the selected hypermarket was developed using "Anylogic" software (version 8.8.2). The current picking method is classified as single order picking; however, it does not provide pickers with specific routes or guidance. This phase details the development of the current simulation model for the practice of grocery order picking. The aim is to use the simulation to reproduce similar results to the current model.

3.4. Model Verification and Validation

In order to validate the accuracy of the model in this study, verification and validation processes were implemented to ensure that it accurately represented the system's actual behavior.

Figure 3 illustrates a broad overview of the verification and validation process. The "Current System" refers to the actual system from which data were obtained. The current system could be a problem, subsystem, or a complete system. The "Model formulation" includes the mathematical equations, conceptual model, and the data needed to model the current system. The "simulation model" symbolizes the software execution of the model formulation. The process of picking characteristics and mathematical approximations that represent the current system in the model formulation is termed modeling. Assessing the accuracy of this modeling is called confirmation. The verification process focuses on identifying and removing errors in the software development. Verification can be achieved by performing two activities: code and calculation verification. Code verification includes identifying and removing errors in the software code. Calculation verification is concerned with the quantification errors introduced during the application of the simulation software. Finally, the validation activity focuses on quantifying the model accuracy by comparing simulation outcomes with experimental data from the actual model [25]. For this study, model validation was achieved by adopting five measures, which were revising the logic and output of the model, observing the actual fulfillment process, observing the model animation, parameter calibration, and a two-sample *t*-test. These measures are discussed in Section 5.5 (Model Verification and Validation).

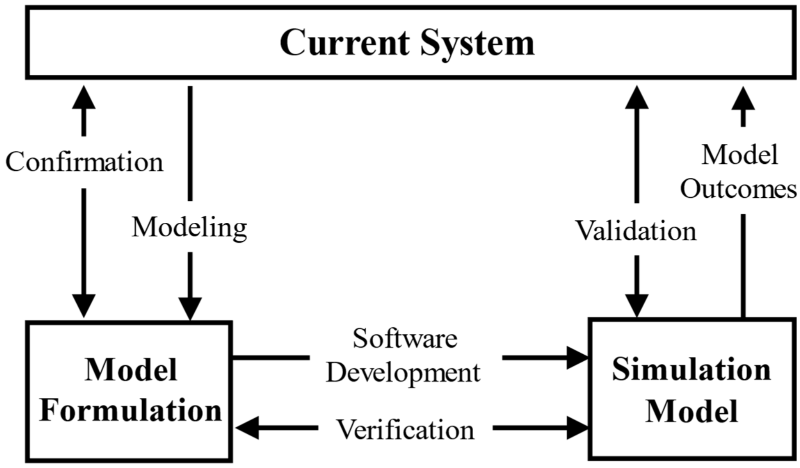

Figure 3. Simplified overview of the verification and validation process.

3.5. Proposed Order Picking Models

In this phase, new models of different picking methods are developed to increase the efficiency and utilization of the online grocery order fulfillment process. The primary objective of these models is to improve the routing and picking methods of grocery orders. Each proposed model uses a different order picking method as follows:

- Single order picking;
- Batch order picking;
- Zone order picking;
- Hybrid order picking, which combines zone order picking with batch order picking.

3.6. Limitations and Assumptions

Following one-to-one discussions with the operation management of a major online grocery app, one has to take multiple assumptions and limitations into consideration, such as the fact that picking will be carried out using hypermarket carts (trolleys). Additionally, the model would be applicable in a supermarket/hypermarket that is fully operational and accessible by regular consumers. Furthermore, the model assumes that the online grocery business cannot change the store's product placements.

4. Current System Modeling

This section presents the simulation model of the selected hypermarket constructed using "Anylogic" software (version 8.8.3). The current picking method is classified as single order picking; however, it does not provide pickers with specific routes or guidance. This section details the development of the simulation model for the current practice of grocery order picking. The aim is to use the simulation to reproduce similar results to historical data. Each following sub-section discusses the process of modeling the current practice in detail, starting with the conceptual model development, simulation software selection, the detailed model design, the simulation execution, and model verification and validation, concluding with the outcome analysis. These processes are explained in detail throughout this section.

4.1. Conceptual Model Development

In this step, a high-level conceptual model is developed to represent the system. This model represents a simplified version of the real-world system, outlining primary entities, their interactions, and key dynamics. The current process starts when a picker receives an order to fulfill using the company app. Then, the picker proceeds to add the required items to the trolley, following random routing and sequencing. When the order is complete, the picker goes to the cashier to process the order for delivery. Figure 4 shows the details of the current order fulfillment process.

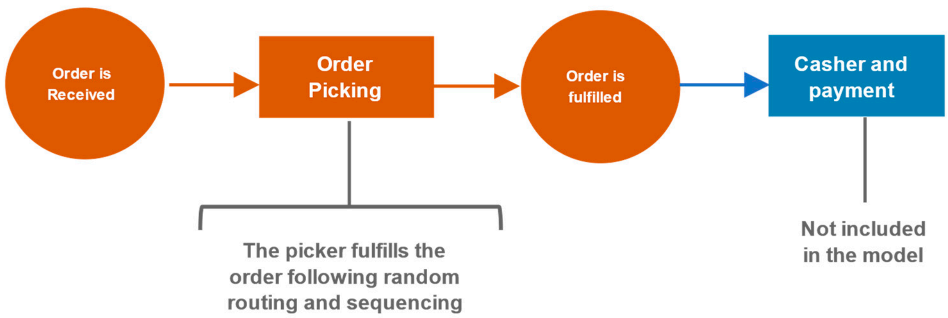

Figure 4. Diagram of the current fulfillment process.

4.2. Simulation Software Selection

Thorough consideration was given to choosing an appropriate simulation software based on the model's complexity, objectives, and the detailed requirements of the study. Well-known choices include software like AnyLogic, Simio, and Arena. The selection of AnyLogic for this study was based on its capability as a multi-method simulation tool that combines three main modeling methodologies: discrete event simulation, agent-based modeling, and system dynamics. AnyLogic version 8.8.2 was used for this research [26].

4.3. Detailed Model Design

Using the simulation software, the current simulation model was developed. This model includes defining system entities, components, events, resources, and the associated logic that controls their behaviors and interactions. The simulation model was designed using agent-based modeling, where agents are the main building blocks. An agent is a unit of the model design that can have memory (historical data), behavior, timing, and contacts. In AnyLogic, agents may represent different things: equipment, projects, products, vehicles, organizations, investments plans, the layout, people in different roles, etc. Four agents were employed in the current research: a layout agent, an order agent, a model agent, and a logic agent. The following sub-sections present a comprehensive explanation of each agent [26].

To account for the current hypermarket layout, a network of paths and nodes was added to the model, as shown in Figure 5. The paths are the hypermarket aisles and any other aisle that the picker may use. The nodes represent the pickup locations from the aisles, start points, and end points of the picking process. Since the study uses the category aisle to define the location of any item, one node with a center location is used for each set of aisles in the same category.

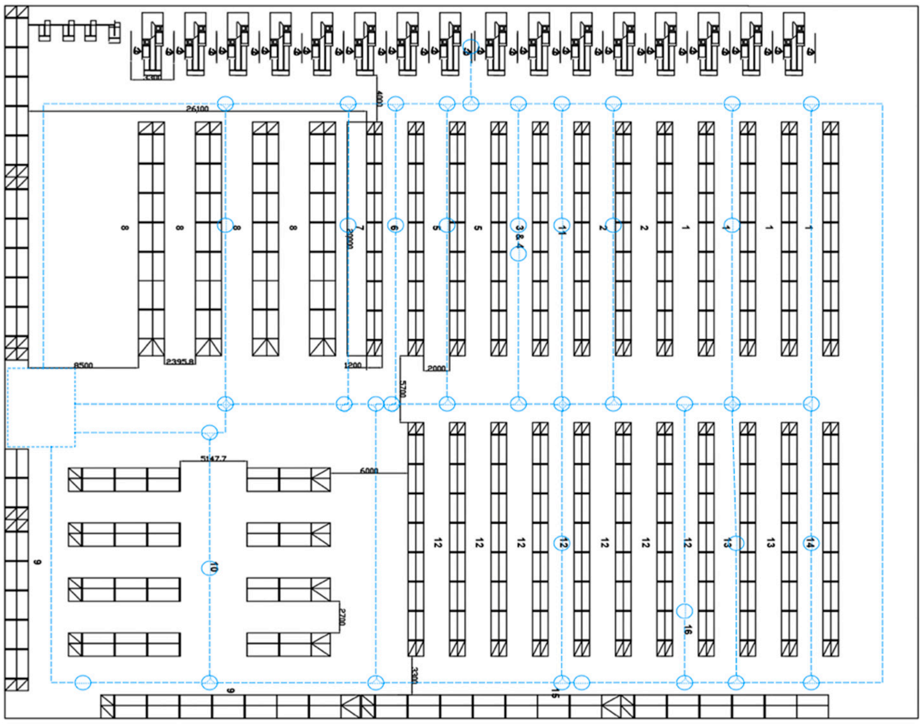

Figure 5. The hypermarket layout with aisle numbers after adding dotted lines, which represent paths, and nodes, which represent interaction points.

Several parameters were incorporated into the model and these can be adjusted to find the output that most accurately aligns with the current model. Since the actual values were not available, these parameters were determined via parameter calibration.

The first parameter was "picker speed", which accounts for the average speed at which the picker moves throughout the hypermarket. The second parameter was "Time to find a product in an aisle", which represents the average amount of time it takes for a picker to search for the required product. The third parameter was the "Time to pick a product". And, if there were additional quantities of the same product, "Time to pick any additional items of the same product" was used as a fourth parameter. The total time to pick a product could be calculated using the following Equation (1):

$$\text{Total Time to pick a product} = T_2 + (Q-1)\delta \tag{1}$$

where T_2 is "Time to pick a product", Q is quantity of each product, and δ is "Time to pick any additional items of the same product". This equation increases the model's accuracy, since picking multiple items of the same product is not the same as picking different products. This difference is attributed to the picker's ability to load multiple items into the cart in one motion. Furthermore, to calculate the total time to fulfill an order, the following Equation (2) was developed, which takes into account the picker's movement between aisles, as well as the time it takes to find products:

$$\text{Total Time to fulfill an order} = \sum\left(\frac{D}{S}\right) + T_1 + T_2 + ((Q-1)\delta)_j \tag{2}$$

where D is the distance between the current picker's location to the placement of the next product on the list, T_1 is "Time to find a product within an aisle, and j is all products in an order.

Subsequently, parameter calibration was used as a measure to improve the accuracy of the model in the validation process. The term parameter calibration refers to the process of making iterative model adjustments, while comparing model outcomes with actual system outcomes [27]. Parameter calibration was performed using Scatter Search, which is a population-based metaheuristic used for optimization. The calibration was performed using OptQuest, which is an optimization module in Anylogic that is based on the Scatter Search methodology and intermittently uses other heuristics techniques to increase the efficiency of the optimization process. OptQuest is commonly utilized due to its seamless integration with the simulation software and its prominent role in the literature as the primary instrument of scatter search methodology [28–33]. The Optimizer treats the simulation model as a 'black box'. This implies that the Optimizer provides the values of the decision variables to the simulation model and, in return, the simulation model provides an objective function calculation [34].

The objective function minimizes the mean square error (MSE) of "Average Fulfillment Time per Product" between the output from the simulation and actual data. The Average Fulfillment Time per Order is, thus, considered as the primary metric to improve the simulation model's validity. Parameter calibration returns a pseudo-optimal solution of a set of parameters that will minimize the MSE. Since this optimization algorithm uses scatter search heuristics for the optimal solution search, realistic constraints are needed for every parameter in order to minimize the simulation time and improve results. These constraints are determined by observing the picker in the real system:

- Picker speed between 1 and 5 km/h;
- Time to find a product within an aisle between 1 and 60 s;
- Time to pick a product between 1 and 5 s;
- Time to pick any additional items of the same product between 0.1 and 2 s.

The results are presented in Table 5.

Table 5. Calibrated parameters and their values.

Parameter	Value	Units
Picker speed	2.877	km/hr
Time to find a product within an aisle	7.561	seconds
Time to pick a product	3.888	seconds
Time to pick any additional items of the same product	1.801	seconds

4.4. Simulation Execution

Based on the function and parameters defined in previous sections, the simulation model was executed. The simulation model was set to cover a 6-month period, starting on 17th of April and ending on 17 October 2021. These dates mirror the dates of the actual data obtained from XYZ. The number of fulfilled orders in the simulation model equaled 14,815 orders, while the number of picked items was 193,364 items. Furthermore, the total number of pickers was 288.

4.5. Model Verification and Validation

The verification process focuses on identifying and removing errors in software implementation. Model verification is achieved by performing two activities: code and calculation verification. Code verification is performed by identifying and removing errors in the simulation software code, whereas calculation verification is accomplished by revising the quantification errors introduced during the application of the simulation software.

In order to validate the accuracy of the model in this study, validation processes were implemented to ensure that the simulation model accurately represented the system's actual behavior. The validation processes are presented below in Figure 6. Validation was firstly achieved by revising the logic and output of the model, with input from XYZ executives on the accuracy of the model. A second measure was implemented to validate the model by observing the actual fulfillment process in the same hypermarket. Furthermore, observing the model animation during the execution of the simulation served as the third validation process; this allowed us to examine the behavior of the model and its different components. The fourth validation process was parameter calibration, which refers to the process of making iterative model adjustments, while comparing the model's outcomes with actual system outcomes. The parameter calibration experiment is discussed in detail in Section 4.3 (Detailed Model Design).

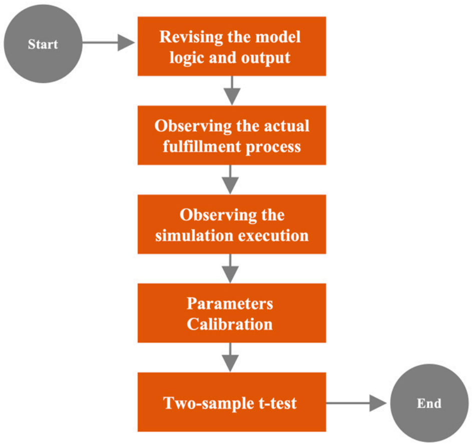

Figure 6. Model validation processes.

These four measures confirmed the validity of the model, and as a fifth and final measure to validate the simulation model, a two-sample *t*-test was conducted to compare actual data with the simulation output. The results of this are presented in the Section 4.6 [35].

4.6. Simulation Model Outcomes Analysis

The analysis of simulation outcomes involved calculating statistical measures and performance metrics; a graphical representation of the results is also presented. Furthermore, a two-sample *t*-test was performed to compare historical data with the simulation output. A descriptive statistical analysis of model outcomes was performed, as shown in Table 6.

Table 6. Simulation model results—descriptives.

Outcomes	Fulfillment Time per Order (Minutes)	Average Fulfillment Time per Product (Seconds)	Average Moved Distance per Product (Meters)
Description	Average fulfillment time in minutes (from the time the picker starts moving from the entrance until the time the picker arrives at the cashier)	Average fulfillment time per product (seconds)	Average moved distance by the picker to fulfill each product (meters)
Mean	12.61	59.82	43.44
Std. Deviation	9.68	8.73	6.42
Minimum	0.57	33.96	20.77
Maximum	104.69	155.99	75.7

For the above table, it can be seen that the average fulfillment time per order is 12.61 min, while 59.82 s is the average fulfillment time per product. Lastly, the average moved distance per product is 43.44 m. Compared to the actual data, a similar mean could be observed for all outcomes, which suggests the simulated model is valid in replicating the actual data. This similarity needs to be statistically proven.

The standard deviation, which quantifies the extent to which results deviate from the average, is consistent with the standard deviation of the actual data. Furthermore, the minimum and maximum are also similar to the corresponding values of the actual data.

The next step in validating the simulation model, as presented in Figure 6, was a two-sample *t*-test. This was performed to compare historical data with the simulation output for each of the three main outcomes presented above in Table 6. This test aimed to investigate whether there were significant differences in the outcomes between historical data and the simulation model. The two hypotheses are as follows:

The null hypothesis (H_0): There is no significant difference in the mean outcomes of actual data (μ_1) and those of the simulation model (μ_2).

The alternative hypothesis (H_a): There is a significant difference in the mean outcomes of actual data (μ_1) and those of the simulation model (μ_2).

A significance level of $\alpha = 0.05$ was used to determine the statistical significance of the results. The detailed findings of these tests are presented below in Table 7.

Table 7. Differences between actual and simulation levels (*t*-test results).

Compared Outcomes	Difference in Means	*p*-Value
Actual Fulfillment Time per Order—Fulfillment Time per Order	0.07	1.000
Actual Average Fulfillment Time per Product—Average Fulfillment Time per Product	1.17	1.000
Actual Moved Distance per Product—Moved Distance per Product	0.93	1.000

Individual confidence level = 99.84%.

As evident in the above table, the *p*-value for each outcome was more than 0.05 and the null hypothesis was not rejected, confirming there were no significant differences between the simulation model and the actual data.

The statistical analysis concluded that there were no significant differences between the actual data and those of the simulation model for all three variables. The individual confidence level of 99.84% corresponded to an error rate of roughly 0.26% or a difference of only 0.026 min between the simulated and actual data output. This confirmed the validity of the simulated model and allowed us to develop the new models proposed in Section 5.

In Section 5, new models of different picking methods were developed to increase the efficiency and utilization of the online grocery order fulfillment process. The primary objective of these models was to improve grocery order routing and picking methods. Each proposed model uses a different order picking method: single order picking, batch order picking, zone order picking, and hybrid order picking, which combines zone and batch order picking.

5. Proposed Order Picking Models

After validating the current simulation model, new models of different picking methods were developed to increase the efficiency and utilization of the online grocery order fulfillment process. The primary objective of these models was to improve grocery order routing and picking methods. Each proposed model uses a different order picking method, as stated below:

- Single order picking;
- Batch order picking;
- Zone order picking;
- Hybrid order picking, which combines zone and batch order picking.

In this section, the optimization approach using a Genetic Algorithm was adopted for each proposed order picking model. The objective was to improve the routing in each model. Subsequently, each proposed order picking model development is presented. This is followed by a comparison analysis discussing improvements in the proposed model over the current simulation model. Finally, this section concludes with an analysis and comparison of all the above proposed models.

Order picking models represent a vehicle routing problem (VRP) and, in this study, they were optimized using a genetic algorithm. The genetic algorithm parameters were added to the optimization approach and adopted in each proposed order picking model.

The parameters were the number of pickers in the population, the number of generations, crossover probability, and mutation probability. These parameters can be described as follows: the number of pickers in the population refers to the initial number of pickers available for each order. The routes of these pickers are chosen randomly (similar to historical data), whereas the number of generations is the number of iterations the optimization repeats. The greater the number, the better the results. Crossover probability represents the percentage of pickers that cross over in each generation. For example, if we have 10 pickers and 0.5 crossover probability, this means that $0.5 \times 10 = 5$ new pickers will be generated at each new generation. Lastly, mutation probability is the probability of a generated crossover route to undergo mutation. Table 8 displays the values for each parameter [36].

Table 8. Selected values for the genetic algorithm parameters.

Parameter	Value
Number of pickers in the population	10
Number of generations	100
Crossover probability	50%
Mutation probability	80%

5.1. Single Order Picking Model

Single order picking refers to the process of picking each order individually. In other words, a single order is picked by a single picker in each order fulfillment process. This proposed model applies the optimization approach to the current simulation model, without introducing any constraints because it uses the same picking method as the existing model.

For this model, the simulation was executed for the 6-month period from 17 April to 17 October. The number of fulfilled orders in this model equaled 14,815 orders, while the number of picked items was 193,364. Furthermore, the total number of pickers was 288. To produce the results, the simulation model was executed along with the optimization process. The outcomes' statistical measures are presented in Table 9.

Table 9. Single order picking model results—descriptives.

Outcomes	Fulfillment Time per Order (Minutes)	Average Fulfillment Time per Product (Seconds)	Average Moved Distance per Product (Meters)
Mean	11.78	54.83	39.46
Std. Deviation	9.74	8.39	5.97
Minimum	0.57	30.12	19.88
Maximum	113.47	155.99	73.61

It is evident from Table 9 that, for the single order picking model, the average fulfillment time per order was 11.78 min, which is lower than the current model (12.61 min). Also, the average fulfillment time per product was 54.83 s, which is lower than the current model (59.82 s). Furthermore, the average moved distance per product was 39.46 m, which is also lower than the current model (43.44 m).

In order to investigate the performance improvement in the single order picking model over the current model, a two-sample *t*-test was performed. This test was performed for each of the three main outcomes presented above in Table 2, in order to investigate whether there was a significant difference in the outcomes between the single order picking model and the current model. The two hypotheses were as follows:

The null hypothesis (H_0): There is no significant difference in the mean outcomes of the single order picking model (μ_1) and the current model (μ_2).

The alternative hypothesis (H_a): There is a significant difference in the mean outcomes of the single order picking model (μ_1) and the current model (μ_2).

A significance level of $\alpha = 0.05$ was used to determine the statistical significance of the results. The detailed findings of these tests are presented in Table 10.

Table 10. Differences and percentage improvements in the single order picking model over the current model.

Model Outcomes	Difference of Means	*p*-Value	Percentage Improvement (Over the Current Model)
Fulfillment Time per Order (minutes)	0.825	0.000	6.54%
Average Fulfillment Time per Product (seconds)	4.9839	0.000	8.33%
Average Moved Distance per Product (meters)	3.9830	0.000	9.17%

As evident in Table 10, the *p*-value for each outcome was less than 0.05 and the null hypothesis was rejected, confirming that there is a significant difference between the single order picking model and the current model. Furthermore, in order to measure the performance improvement in the proposed model over the current model, the relative change percentage was calculated for each outcome. This was calculated using the following Equation (3):

$$C = \frac{x_2 - x_1}{x_1} \times 100 \tag{3}$$

where C is the relative change percentage, x_1 is the initial value (current model performance), and x_2 is the new value (proposed model performance). Table 10 above presents the percentage improvement in the single order picking model over the current model for each outcome.

Clear improvements can be observed in each performance measure of the single order picking model over the current model. Since the single order picking method is already used in the current model, these improvements are due to the optimization of the picker routing during order fulfilment. Since it does not impose any changes in the picking method, the implementation of the proposed method would be straightforward. When applying the proposed model, the picker would fulfill the order in the optimized product sequence, instead of relying on common sense or using a random sequence.

5.2. Batch Order Picking Model

The batch order picking method involves consolidating many orders into a picking tour performed by a single picker. This picking method is ideal for small orders because it reduces routing times by picking multiple orders in a single tour. This model is designed to improve the performance of the current model by optimizing both the picking method and sequence.

Three new parameters are introduced in the batch order picking model: waiting time to batch, maximum number of orders in a batch, and maximum number of items in a batch. These are constraining parameters, and the picker will start the fulfillment process when any of the three constraints is met. The first parameter, waiting time to batch, represents the length of time the picker will wait before starting to collect the batch of orders, unless either of the two other constraints is met. The waiting time is set to 30 min, which accommodates the actual time window that customers are expected to receive their orders, with a maximum limit of 2 h. The second parameter, maximum number of orders in a batch, represents the maximum number of orders permitted to be picked in a single fulfillment tour. This parameter is set to four orders/batch because of the limitation of using a normal hypermarket cart. Lastly, the parameter maximum number of items in a batch is the maximum number of items from all orders that are allowed to be picked in a single fulfillment tour. This parameter is set to 155 items/batch, since it represents the largest order in the current model. Lowering this parameter below this value will lead to the optimization model not being fully executed. Table 11 summarizes the values selected for each batching parameter.

Table 11. Parameter values selected for the proposed model.

Parameter	Value	Units
Waiting time to batch	30	Minutes
Maximum number of orders in a batch	4	Orders/batch
Maximum number of items in a batch	155	Items/batch

In order to incorporate the batching method into the simulation model, a timer was added to calculate the first parameter mentioned above. When the first order is received, the timer starts. Once the timer reaches the specified waiting time to batch parameter, all the orders received during this duration will be assigned to one picker. If either the maximum number of orders in a batch or maximum number of items in a batch parameter is met before the time duration passes, the batch is picked with the current collected orders. The timer starts again when the next order is received and the same batching process is repeated.

Similar to the last proposed model, the simulation model was executed for a 6-month period from 17 April to 17 October. The number of fulfilled orders in the proposed model equaled 14,815 orders, while the number of picked items was 193,364 items. Additionally, the total number of pickers was 288. The simulation model was executed along with the optimization process, in order to produce the results and statistical measures displayed in Table 12.

Table 12. Batch order picking model results—descriptives.

Outcomes	Fulfillment Time per Order (Minutes)	Average Fulfillment Time per Product (Seconds)	Average Moved Distance per Product (Meters)
Mean	12.42	55.76	40.54
Std. Deviation	7.19	3.5	2.72
Minimum	0.69	37.83	26.84
Maximum	107.7	121.58	67.57

It is evident from Table 6 that, for the batch order picking model, the average fulfillment time per order was 12.42 min, which is marginally lower than that for the current model (12.61 min), while the average fulfillment time per product was 55.76 s, which is considerably lower than that for the current model (59.82 s). Furthermore, the average moved distance per product was 40.54 m, which is also lower than that for the current model (43.44 m).

Compared to the current model, a slightly lower mean fulfillment time per order was observed, while the average fulfillment time per product and average moved distance per product showed considerably lower means. This difference suggests the batch order picking model saw improvements in efficiency over the current model. In order to investigate the performance improvement of the new model over the current model, a two-sample *t*-test was performed. This test was performed for each of the three main outcomes presented above in Table 6, with the aim of investigating whether there was a significant difference in the outcomes between the batch order picking model and the current model. The two hypotheses were as follows:

The null hypothesis (H_0): There is no significant difference in the mean outcomes of the batch order picking model (μ_1) and the current model (μ_2).

The alternative hypothesis (H_a): There is a significant difference in the mean outcomes of the batch order picking model (μ_1) and the current model (μ_2).

A significance level of $\alpha = 0.05$ was used to determine the statistical significance of the results. The detailed findings of these tests are presented in Table 13.

Table 13. Differences and percentage improvements in the batch order picking model over the current model.

Model Outcomes	Difference in Means	p-Value	Percentage Improvement (Over the Current Model)
Fulfillment Time per Order (minutes)	0.182	0.153	No significant improvement
Average Fulfillment Time per Product (seconds)	4.0543	0.000	6.78%
Average Moved Distance per Product (meters)	2.8972	0.000	6.67%

As evident in the above table, the p-values for the average fulfillment time per product and the average moved distance per product were less than 0.05 and the null hypothesis was rejected, leading to the conclusion that there was a significant difference between the batch order picking model and the current model regarding these two metrics. However, the p-value for the fulfillment time per order was more than 0.05 and the null hypothesis was not rejected, confirming that there was no significant difference between the batch order picking model and the current model regarding this metric. This insignificance was due to the fact that batch order picking method does not optimize the fulfilment time for each order, but instead improves the overall efficiency of all orders, since the picker fulfill multiple orders at the same time.

Furthermore, the performance improvement in the proposed model over the current model is presented above in Table 8. This percentage was measured using the relative change Equation (3) from the last section.

Clear improvements can be observed in the average fulfillment time per product and average moved distance per product in the batch order picking model over the current model, while the fulfillment time per order is not significantly improved in the proposed model. These improvements were due to the optimization of both the picking method and routing during order fulfilment. The application of this proposed method requires placing four shopping baskets in each cart to accommodate up to four orders at the same time. When using the proposed model, the picker would fulfill the order in the optimized sequence, placing each product in the assigned basket.

5.3. Zone Order Picking Model

The zone order picking method involves dividing the picking area into multiple zones, with each picker being assigned to one zone. This means each picker only picks the part of the order corresponding to their designated zone. The hypermarket aisles are divided into six zones (A, B, C, D, E, and F), as shown below in Figure 7 and Table 14.

Table 14. Placement of different categories inside the store and the corresponding zone.

Aisle Number	Product Category Code	Product Category	Zone
1	PC01	Personal Care	B
2	PC02	Snacks	B
3	PC03	Bakery	C
4	PC04	Breakfast Cereals	C
5	PC05	Organic and Healthy	C
6	PC06	Dairy Products	C
7	PC07	Beverages	D
8	PC08	Frozen Food	D
9	PC09	Fresh Food (meats)	A
10	PC10	Fruits and Vegetables	A
11	PC11	Breakfast Goods	B
12	PC12	Cooking Supplies	E
13	PC13	Home Cleaning	F
14	PC14	Baby Products	F
15	PC15	Water	F
16	PC16	Pet Supplies	F

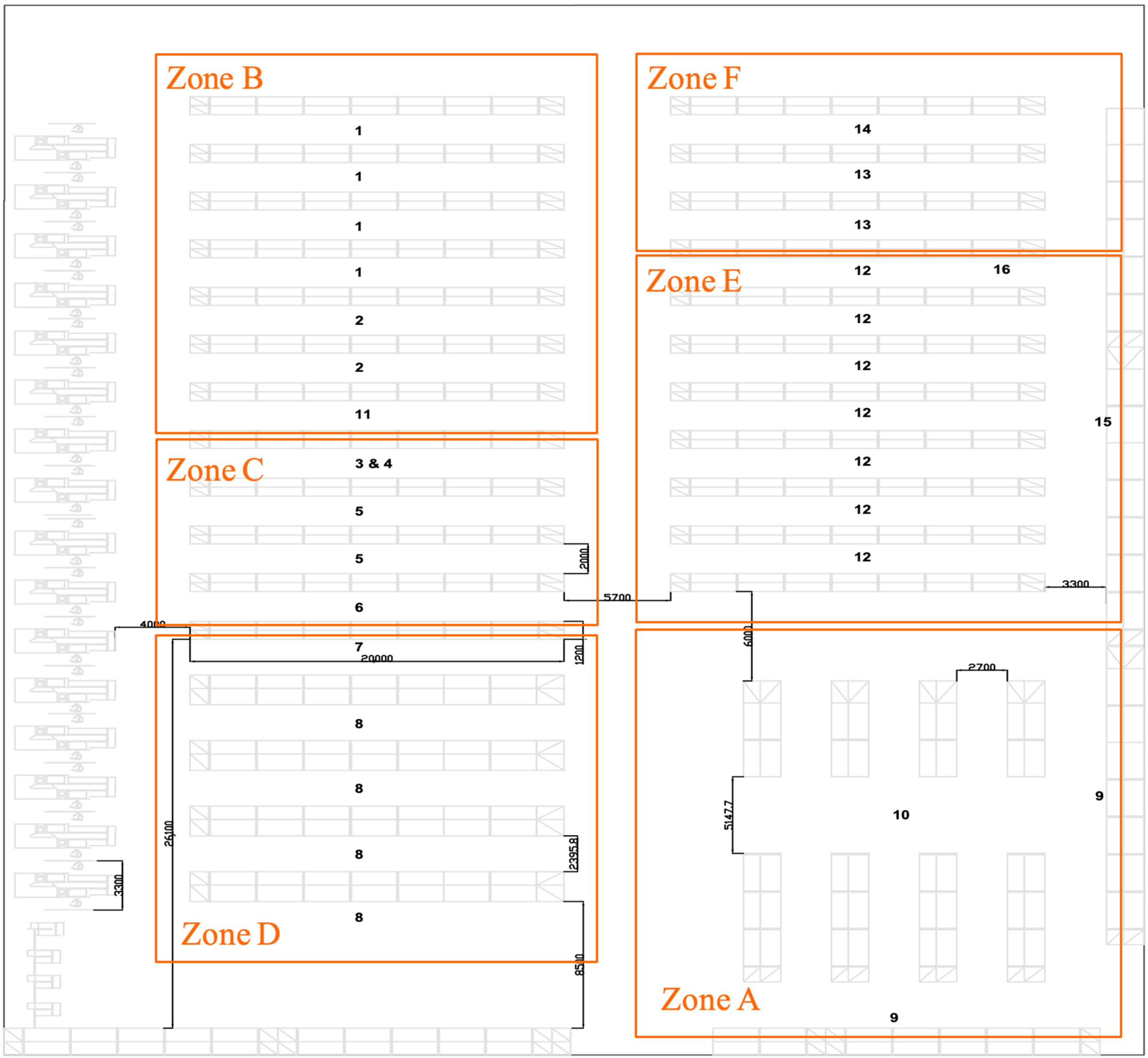

Figure 7. Hypermarket layout showing aisle numbers and zones.

The zones displayed in Figure 7 and Table 14 were created based on three factors. The first factor was the proximity of aisles within each zone, minimizing the need for the picker to cover long distances within the same zone. The second factor considered in creating the zones was product similarity, since picker specialization would improve the picking process over time. The last factor was the history of picked items in each zone created; Table 15 shows historical numbers of items that were picked in each corresponding zone.

Table 15. Historical picked items per zone.

Zone	Historical Numbers of Picked Items
A	204,057
B	191,355
C	223,416
D	143,079
E	167,741
F	108,930

Similar to the previously proposed models, the simulation model was executed for the 6-month period from 17 April to 17 October. The number of fulfilled orders in the proposed model equaled 14,815 orders, while the number of picked items was 193,364 items. Furthermore, the total number of pickers was 288. The simulation model was executed, along with the optimization process, to produce the results and statistical measures displayed in Table 16.

Table 16. Zone order picking model results—descriptives.

Outcomes	Fulfillment Time per Order (Minutes)	Average Fulfillment Time per Product (Seconds)	Average Moved Distance per Product (Meters)
Mean	12.14	57.98	41.97
Std. Deviation	9.21	9	6.59
Minimum	0.57	30.12	19.88
Maximum	99.69	155.99	73.61

From the above table, it is evident that the average fulfillment time per order was 12.14 min, which is lower than the current model (12.61 min). Also, the average fulfillment time per product was 57.98 s, which is lower than the current model (59.82 s). Furthermore, the average moved distance per product was 41.97 m, which is also lower than the current model (43.44 m).

Compared to the current model, a lower mean can be observed across all outcomes, which suggests improvements in efficiency in the zone order picking model over the current model. In order to investigate the improvement in the performance of the new model over the current model, a two-sample *t*-test was performed. The two-sample *t*-test was performed for each of the three main outcomes presented above in Table 11, with the aim of investigating whether there was a significant difference in the outcomes between the zone order picking model and the current model. The two hypotheses were as follows:

The null hypothesis (H_0): There is no significant difference in the mean outcomes of the zone order picking model (μ_1) and the current model (μ_2).

The alternative hypothesis (H_a): There is a significant difference in the mean outcomes of the zone order picking model (μ_1) and the current model (μ_2).

A significance level of $\alpha = 0.05$ was used to determine the statistical significance of the results. Detailed findings of these tests are presented in Table 17.

Table 17. Differences and percentage improvements in the zone order picking model over the current model.

Model Outcomes	Difference in Means	*p*-Value	Percentage Improvement (Over the Current Model)
Fulfillment Time per Order (minutes)	0.463	0.000	3.67%
Average Fulfillment Time per Product (seconds)	1.840	0.000	3.08%
Average Moved Distance per Product (meters)	1.4706	0.000	3.39%

As evident in the above table, the *p*-value for each outcome was less than 0.05 and the null hypothesis was rejected, confirming that there was a significant difference between the zone order picking model and the current model. Furthermore, in order to measure the performance improvement in the proposed model over the current model, the relative change percentage was calculated for each outcome using Equation (3) (see Section 5.1). Performance percentages are presented above in Table 17.

Marginal improvements can be observed in each performance measure of the zone order picking model over the current model. These improvements were due to the optimization of both the picking method and routing during order fulfilment. The application of this proposed method requires virtually dividing the hypermarket into six zones; each zone could have multiple pickers. When using the proposed model, each picker would fulfill the order in the optimized sequence within their designated zone.

5.4. Hybrid Order Picking Model

The hybrid order picking method combines batch order picking with zone order picking. In other words, it can be considered a special case of zone order picking, where the picker fulfills multiple orders at the same time within the assigned zone. Since it has the same conditions and reasonings, this method uses the same parameters, constraints, and values of the batch order picking model.

Similar to all the other proposed models, the simulation model was executed for the 6-month period from 17 April to 17 October. The number of fulfilled orders in the proposed model equaled 14,815 orders, while the number of picked items was 193,364 items. Furthermore, the total number of pickers was 288. The simulation model was executed, along with the optimization process, in order to produce the results and statistical measures presented in Table 18.

Table 18. Hybrid order picking model results—descriptives.

Outcomes	Fulfillment Time per Order (Minutes)	Average Fulfillment Time per Product (Seconds)	Average Moved Distance per Product (Meters)
Mean	11.40	51.92	37.48
Std. Deviation	6.27	2.89	2
Minimum	0.69	38.67	27.51
Maximum	92.99	121.58	67.57

From the above table, it is evident that the average fulfillment time per order was 11.40 min, which is lower than the current model (12.61 min). Also, the average fulfillment time per product was 51.92 s, which is lower than the current model (59.82 s). Furthermore, the average moved distance per product was 37.48 m, which is also lower than the current model (43.44 m).

Compared to the current model, a lower mean can be observed across all outcomes, which suggests an improvement in the efficiency of the hybrid order picking model over the current model. In order to investigate the improvement in the performance of the new model over the current model, a two-sample *t*-test was performed. This test was performed for each of the three main outcomes presented above in Table 13, with the aim of investigating whether there was a significant difference in the outcomes between the hybrid order picking model and the current model. The two hypotheses were as follows:

The null hypothesis (H_0): There is no significant difference in the mean outcomes of the hybrid order picking model (μ_1) and the current model (μ_2).

The alternative hypothesis (H_a): There is a significant difference in the mean outcomes of the hybrid order picking model (μ_1) and the current model (μ_2).

A significance level of $\alpha = 0.05$ was used to determine the statistical significance of the results. Detailed findings of these tests are presented in Table 19.

Table 19. Differences and percentage improvements in the hybrid order picking model over the current model.

Model Outcomes	Difference in Means	*p*-Value	Percentage Improvement (Over the Current Model)
Fulfillment Time per Order (minutes)	1.203	0.000	9.54%
Average Fulfillment Time per Product (seconds)	7.8933	0.000	13.20%
Average Moved Distance per Product (meters)	5.9652	0.000	13.73%

As evident in the above table, the *p*-value for each outcome was less than 0.05 and the null hypothesis was rejected, confirming that there was a significant difference between the hybrid order picking model and the current model. Furthermore, the performance improvement in the proposed model over the current model is presented above in Table 19. This percentage was measured using the relative change Equation (3) in Section 5.1.

Significant improvements can be observed in each performance measure of the hybrid order picking model over the current model. These improvements were due to the optimization of both the picking method and routing during order fulfilment. The application of this proposed method, similar to the zone order picking model, requires virtually dividing the hypermarket into six zones; each zone could have multiple pickers. Also, similar to the batch order picking model, this model requires placing four shopping baskets in each cart to accommodate up to four orders at the same time. When using the proposed model, the picker would fulfill the order in the optimized sequence, placing each product in the assigned basket within their designated zone.

5.5. Models Comparison

A comparison of all the models' outcomes is summarized in Table 20, as well as an order fulfillment example across all models.

Table 20. Summary of proposed methods' simulation outcomes and an order fulfillment example of each model.

	Outcomes	**Current Model**	**Single Order Picking Model**	**Batch Order Picking Model**	**Zone Order Picking Model**	**Hybrid Order Picking Model**
Overall Outcomes	Average Fulfillment Time per Order (Min/order)	12.61	11.78	12.42	12.14	11.40
	Average Fulfillment Time per Product (Seconds/product)	59.82	54.83	55.76	57.98	51.92
	Average Moved Distance per Product (Meters/product)	43.44	39.46	40.54	41.97	37.48
Sample Order	Order ID	N93E392	N93E392	N93E392	N93E392	N93E392
	No. of products	11	11	11	11	11
	Order picking sequence	PID10037438, PID10004505, PID10204793, PID10031055, PID10028712, PID10023846, PID10037095, PID10000677, PID10243870, PID10028608, PID10191937	PID10243870, PID10000677, PID10037095, PID10191937, PID10028608, PID10028712, PID10204793, PID10031055, PID10023846, PID10004505, PID10037438	PID10028712, PID10004505, PID10037438, PID10031055, PID10037095, PID10243870, PID10028608, PID10204793, PID10191937, PID10000677, PID10023846	PID10000677, PID10028608, PID10191937, PID10031055, PID10028712, PID10243870, PID10037095, PID10204793, PID10023846, PID10004505, PID10037438	PID10191937, PID10028608, PID10000677, PID10243870, PID10037095, PID10004505, PID10037438, PID10023846, PID10204793, PID10031055, PID10028712
	Fulfillment Time per Order (minutes)	10.44	9.52	17.21	10.17	16.11
	Average Fulfillment Time per Product (seconds)	56.96	51.92	55.30	55.47	51.78
	Average Moved Distance per Product (meters)	41.50	37.47	39.93	40.30	37.12

From the outcomes of the simulation models, efficiency improvements can be observed when compared with the current model. In order to statistically compare the different models, a one-way ANOVA test was performed between the five models: the current model, the single order picking model, the batch order picking model, the zone order picking model, and the hybrid order picking model. This test was conducted in order to investigate whether there was a significant difference in efficiency, defined by the "Average Fulfillment Time Per Product" between picking models. The two hypotheses were as follows:

The null hypothesis (H_0): There is no significant difference in the means of all models.

The alternative hypothesis (H_a): There is a significant difference in the means of all models.

A significance level of $\alpha = 0.05$ was used to determine the statistical significance of the results. The results of these tests are shown in detail in Table 21.

Table 21. One-way ANOVA test between different order picking models.

Difference in Levels	Difference in Means	Adjusted *p*-Value
Single order picking model–Current model	−4.9839	0.000
Batch order picking model–Current model	−4.054	0.000
Zone order picking model–Current model	−1.8401	0.000
Hybrid order picking model–Current model	−7.893	0.000
Batch order picking model–Single order picking model	0.930	0.000
Zone order picking model–Single order picking model	3.1437	0.000
Hybrid order–Single order picking model	−2.909	0.000
Zone order picking model–Batch order picking model	2.214	0.000
Hybrid order picking model–Batch order picking model	−3.839	0.000
Hybrid order picking model–Zone order picking model	−6.053	0.000

As evident in the above table, the *p*-value for each outcome was less than 0.05 and the null hypothesis was rejected, confirming that there was a significant difference in the means of all models. A statistical analysis indicated an individual confidence level of 99.37%. Table 22 shows the ranking of the proposed models in terms of percentage improvements compared to the current model.

Table 22. Ranking of proposed models with percentage improvements over the current model.

Proposed Model	Ranking	Improvement Percentage		
		Fulfillment Time per Order	Fulfillment Time per Product	Moved Distance per Product
Single order picking model	2	6.54%	8.33%	9.17%
Batch order picking model	3	No significant improvement	6.78%	6.67%
Zone order picking model	4	3.67%	3.08%	3.39%
Hybrid order picking model	1	9.54%	13.20%	13.73%

6. Conclusions

This study aimed to improve the grocery order picking process by adopting real-world data into a simulation model. Subsequently, four proposed models were developed to improve the efficiency and sustainability of the online grocery order fulfillment process. After comparing the different proposed models, the hybrid order picking model showed the highest improvement in efficiencies across all measures: fulfillment time per order, fulfillment time per product, and moved distance per product. The hybrid order picking method combines batch order picking with zone order picking.

These order picking models could be adopted by retailers and online grocery apps in order to increase efficiency. Furthermore, improving efficiency would increase not only company profits but also picker wages, which would increase the pickers' Saudization. In addition, increasing order picking efficiency would result in faster responses and greater flexibility to increase throughput during times of crisis.

This research has multiple limitations that were added to make the model applicable for any online grocery fulfillment. One limitation is using existing hypermarket product placements. This model assumes that product placements are fixed. Future work could expand on this by adding the ability to change product placements. Another limitation is using only the standard shopping trolly since this makes the model applicable to any supermarket. Adding special trolleys for picking more than four simultaneous orders could further increase efficiency. These improvements are possible if a hypermarket manages its own online grocery store. Furthermore, as a limitation of this study, product placement is determined by the corresponding aisle. Future work could improve accuracy and efficiency using the exact location of each product.

Author Contributions: Conceptualization, M.A.A. and A.U.R.; methodology, M.A.A. and A.U.R.; software, M.A.A.; validation, M.A.A. and A.U.R.; formal analysis, M.A.A.; investigation, A.U.R.; resources, M.A.A.; data curation, M.A.A.; writing—original draft preparation, M.A.A.; writing—review and editing, A.U.R. and I.M.A.; visualization, M.A.A.; supervision, A.U.R. and I.M.A.; project administration, M.A.A. and A.U.R.; funding acquisition, A.U.R. and I.M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research is funded by the Researchers Supporting Project number (RSPD2024R701), King Saud University, Riyadh, Saudi Arabia.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets presented in this article are not readily available because of the non-disclosure agreement (NDA) signed with XYZ.

Acknowledgments: The authors extend their appreciation to the Researchers Supporting Project number (RSPD2024R701), King Saud University, Riyadh, Saudi Arabia.

Conflicts of Interest: The authors declare no conflicts of interest.

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