Comparison Between Amazon Go Stores and Traditional Retails Based on Queueing Theory

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Abstract. The Amazon Go Store model's introduction posed a breakthrough in the shopping market due to its ground-braking approach, in which customers exercise the so-called self-service checkout. Although many qualitative analysis studies can be found, along with some quantitative approaches, a literature review on this matter shows a lack of comparative analysis between this model and traditional retail models using queueing theory, which could provide powerful insight into the improvements introduced by Amazon Go Store system. This work sets out the path to quantitative approaches for such comparison, as it aims to provide a performance analysis through queueing theory. The article compared two queueing systems; a traditional retail store vs. the Amazon Go Store. Both systems were analyzed as queueing stochastic networks. First, the traditional retail store was modeled as a two-stage (shopping and payment) network. On the other hand, the Amazon Go Store was modeled as a single-stage (shopping + payment) network. Both systems were assessed in two case scenarios: a high-demand typical day and a low-demand typical day. The implemented methodology allowed obtaining, for both compared systems, the key performance indicators (KPIs) such as the cycle time (CT), work in process (WIP), and the throughput (TP), revealing that the Amazon Go Store model exhibits better performance regarding the WIP and CT. Therefore, the Amazon Go Store model renders a higher-quality, more cost-effective service in the retail sector.

Keywords: Queuing theory · Markovian model · Jackson networks · Retail shopping · Amazon Go Store

1 Introduction

A supermarket is a commercial enterprise that provides a service instead of an own product in the usual sense. Conversely, the supermarket adds value to existing products acquired from suppliers located far between, assembled in regional factories, or distributed in local stores. These products are finally sold to local customers, sparing them the need to go long distances to find the variety of supplies they need [1].

The queueing models apply to a variety of systems, including supermarkets [2–6]. Such models have been used to study supermarkets through different approaches. Some studies address the efficient management of supermarket queues [7, 8], the queueing theory-based analysis of checkout points' operations [9], the mathematical analysis of multiple-server, single-queue models and multiple-server, multiple-queue models [10], the assessment of the queueing theory application on the checkout systems in supermarkets [11], among other matters. A well-known queueing model for supermarkets is the single-server, n-queues model. Customers arrive at the supermarket following a Poisson process with an arrival rate λ_n, where λ (subject to $0 < \lambda < 1$) is a constant. Upon arrival, each customer uniformly heads to one of the waiting lines (queues) randomly and with replacement, and then he or she joins the shortest waiting line (queue) among those available (ties are broken choosing the nearest of the shortest queues available). Customers are served according to the first-in-first-out (FIFO) dynamic [1].

An indicator of service quality in a supermarket is the residence time, which plays a significant role and influences the customers' shopping decision, as too long residence times lead them to do something else and come back later [12], or even discourage them from shopping, thus generating a significantly negative impact on the profits. Also, the number of customers in the queue has a similar impact on the shopping incidence [13]. The study of the diverse waiting line systems and their performance has drawn particular attention in the literature. Multiple works have addressed the study of the phenomena in different commercial settings, elucidating how these phenomena influence the service quality and profits in supermarkets [14–16].

As of 2018, the Amazon Go Store supermarkets were launched [17], implementing the so-called self-service checkout, in which customers serve themselves. This new system introduces an utterly novel shopping dynamic relying on the Just Walk-Out technology (JWOT), which utilizes artificial intelligence (AI)-based technologies called AIPARS (AI-powered automated retail stores). AIPARS technologies and machine learning and image recognition techniques are meant to be the next breakthrough for in-person retail markets [18–20].

The self-service checkout system's dynamic goes as follows: the customers must install an app on their cellphones, a code outputting the app on the cellphone is scanned at the store's entrance, then the customers are tracked in real-time during the shopping, as the list of products put in the cart is recorded, and finally, the customers can leave the store without heading to a checkout line as they are automatically charged. This technology eliminates the need for waiting lines and checkout servers [21, 22].

We conducted a literature search using the Scopus database. The period to retrieve data was set as 2018 to 2021. The research data includes journal articles published before March 5, 2021. Five search Boolean queries were used: TITLE: (Amazon Go Store AND (Queuing Theory OR Queuing Theory) OR Performance), TITLE: (Amazon Go Store AND (Queuing System* OR Queuing System*) OR Performance), TITLE: (Amazon Go Store AND (Queueing OR Queueing OR Performance), TITLE: (Amazon Go Store AND Traditional AND (Supermarket OR Store OR Retail)), TITLE: (Amazon Go Store AND Jackson Networks).

The retail-related search showed that literature lacks research addressing the quantitative estimation of Amazon Go Store supermarkets' performance based on queueing theory. Therefore, this article's purpose is to model and estimate the performance of Amazon Go Store's queueing system, comparing its KPIs with those of traditional retail. The manuscript is organized as follows: Sect. 2 explains in detail the methodology used for the study, Sect. 3 shows the results obtained for both retail models, and finally, Sect. 4 presents the conclusions and future work related to this research.

2   Methodology

The methodology of this work comprises four steps explained in detail below:

Step 1 – Data Gathering and Tabulation: Data was retrieved from a primary source (i.e., traditional retail) through direct quantitative-oriented observation by the research team, gathering it on an hourly basis. The measured variables include the time between customers' arrivals at the supermarket $\frac{1}{\lambda_1(t)}$, the self-service residence time $\frac{1}{\mu_1(t)}$, the average arrival rate to a server $\lambda_2(t)$, the servers' service rate $\mu_2(t)$, and the number of available servers n. Data was gathered for both a high-demand day and a low-demand day. Data is further tabulated as in Table 1.

Step 2 – Systems Modeling: Both queueing systems (traditional retail and Amazon Go Store) were mathematically modeled. Subsections 2.1 and 2.2 explain such mathematical models in detail, along with the assumptions and parameters considered for either system.

Table 1. Table array used for data gathered from traditional retail.

| Time | Stage 1 | | | | Stage 2 | | | | | |
| | High demand | | Low demand | | High demand | | | Low demand | | |
	(s)	(min)	(s)	(min)	(Customers/h)	(Customers/h)	n(t)	(Customers/h)	(Customers/h)	n(t) (Customers)
7:00 a.m	24,39	50	56,29	36,38	23,52	38,70	7	28,20	48,00	3
8:00 a.m	17,04	71,2	61,71	46,88	10,26	12,78	20	7,32	48,00	7
9:00 a.m	25,40	87,31	62,31	36,29	10,74	14,16	29	8,58	8,94	12
10:00 a.m	26,94	89,79	66,12	37,06	8,70	9,54	29	10,62	14,52	16
11:00 a.m	23,93	78,61	109,80	37,06	14,76	100,02	29	9,84	14,82	15
12:00 p.m	52,48	77,23	92,26	37,25	7,38	7,86	31	7,20	15,60	12
1:00 p.m	27,54	74,84	108,70	36,36	4,74	8,58	23	8,58	10,98	9
2:00 p. m	26,22	46,68	84,54	26,11	12,84	17,40	21	12,90	20,28	8
3:00 p.m	25,21	52,54	64,75	28,00	8,70	9,90	25	18,66	21,96	8
4:00 p.m	30,57	53,27	63,08	23,75	21,18	23,70	21	12,24	19,62	9
5:00 p.m	17,22	59,91	93,99	33,73	15,54	16,20	15	5,22	20,94	10
6:00 p.m	25,07	34	110,15	23,60	13,80	24,84	18			11

2.1 Traditional Retail Model

The traditional retail was considered as a two-stage open Jackson Network. An M/M/∞ (self-service) model is used for Stage 1, while the n-queue Stage 2 uses an M/M/1 model with a time-varying number of servers, set empirically by the store's manager/staff as a response to online demand. For Stage 1, times between arrivals are assumed to fit an exponential behavior, and self-service times are also assumed exponential and equivalent to having infinite parallel servers. As for the customers, once within the system, they serve themselves without heading to queues. For Stage 2, the customers' arrival rate to the servers is also assumed exponential, and so are the service times with a service rate μ_2. Figure 1 depicts an operations diagram of the two-stage model proposed for the traditional retail.

According to Taha [23], the M/M/∞ model (as in Stage 1) has an unlimited number of servers, as customers act as their own servers with continuous arrival rates (λ) and service rates (μ), so that: $\lambda_n = \lambda$, and $\mu_n = n\mu$, for $n = 0, 1, 2, \ldots$. On the other hand, the M/M/1 model (as in Stage 2) features independent and exponentially distributed arrival and service times with a single server, infinite system capacity, and follows the FIFO dynamic.
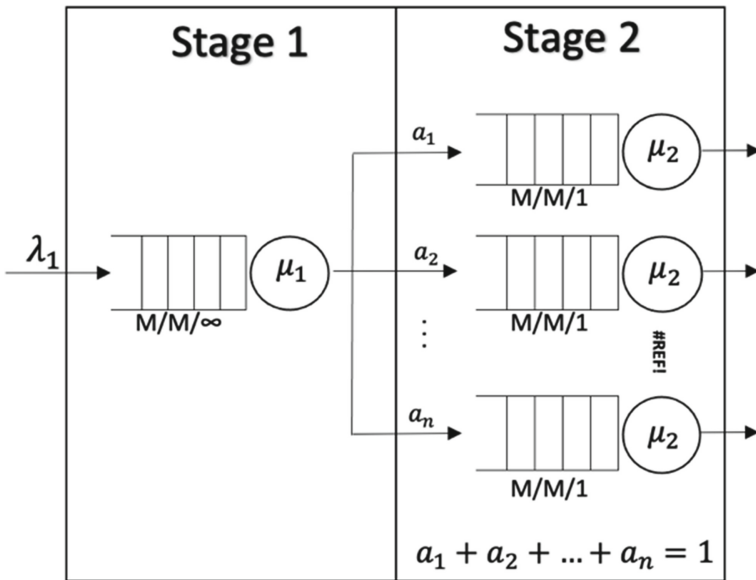

Fig. 1. Operations diagram of the two-stage model proposed for the traditional retail.

The model's underlying equations are now presented. For Stage 1, the utilization factor, ρ, is computed as in Eq. (1):

$$\rho(t) = \frac{\lambda(t)}{\mu(t)} \tag{1}$$

The average number of customers in the node, L_s, is:

$$L_s(t) = L_q(t) + \frac{\lambda(t)}{\mu(t)} \tag{2}$$

The average waiting time (in hours) at the stage, W_s, is:

$$W_s(t) = W_q(t) + \frac{1}{\mu(t)} \tag{3}$$

For Stage 2 (checkout), the utilization factor is also computed using Eq. (1), and the average number of customers in the node, L_q, is calculated as in Eq. (2) as well. The total number of customers at the node, $L_{s_{total}}$, is further calculated as in Eq. (4).

$$L_{s_{total}}(t) = L_s(t) \times n(t). \tag{4}$$

The average waiting time (in hours) in the queue, W_q, is:

$$W_q(t) = \frac{L_q(t)}{\lambda(t)} \tag{5}$$

The average waiting time (in hours) at the Stage, W_s, is:

$$W_s(t) = W_q(t) + \frac{1}{\mu(t)} \tag{6}$$

Finally, as the system undergoes a self-service Dynamic: $L_s = \rho$, and $L_q. = W_q = 0$.

2.2   Amazon Go Store Model

This system was modeled as a M/M/∞. Jackson Network [24]. The customers are charged as they are shopping and putting products in the carts. Figure 2 depicts the operations diagram of the model proposed for the Amazon Go Store.
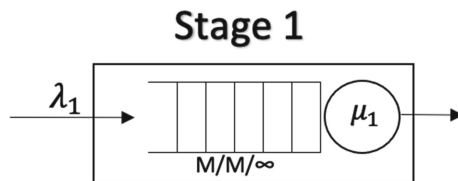

Fig. 2. Operations diagram of the model proposed for the Amazon Go Store.

Step 3 – Calculating the Key Performance Indicators (KPIs): The KPIs were calculated for both queueing models using Little's Law. According to Little and Graves [25], the TP is defined as a system's average production rate per unit time, the WIP is the inventory between the beginning and the end of a product's route, and the CT is the average time elapsed from liberation to the start of the product's routing. These KPIs are mathematically defined in Eqs. (7)–(9).

$$TP = \lambda Stage1. \tag{7}$$

$$WIP = L_s Stage1 + L_{s_{total}} Stage2 \tag{8}$$

$$CT = \frac{WIP}{TP} \tag{9}$$

Step 4 – Results Comparison. Once the KPIs were calculated for both systems, their performance is assessed and compared according to those indicators (TP, CT, and WIP).

3   Results

From the traditional retail model, Tables 2 and 3 are obtained. Table 2 presents the outcomes for Stages 1 and 2 in the high-demand scenario. Table 3 presents the outcomes for Stages 1 and 2 in the low-demand scenario.

Table 2 contains the hourly values for parameters and variables of the traditional retail system for the high-demand scenario, which exhibit a dynamic behavior and inform on the system performance, providing quantitative information to compare this system with the Amazon Go Store.

Analogously to Tables 2 and 3 contains the hourly values for parameters and variables of the traditional retail system for the low-demand scenario. Such information will be further used to perform a quantitative comparison (performance-wise) with the Amazon Go Store.

The Amazon Go Store model comprises a single stage in which both the shopping and payment are made simultaneously during the service time (see Fig. 2). This model was implemented using the same parameters featured by the traditional retail model. From the Amazon Go Store model, results for the high-demand and low-demand scenarios are presented in Tables 4 and 5, respectively.

Tables 4 and 5, analogously to Tables 2 and 3, show the hourly values for parameters and variables of the Amazon Go Store system, which will further inform on the system's performance and allow its comparison with the traditional retail system.

Table 2. Traditional retail model outcomes for the high-demand scenario.

	High demand - Stage 1							High demand - Stage 2								
Time	$\frac{1}{\lambda_1(t)}$ (s)	$\lambda_1(t)$ (Customers/h)	$\frac{1}{\mu_1(t)}$ (s)	$\mu_1(t)$ (Customers/h)	$\rho_1(t)$	Ls (t) (Customers)	Ws (t) (h)	$\lambda_2(t)$ (Customers/h)	$\mu_2(t)$ (Customers/h)	$\rho_1(t)$	Ls (t) ((Customers)	Lq (t) (Customers)	Ws (t) (h)	Wq(t) (h)	n(t) (Units)	$Ls_{Total}(t)$ (Customers)
7:00 a.m	24,39	147,63	50	1,2	123,03	123,03	0,83	23,52	38,7	60,78%	1,55	0,94	0,07	0,04	7	10,85
8:00 a.m	17,04	211,33	71,2	0,84	250,78	250,78	1,19	10,26	12,78	80,28%	4,07	3,27	0,4	0,32	20	81,43
9:00 a.m	25,4	141,73	87,31	0,69	206,24	206,24	1,46	10,74	14,16	75,85%	3,14	2,38	0,29	0,22	29	91,07
10:00 a.m	26,94	133,66	89,79	0,67	200,01	200,01	1,5	8,7	9,54	91,19%	10,36	9,45	1,19	1,09	29	300,36
11:00 a.m	23,93	150,44	78,61	0,76	197,1	197,1	1,31	14,76	100,02	14,76%	0,17	0,03	0,01	0	29	5,02
12:00 p.m	52,48	68,6	77,23	0,78	88,3	88,3	1,29	7,38	7,86	93,89%	15,38	14,44	2,08	1,96	31	476,62
1:00 p.m	27,54	130,72	74,84	0,8	163,05	163,05	1,25	4,74	8,58	55,24%	1,23	0,68	06	0,14	23	28,39
2:00 p.m	26,22	137,3	46,68	1,29	106,82	106,82	0,78	12,84	17,4	73,79%	2,82	2,08	0,22	0,16	21	59,13
3:00 p.m	25,21	142,83	52,54	1,14	125,07	125,07	0,88	8,7	9,9	87,88%	7,25	6,37	0,83	0,73	25	181,25
4:00 p.m	30,57	117,76	53,27	1,13	104,55	104,55	0,89	21,18	23,7	89,37%	8,4	51	0,4	0,35	21	176,5
5:00 p.m	17,22	209,12	59,91	1	208,81	208,81	1	15,54	16,2	95,93%	23,55	22,59	1,52	1,45	15	353,18
6:00 p.m	25,07	143,63	34	1,76	81,39	81,39	0,57	13,8	24,84	55,56%	1,25	0,69	0,09	0,05	18	22,5
PROM.		144,56		1		154,6		12,68	23,64							

Table 3. Traditional retail model outcomes for the low-demand scenario.

Low demand - Stage 1								Low demand - Stage 2									
Time	$\frac{1}{\lambda_1(t)}$ (s)	$\lambda_1(t)$ (Customers/h)	$\frac{1}{\mu_1(t)}$ (s)	$\mu_1(t)$ (Customers/h)	$\rho_1(t)$	Ls (t) (Customers)	Ws (t) (h)	$\lambda_2(t)$ (stomers/h)	$\mu_2(t)$ (Customers/h)	$\rho_1(t)$	Ls (t) (Customers)	Lq (t) (Customers)	Ws (t) (h)	Wq(t) (h)	n(t) (Units)	$Ls_{Total}(t)$ (Customers)
7:00 a.m	56,29	63,96	36,38	1,65	38,78	38,78	0,61	28,2	48	0,59	1,42	0,84	0,05	0,03	3	4,27
8:00 a.m	61,71	58,33	46,88	1,28	45,57	45,57	0,78	7,32	48	0,15	0,18	03	0,02	0	7	1,26
9:00 a.m	62,31	57,77	36,29	1,65	34,95	34,95	0,6	8,58	8,94	0,96	23,83	22,87	2,78	2,67	12	286
10:00 a.m	66,12	54,45	37,06	1,62	33,63	33,63	0,62	10,62	14,52	0,73	2,72	1,99	0,26	0,19	16	43,57
11:00 a.m	109,8	32,79	37,06	1,62	20,25	20,25	0,62	9,84	14,82	0,66	1,98	1,31	0,2	0,13	15	29,64
12:00 p.m	92,26	39,02	37,25	1,61	24,23	24,23	0,62	7,2	15,6	0,46	0,86	0,4	0,12	0,05	12	10,29
1:00 p.m	108,7	33,12	36,36	1,65	20,07	20,07	0,61	8,58	10,98	0,78	3,58	2,79	0,42	0,33	9	32,18
2:00 p.m	84,54	42,59	26,11	2,3	18,53	18,53	0,44	12,9	20,28	0,64	1,75	1,11	0,14	0,09	8	13,98
3:00 p.m	64,75	55,6	28	2,14	25,95	25,95	0,47	18,66	21,96	0,85	5,65	4,8	0,3	0,26	8	45,24
4:00 p.m	63,08	57,07	23,75	2,53	22,59	22,59	0,4	12,24	19,62	0,62	1,66	1,03	0,14	0,08	9	14,93
5:00 p.m	93,99	38,3	33,73	1,78	21,53	21,53	0,56	5,22	20,94	0,25	0,33	0,08	0,06	0,02	10	3,32
6:00 p.m	110,15	32,68	23,6	2,54	12,86	12,86	0,39	16,44	17,82	0,92	11,91	10,99	0,72	0,67	11	131,04
PROM.		**47,14**		**1,86**				**12,15**	**21,79**							

Table 4. Amazon Go Store model outcomes for the high-demand scenario.

High demand							
Time	$\frac{1}{\lambda_1(t)}$ (s)	$\lambda_1(t)$ (Customers/h)	$\frac{1}{\mu_1(t)}$ (s)	$\mu_1(t)$ (Customers/h)	$\rho_1(t)$	Ls (t) (Customers)	Ws (t) (h)
7:00 a.m	24,39	147,63	50,00	1,20	123,03	123,03	0,83
8:00 a.m	17,04	211,33	71,20	0,84	250,78	250,78	1,19
9:00 a. m	25,40	141,73	87,31	0,69	206,24	206,24	1,46
10:00 a.m	26,94	133,66	89,79	0,67	200,01	200,01	1,50
11:00 a.m	23,93	150,44	78,61	0,76	197,10	197,10	1,31
12:00 p.m	52,48	68,60	77,23	0,78	88,30	88,30	1,29
1:00 p.m	27,54	130,72	74,84	0,80	163,05	163,05	1,25
2:00 p.m	26,22	137,30	46,68	1,29	106,82	106,82	0,78
3:00 p.m	25,21	142,83	52,54	1,14	125,07	125,07	0,88
4:00 p.m	30,57	117,76	53,27	1,13	104,55	104,55	0,89
5:00 p.m	17,22	209,12	59,91	1,00	208,81	208,81	1,00
6:00 p.m	25,07	143,63	34,00	1,76	81,39	81,39	0,57
Average		**144,56**		**1,005**		**154,596**	

Table 5. Amazon Go Store model outcomes for the low-demand scenario.

Low demand							
Time	$\frac{1}{\lambda_1(t)}$ (s)	$\lambda_1(t)$ (Customers/h)	$\frac{1}{\mu_1(t)}$ (s)	$\mu_1(t)$ (Customers/h)	$\rho_1(t)$	Ls (t) (Customers)	Ws (t) (h)
7:00 a.m	56,29	63,96	36,38	1,65	38,78	38,78	0,61
8:00 a.m	61,71	58,33	46,88	1,28	45,57	45,57	0,78
9:00 a.m	62,31	57,77	36,29	1,65	34,95	34,95	0,60
10:00 a.m	66,12	54,45	37,06	1,62	33,63	33,63	0,62
11:00 a.m	109,80	32,79	37,06	1,62	20,25	20,25	0,62
12:00 p.m	92,26	39,02	37,25	1,61	24,23	24,23	0,62
1:00 p.m	108,70	33,12	36,36	1,65	20,07	20,07	0,61
2:00 p.m	84,54	42,59	26,11	2,30	18,53	18,53	0,44
3:00 p.m	64,75	55,60	28,00	2,14	25,95	25,95	0,47
4:00 p.m	63,08	57,07	23,75	2,53	22,59	22,59	0,40
5:00 p.m	93,99	38,30	33,73	1,78	21,53	21,53	0,56
6:00 p.m	110,15	32,68	23,60	2,54	12,86	12,86	0,39
Average		**47,14**		**1,86**			

The KPIs (TP, WIP, and CT) were calculated for both models. Results are shown in Table 6 for both the high-demand and low-demand scenarios.

Table 6. KPIs obtained for traditional retail and Amazon Go Store.

| | Traditional retail | | | | | | Amazon Go Store supermarket | | | | | |
| | High demand | | | Low demand | | | High demand | | | Low demand | | |
Time	WIP (Customers)	CT (h)	TP (Customers/h)	WIP (Customers)	CT (h)	TP (Customers/h)	WIP (Customers)	CT (h)	TP (Customers/h)	WIP (Customers)	CT (h)	TP (Customers/h)
7:00 a.m	133,87	0,91	147,63	43,05	0,67	63,96	123,03	0,83	147,63	38,78	0,61	63,96
8:00 a.m	332,21	1,57	211,33	46,83	0,8	58,33	250,78	1,19	211,33	45,57	0,78	58,33
9:00 a.m	297,31	2,1	141,73	320,95	5,56	57,77	206,24	1,46	141,73	34,95	0,6	57,77
10:00 a.m	500,37	3,74	133,66	77,2	1,42	54,45	200,01	1,5	133,66	33,63	0,62	54,45
11:00 a.m	202,12	1,34	150,44	49,89	1,52	32,79	197,1	1,31	150,44	20,25	0,62	32,79
12:00 p.m	564,92	8,24	68,6	34,51	0,88	39,02	88,3	1,29	68,6	24,23	0,62	39,02
1:00 p.m	191,44	1,46	130,72	52,24	1,58	33,12	163,05	1,25	130,72	20,07	0,61	33,12
2:00 p.m	165,95	1,21	137,3	32,52	0,76	42,59	106,82	0,78	137,3	18,53	0,44	42,59
3:00 p.m	306,32	2,14	142,83	71,18	1,28	55,6	125,07	0,88	142,83	25,95	0,47	55,6
4:00 p.m	281,05	2,39	117,76	37,52	0,66	57,07	104,55	0,89	117,76	22,59	0,4	57,07
5:00 p.m	561,99	2,69	209,12	24,85	0,65	38,3	208,81	1	209,12	21,53	0,56	38,3
6:00 p.m	103,89	0,72	143,63	143,9	4,4	32,68	81,39	0,57	143,63	12,86	0,39	32,68
Average	**303,45**	**2,1**	**144,56**	**77,89**	**1,68**	**47,14**	**154,6**	**1,07**	**144,56**	**26,58**	**0,56**	**47,14**

Finally, Table 7 summarizes the improvements (as percentages of KPIs change) achieved by the Amazon Go Store model compared to the traditional retail model regarding the TP, WIP, and CT.

Table 7. KPIs comparison; Amazon Go Store vs. traditional retail.

Time	Traditional retail vs. Amazon Go Store – High demand		Traditional retail vs. AMAZON GO STORE – Low demand	
	% Improvement WIP	% Improvement CT	% Improvement WIP	% Improvement CT
7:00 a.m	91,90	91,90	111,02	111,02
8:00 a.m	75,49	75,49	102,76	102,76
9:00 a.m	69,37	69,37	918,38	918,38
10:00 a.m	39,97	39,97	229,55	229,55
11:00 a.m	97,52	97,52	246,33	246,33
12:00 p.m	15,63	15,63	142,46	142,46
1:00 p.m	85,17	85,17	260,33	260,33
2:00 p.m	64,37	64,37	175,45	175,45
3:00 p.m	40,83	40,83	274,35	274,35
4:00 p.m	37,20	37,20	166,08	166,08
5:00 p.m	37,15	37,15	115,42	115,42
6:00 p.m	78,34	78,34	1119,38	1119,38
Average	**50,95**	**50,95**	**293,05**	**300,93**

The implications of the results are discussed in the following section.

4   Discussion

The performance assessment revealed that, compared to the traditional retail, the Amazon Go Store achieved better CT and WIP, as shown in Table 7. When implementing the Amazon Go Store model, the WIP changed from 303,45 (for the traditional retail model) to 154,6 customers, yielding an improvement of 50,95% during high-demand days. Moreover, for low-demand days, the WIP changed from 77,89 to 26,58 customers, a 293,05% improvement. On the other hand, the CT changed from 2,1 to 1,07 h in high-demand days and 1,68 to 0,56 h in low-demand days, achieving 50,95% and 300,93% improvement, respectively. Nevertheless, the TP remained unchanged for both systems in both demand scenarios, as observed in Table 7. That is the reason why the TP improvement was not included in Table 7. Figure 3 shows a comparative chart for the WIP's time evolution for both systems in both demand scenarios, while Fig. 4 shows the same for the CT.
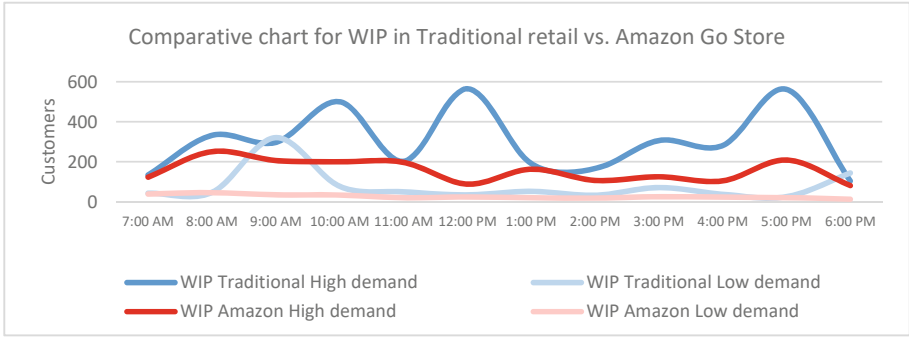
Comparative chart for WIP in Traditional retail vs. Amazon Go Store

Fig. 3. Hourly WIP comparison: traditional retail vs. Amazon Go Store.

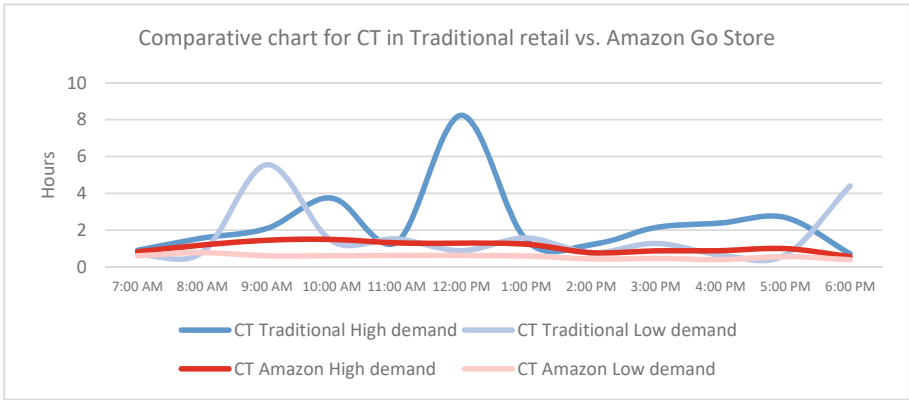Comparative chart for CT in Traditional retail vs. Amazon Go Store

Fig. 4. Hourly CT comparison: Traditional retail vs. Amazon Go Store.

5 Conclusions

A literature review on M/M/∞ queues applied in the supermarket's context revealed that there is relatively little information on this matter. Moreover, no work was found to quantitatively compare the Amazon Go Store's performance with that of traditional retail. Therefore, this work compared, based on queueing theory, the systems for the traditional retail and the Amazon Go Store using the throughput (TP), cycle time (CT), and the work in process (WIP) as performance indicators.

Results showed a better performance for the Amazon Go Store regarding the WIP and CT, while the TP remained the same for both systems. The improvements found in the Amazon Go Store system arise from the fact that this system does not involve a checking-out stage since customers are automatically charged as they shop. Thus, this quantitative study concludes that, overall, the Amazon Go Store model achieves important improvements regarding the customers' residence time at the supermarkets. In addition, this article sets out the path for future quantitative-oriented studies aiming to analyze and compare new upcoming shopping paradigms with the currently existing regarding their performance.

Future works should give more attention to quantitative approaches to elucidate the Amazon Go Store model's drawbacks and advantages. This article contributes to creating a quantitative-oriented body of knowledge on this issue. Moreover, future works should propose changes to improve the performance of both Amazon GO and traditional retail regarding their performance (measured through the KPIs) and propose novel, more adequate performance metrics that can adapt more flexibly to new upcoming shopping paradigms. Finally, future works could characterize the AIPARS individually to determine which technologies impact the most on supermarkets' performance.

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