Towards Accurate Modelling of Queueing Behaviour in Hybrid Checkout Systems in Grocery Retail: A Simulation-Based Approach

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Abstract. Given the growing importance of the grocery retail sector as a field of research, driven by increasing customer expectations for shorter waiting times, rising labour costs, and the ongoing digital transformation of retail operations, this study examines queue formation at hybrid checkout systems.

Using real-world data provided by a reference store for a specific weekday, a discrete-event simulation was developed in AnyLogic.

The resulting model, which is flexible regarding input parameters, applies a Monte Carlo approach to estimate expected queue lengths throughout the day. These simulation results were compared against empirical observations and validated for accuracy.

Additionally, the study highlights the relevance of self-checkout systems and smart shopping carts in enhancing operational efficiency.

Introduction

Consumer purchasing behaviour has changed due to ongoing digitalization [22, 10]. This change was accelerated by the COVID-19 pandemic, during which the high risk of infection required a contactless shopping experience [7].

In connection with the need for innovation [19, 9], partly driven by competitive and cost pressures and by the increasing market penetration of providers in online grocery retail [4], the development of new technological capabilities for process automation and efficiency enhancement in brick-and-mortar retail has been advanced [10]. For example, self-checkout (SCO) systems and smart shopping carts (SSC) have emerged as promising technologies, and they are gaining increasing importance [19, 21, 8].

A central aspect of this innovation is the minimization of waiting times and the reduction of shopping process complexity, aiming to positively influence customer satisfaction and repeat purchase rates [9, 16]. In addition, they enable the grocery retail sector to optimize store, product, and staffing management and thus increase (cost-) efficiency [10]. The extent of these efficiency gains, particularly regarding the optimal integration of new checkout technologies (e.g., SCO and SSC), has so far been insufficiently studied [5, 13].

Against this background, the present study aims to capture the current state regarding the effects of the hybrid use of checkout systems on queue formation and thus provides a basis for further analyses of potential optimization opportunities.

This is carried out using computer simulation, which, due to the dynamic system characteristics in terms of state and time progression as well as the stochastic distribution of customer inflows and related parameters, proves to be a more practical method compared to closed-form solutions based on queueing theory approaches [25].

In addition, computer simulation allows complex systems to be mapped precisely and the interaction of various sub-problems to be examined [25, 24, 11]. The processes depicted in the simulation are based on real transaction data of an idealized weekday, provided by EDEKA Minden-Hannover Stiftung & Co. KG for a reference market (representative of the 1,500 markets of the industry partner).

The results provide the grocery retail sector with an overview of the time-of-day dependent development of queue lengths and form a basis for potential cost savings through optimized personnel planning [2]. Furthermore, they provide insights into queue behaviour in hybrid checkout systems and serve as a starting point for further investigations.

The following sections present the literature relevant to the study and related (simulation-based) research in the context of hybrid checkout systems. Subsequently, the methodology and the development of the simulation model are described. This is followed by a presentation and analysis of the simulation results, with a special focus on queue development. Finally, the study outlines key implications for practice and research and provides an outlook on further investigations.

1 Theoretical Background

The checkout process plays an important role as a key customer interface for the shopping experience, as it significantly influences customer perception of service quality [13]. 75% of customers perceive waiting in a queue as particularly annoying [10]. In this context, the length of the queue relative to the waiting time proves to be a significant factor, as customers generally perceive the queue length rather than the speed of its change. This has a non-linear, negative impact on willingness to purchase, highlighting the relevance of queue management for grocery retail [12]. New technologies such as SCO and SSC are changing the checkout process and have become a focus of current research [13].

The potential of these technologies regarding efficiency gains, such as time and cost reduction and improvements in the shopping experience, has been widely demonstrated [9, 19, 18].

However, the optimal implementation of these systems in the checkout area still requires clarification [13].

In a simulation study by [14], the effects of implementing SCO on customer waiting time and throughput were quantified by modelling and evaluating various configurations of both types of checkouts.

Based on the configurations studied, the research concludes that a balanced ratio of both checkout types enables the highest customer throughput and that a complete replacement of traditional checkouts by SCO is likely to be inefficient.

Additionally, [2] conducted a simulation study including traditional and SCO checkouts, investigating customer decision-making in selecting a queue. The central finding of the study is that providing information, such as displaying expected waiting times, leads to minimized waiting and more efficient staff deployment in the checkout area.

Moreover, it was found that the payment process at SCO checkouts tends to take longer than at conventional checkouts, possibly due to lower routine among customers compared to trained cashier staff. Both studies illustrate the potential of SCO checkouts but also point out limitations and highlight further research needs.

SSC extend conventional shopping carts with a variety of technical applications (e.g., barcode scanners, touchscreen displays, scales) to provide real-time information, reduce shoplifting, and increase the efficiency of the shopping process [20, 23]. Integrated functions contributing to this include the ability to create shopping lists in advance and transfer them to the SSC, route guidance to locate desired products faster, and the provision of special offers based on individual purchase history. At the same time, grocery retailers can analyse shopping patterns and thereby optimize operational processes, particularly staff scheduling and real-time inventory management [20, 3].

Furthermore, scanning items during the shopping process by customers eliminates the need for manual item registration at the checkout. This leads to a reduction in transaction time and thus reduced queue formation in the checkout area [23]. For instance, using an SSC prototype compared with the traditional checkout system for baskets with more than ten items resulted in a time savings of up to 84% [15]. [3] demonstrated in a simulation study that introducing an SSC system reduced average waiting time by 62%, maximum waiting time by 55%, and the number of open checkouts to two.

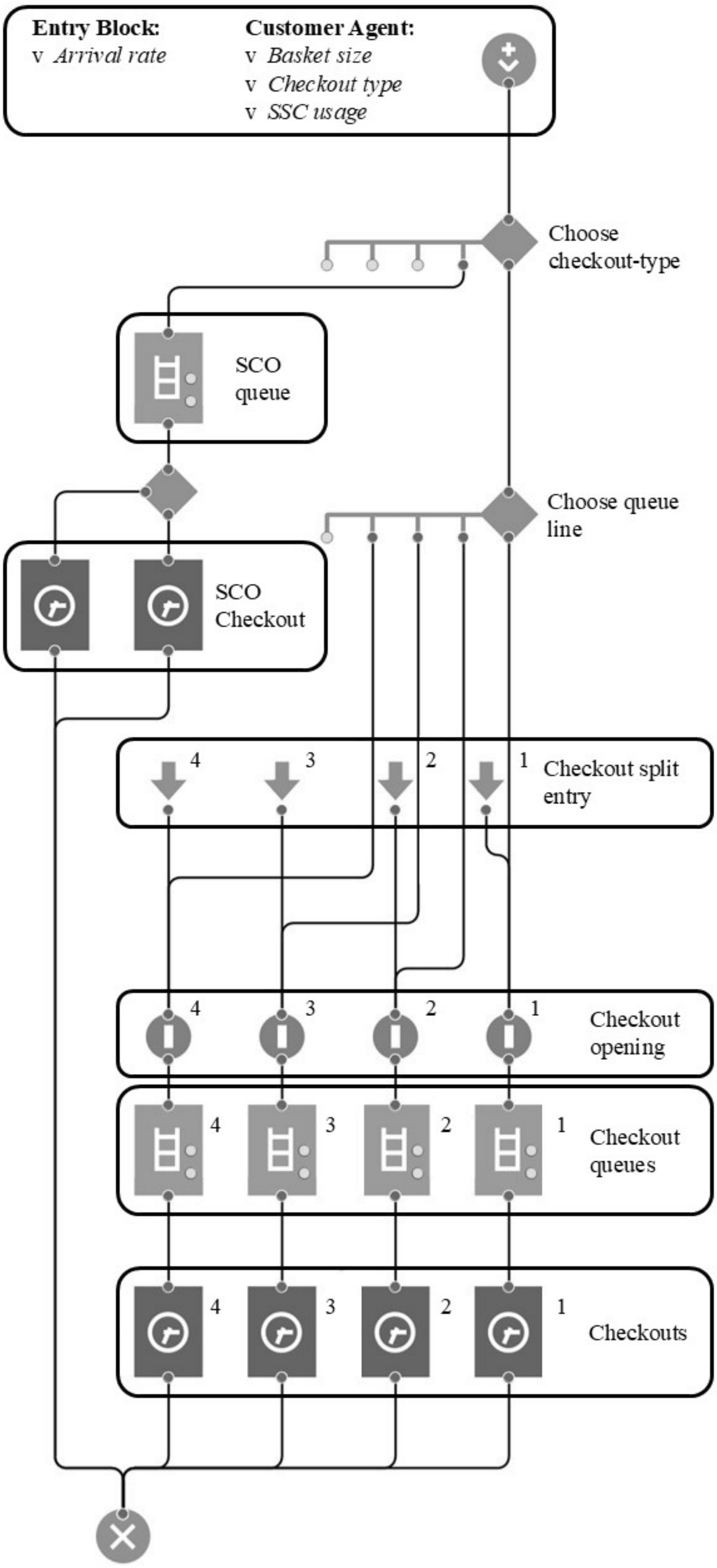

Figure 1: Simulation model architecture showing the checkout process flow.

Although various studies have demonstrated the significant potential of SSC and SCO technologies for reducing queue length, minimizing waiting time, and increasing checkout efficiency, research on these topics still offers considerable opportunities for further exploration [19]. Simulation studies examining the interaction of these technologies are limited in the literature.

2 Methodology

The methodological approach for the development of the simulation model was based on the procedure for conducting a simulation project according to [17].

The study is based on real data provided by EDEKA. This includes the complete transaction data of April 8, 2025 (reference day), from a typical grocery retail store near Osnabrück, Germany, which exhibits all structural and organizational characteristics relevant for the study. The checkout configuration comprises four traditional checkouts each with its own queue, two SCO checkouts with a shared queue, as well as the option to use SSC, which can be processed both at the SCO and at two of the traditional checkouts.

The provided transaction data contain information on the start of item scanning, checkout type and number, the use of SSC, and the number of purchased items. In addition to the provided data, a 12-hour observation of the checkout area in the reference store was conducted on the specific reference day. The first and second authors of this study recorded the development of queue lengths at all checkouts every five minutes. Additionally, the checkout duration for 100 customers was sampled, considering the type of checkout. The time required for scanning items was documented separately.

The observation served to validate the input data (input validity), to enrich the provided dataset for determining relevant parameters, and as a basis for validating the simulation results (output validity).

During model development, which was carried out in close coordination with EDEKA (dialog validity; [17]), it was decided to model the checkout area in its real configuration and to base the considered time intervals on the 15-minute intervals customary for staff scheduling in the reference store.

A simulation-based approach was chosen due to the system complexity and stochastic parameter distributions [24]. The simulation was implemented using AnyLogic 8.9.3 Professional, which supports the creation of discrete-event, agent-based, and system dynamics models. To realistically represent customer-induced behaviour and interactions in checkout processes in grocery retail, a discrete-event modelling approach was applied (Figure 1), as it is particularly suitable for processes with clearly defined state changes, such as the checkout process.

During the model-building phase, based on the transaction data validated by the market observation, key parameters for the customers represented as agents in the simulation were systematically recorded and defined, considering the selected temporal resolution. These parameters include arrival rate, basket size, checkout type selection, and SSC usage. The arrival rate, checkout type selection, and SSC usage were determined by interpolating the values from the provided data for each defined time interval.

The result was then converted to the simulation's minute scale, yielding an expected value per time unit. Basket sizes were empirically recorded as average values per time interval and checkout type. For agent parameterization, a geometric distribution based on interpolated average values of neighbouring intervals was applied. This distribution is suitable for modelling the higher probability of small baskets and is well-suited for discrete stochastic processes.

Based on the additionally collected market observation data, the average checkout duration was determined. This includes scanning, paying, and bagging items, while differences in cashier speed were considered negligible [2].

Since customers sometimes bagged items simultaneously with scanning and sometimes only afterward, and no consistent pattern could be detected, the checkout process was modelled in two phases.

The scanning time was modelled as dependent on basket size, while the checkout dwell time, consisting of bagging and paying, was modelled as independent of basket size. The process was separated because no correlation between checkout dwell time and basket size was found, and this variable potentially depends on multiple other factors (e.g., payment method, willingness to interact, individual personal attributes). Both values were determined for each agent using a log-normal distribution, where the scanning time was multiplied by the basket size, and the result was added to the checkout dwell time.

The choice of this distribution was based on the positive-only nature of time, the right-skewed distribution of the data, and the ability to adequately represent extreme outliers. The practical minimum per checkout type and the μ and σ values shown in Table 1 were used.

	Classic Checkout		SCO		SSC	
	μ	σ	μ	σ	μ	σ
Scanning	0.903	0.452	1.814	0.438	n.a.	n.a.
Dwell time	3.325	0.478	2.943	0.823	3.172	0.526

Table 1: μ and σ of scanning and checkout dwell time.

Regarding the criteria by which customers choose a queue, the literature does not provide a consistent view [2]. [1] showed in their approach that the choice is not random but is mainly determined by the queue length (60%) and the total number of items of the waiting customers (40%). Both factors were weighted accordingly in the present study.

Concerning the timing of opening additional checkouts, no regular pattern could be identified, indicating that the decision depends on the subjective assessment of the checkout staff. To model this variability, a logistic function was implemented based on observations. It was observed that additional checkouts were never opened for queue length of three or less, while openings were still observed at higher queue lengths up to seven customers.

Since the decision is evaluated upon each customer arrival, the likelihood of opening increases through repeated stochastic evaluations rather than a single deterministic threshold. The midpoint of the logistic function was therefore set to seven as a calibration point that reproduces the observed overall system behaviour, where higher queue lengths lead to more frequent openings over time rather than at a fixed triggering value.

A relatively steep slope was chosen to reflect the strong sensitivity of the opening probability to increasing queue length. Additionally, approximately one-third of customers were observed to switch queues when a new checkout was opened, which was incorporated into the model with the checkoutSplit-function in Listing 1.
To generate the simulation results, a Monte-Carlo approach was used, as this method is suitable for analysing stochastic systems with known probability distributions [6].

```
void checkoutThreeOpening(){
   if(Queue1.size()>=3){
      if(randomTrue(1/(1+Math.exp(-
      3*(Queue1.size()-7)))) &&
      hold3.isBlocked()){
         hold3.unblock();
         checkoutOneSplit();
      }
   }
   else if(Queue1.size()<3 &&
   !hold3.isBlocked()){
      hold3.block();
   }
}
void checkoutOneSplit() {
   int size = Queue1.size();
   int startIndex = (int) (size / 1.5);
   for (int i = size - 1; i > startIndex;
   i--) {
      Customer customer = Queue1.get(i);
      Queue1.remove(customer);
      enter3.take(customer);
   }
}
```

Listing 1: Checkout opening function.

3 Results

The results of the Monte Carlo approach based on 10,000 simulation runs show that the number of generated agents (customers) deviates by an average of 0.07%. The choice of checkout type and the use of SSC show a total deviation of 0.78%, while the arrival rate per 15 minutes, with a total customer count of 852, deviates on average by 2 persons from the empirically collected values. Basket size shows small deviations for all checkout types: 4.76% for conventional checkouts, 6.40% for SSC, and 0.97% for SCO. Queue formation is recorded throughout the day from 06:00 to 19:00 for each checkout and per simulation run. Based on the statistical distribution, the respective state is evaluated.

The following central intervals around the median are used for classification: 25%, 50%, and 75%. The analysis of the results shows that queues form exclusively at checkouts 1 and 3. This finding is consistent with the observational data, indicating that the simulation realistically reproduces this section.

The simulated queue formation at checkout No. 1 follows the expected time-of-day fluctuations in customer arrival rates. Regarding the 25% central range, queue lengths of zero to one occur between 07:00 (opening) and 09:00. From 09:00 to 10:15, the queue length increases and reaches a peak of six persons. Subsequently, the queue length decreases and fluctuates between six and three until 13:30. Between 13:30 and 16:30, queue lengths of zero to one appear again, with two significant spikes to three persons at 14:30 and 15:30. From 16:30, the queue length rises again to six and fluctuates between four and five until 18:30. Shortly before 19:00, a final decrease to two or three persons can be observed.

At checkout No. 3, the 25% central range shows that the queue length remains zero until 10:15. It then rises to four waiting customers before dropping back to zero at 10:30. A similar increase occurs at 11:30, with the queue returning to zero by 12:00. The queue length remains unchanged until 16:30. Between 16:30 and 18:30, several spikes occur: it rises to two at 16:45, reaches three at 18:00, and drops to two by 18:30. Afterward, the queue length finally returns to zero by 19:00.

The timing of changes in queue length at checkout No. 3 correlates with previously observed longer queues at checkout No. 1. During 10:15 to 13:30 and 16:30 to 18:30, the observed patterns suggest that activating or increasing the use of checkout 3 is a response to the higher load at checkout No. 1. As shown in Figure 2, the queue behaviour at checkouts 1 and 3 largely matches the observed patterns.

The comparison of observations with simulated values shows that the model adequately reproduces the trend in queue development; the match in the 50% central range is 72.32% for checkout No. 1 and 89.81% for checkout No. 3. Observed deviations are likely due to limited data granularity, which may have missed short-term peaks in queue formation.

This limitation particularly affects busy periods, such as midday or evening hours, when customer traffic fluctuates more.

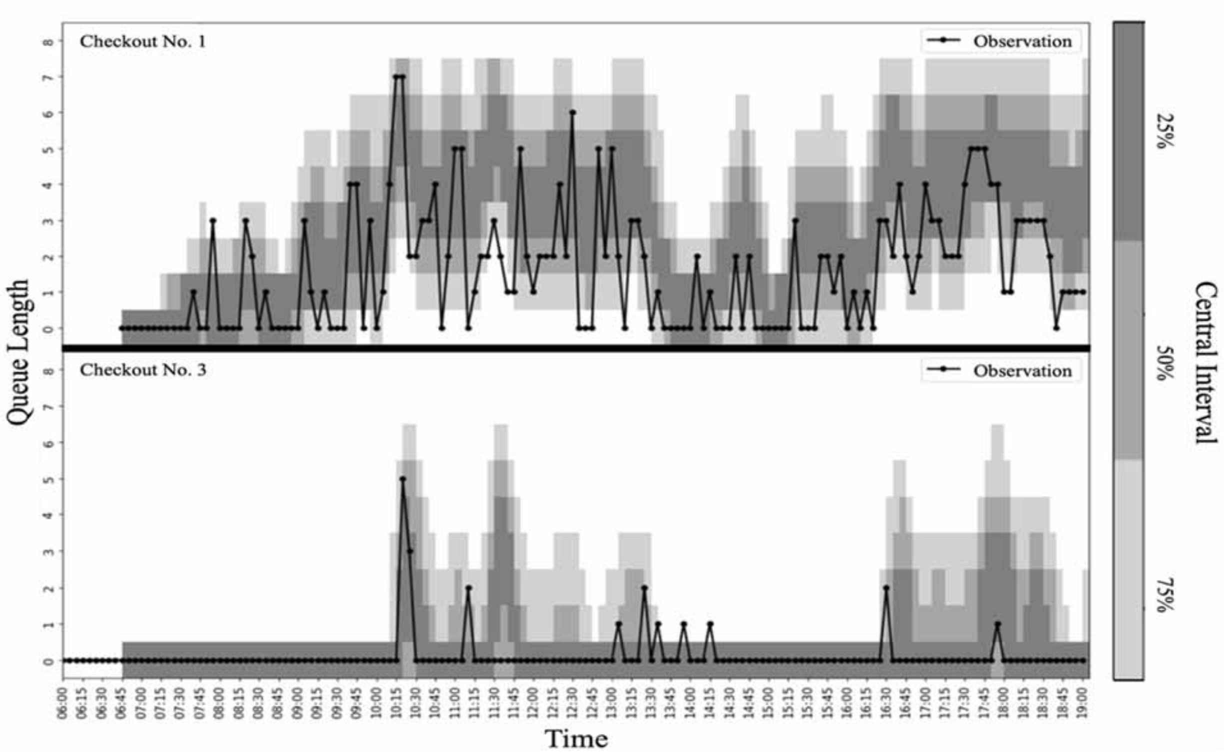

Figure 2: Comparison of simulated queue length and observation of checkout, No. 1 (top) and No. 3 (bottom).

An example is between 18:05 and 18:10, where the opening of checkout 3 and four subsequent transactions were recorded, but potential queue formation was not captured due to the observation schedule.

Another possible explanation may be the presence of unknown influencing factors not accounted for in the model. Despite minor deviations, the high agreement rates of queue patterns at checkouts 1 and 3 show that the modelled decision logic for opening checkouts and redistributing waiting customers is robust.

In addition to the proven accuracy of queue modelling, significant differences in checkout processing times were observed per checkout type. Conventional checkouts required an average of 10.06 seconds per item, while SCO checkouts required 16.60 seconds, an increase of 64.99%. Furthermore, the average queue length for checkout No. 1 throughout the day in the 25% central range was 2.91, worsening to 3.32 when the SSC option was omitted.

4 Discussion & Conclusion

This study developed a discrete-event simulation model to analyse queue formation in a hybrid checkout environment based on real-world data from a grocery retail store. The results demonstrate that the model is capable of accurately reproducing observed queue dynamics and capturing time-dependent fluctuations in customer flow. The high level of agreement between simulated and empirical data indicates that the implemented decision logic for checkout opening and customer redistribution provides a robust approximation of real-world system behaviour.

From a managerial perspective, the findings highlight the importance of dynamically adapting checkout capacity to fluctuating demand. The results show that the activation of additional checkouts effectively reduces peak queue lengths and stabilizes system performance during high-demand periods.

Furthermore, the results confirm significant differences in processing times across checkout types. In line with prior research, SCO systems require more time per item than conventional checkouts, likely due to lower user routine and occasional interaction issues. Despite this, SCO systems contribute positively to overall system performance, particularly for customers with small basket sizes, as reflected by the absence of persistent queue formation in the SCO area. This finding underlines the importance of maintaining a balanced mix of checkout types rather than fully replacing traditional checkouts. The inclusion of SSC further demonstrates substantial efficiency gains.

The simulation results indicate that removing the SSC option leads to a measurable increase in average queue lengths, confirming their potential to reduce checkout workload by shifting scanning activities into the shopping process. This supports existing research emphasizing the role of SSC technologies in improving operational efficiency and enhancing the customer experience.

In addition to these insights, the study highlights the importance of customer behaviour in queue dynamics. The modelled queue selection mechanism proved sufficient to reproduce realistic system behaviour. However, real-world decision-making may also be influenced by additional factors such as perceived waiting time, visibility of queues, or individual preferences, which were not explicitly modelled in this study.

Despite its contributions, the study has several limitations. First, the empirical data used for validation are subject to limited temporal resolution, which may result in short-term fluctuations not being captured. Second, certain behavioural aspects such as customer impatience or reneging were not included in the model but may influence queue dynamics in practice. Third, the logistic checkout opening function remains a simplified representation of human decision-making and may benefit from further calibration.

Future research should address these limitations by incorporating higher-resolution data collection methods and more detailed behavioural rules. In addition, real-time information systems such as displayed waiting times could further improve system efficiency. In conclusion, this study demonstrates the value of simulation-based approaches for analysing complex stochastic systems in grocery retail. The developed model provides a flexible and empirically grounded tool for evaluating checkout configurations and supports data-driven decision-making in store operations.

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