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SELF-ORGANIZATION IN CROWD-SOURCED FOOD DELIVERY SYSTEMS

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ABSTRACT

This paper presents an open-source agent-based simulation model to study crowd-sourced last-mile food delivery. Within this context, we focus on a system that allows couriers with varying degrees of autonomy and cooperativeness to make decisions about accepting orders and strategically relocating. We model couriers as agents in an agent-based simulation model implemented in NetLogo. Our approach provides the necessary parameters to control and balance system performance in terms of courier productivity and delivery efficiency. Our simulation results show that moderate levels of autonomy and cooperation lead to improved performance, with significant gains in workload distribution and responsiveness to changing demand patterns. Our findings highlight the potential of self-organizing and decentralized strategies to improve scalability, adaptability, and fairness in platform-based food delivery logistics.

1 INTRODUCTION

The transition to efficient and sustainable last-mile logistics is crucial for urban environments facing rising delivery demands. The impact of food delivery systems on last-mile logistics is significant, transforming urban transportation and consumer behavior. Online food delivery platforms have revolutionized the last-mile of food distribution, increasing congestion in urban centers and changing the nature of delivery work through the gig economy (Lord et al. 2023). These systems face challenges in optimizing logistics while meeting changing consumer expectations and addressing sustainability concerns (Trienekens et al. 2017). Platforms like Uber Eats, TakeAway, and Deliveroo must dynamically match orders to couriers, route deliveries efficiently, and maintain service quality under stochastic conditions (e.g., variable courier availability and traffic congestion).

Typically, a centralized platform is used in crowd-sourced food delivery systems. Using a centralized approach to orchestrate the delivery system may suffer from several weaknesses, including (i) a severe increase in complexity for larger instances, (ii) the sensitivity to information updates, (iii) the inability to adequately reflect the interests and preferences of competing couriers, and (iv) the lack of flexibility to deal with dynamic environments. Moreover, Behrendt et al. (2024) highlight that while centralization can enhance the reliability of the workforce, it can also limit the autonomy of couriers, which affects their job satisfaction and performance. Additionally, Lee et al. (2022) point out that the complexity of centralized systems can negatively affect workers' job commitment and performance, suggesting that social factors like trust and networks are crucial in mitigating these risks. Although centralized systems enable global optimization, the operational costs are not necessarily lower compared to decentralized systems (Behrendt et al. 2024). Centralized approaches exhibit substantial challenges affecting couriers and operational efficiency. With the continued expansion of online food retail, the industry faces the complex task of balancing economic, social, and environmental sustainability in last-mile logistics operations (Melkonyan et al. 2020).

Inspired by complex adaptive systems research, which explores emergence and self-organization across natural and artificial systems, a compelling solution to this challenge emerges in the form of agent-based systems. In this approach, agents represent stakeholder interests (such as couriers or restaurants) and

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adapt continuously to their environment through autonomous decision-making that aligns with their specific objectives. Consider, for example, a courier in an urban environment containing multiple restaurant clusters. This requires couriers' decision-making regarding job acceptance, strategic waiting periods at particular locations, or deliberate repositioning to optimize economic, social, and environmental performance.

In this paper, we focus on a multi-agent simulation approach to model courier decision-making based on varying levels of autonomy and cooperation. The goal of our approach is two-fold: (i) maximize courier efficiency by incentivizing couriers to visit areas with high job potential, and (ii) minimize job waiting times by ensuring couriers respond efficiently to demand patterns. To achieve these goals, we develop a model that incorporates memory-based decision-making, where couriers learn from past experiences to optimize their future decision-making. Our work builds upon the existing literature by introducing a comprehensive agent-based model in NetLogo that explicitly parameterizes autonomy and cooperation levels. The key contribution of our simulation is its structured approach to memory-based decision-making across varying levels of autonomy and cooperation, providing an open-source platform for investigating how self-organization emerges under different conditions and how simple coordination rules can enhance system performance.

The remainder of this paper is structured as follows. Section 2 presents a brief discussion of the related literature. Section 3 presents our self-organizing courier model with varying levels of autonomy and cooperation. In Section 4, we present our conceptual model. The corresponding NetLogo implementation is described in Section 5, and the results are discussed in Section 6. The paper closes with conclusions and directions for further research in Section 7.

2 RELATED LITERATURE

Recent research on crowd-sourced food delivery systems has explored Agent-Based Simulation (ABS) to study the complex interactions in food delivery systems. ABS offers several advantages when modeling crowd-sourced food delivery operations, particularly in its ability to represent heterogeneous actors with varying decision-making processes and control hierarchies. Among the studies that explicitly address control hierarchies, Zou et al. (2021) and Mittal et al. (2021) implemented decentralized control structures, and Samouh et al. (2020) utilized a centralized dispatching system. In a comparable system with on-demand transportation services, Čertický et al. (2014) designed an ABS testbed to study both centralized and decentralized control hierarchies to evaluate their respective impacts on system performance. Another study, focusing again on food delivery systems, found that despite potential advantages in global optimization, centralized approaches may introduce higher operational costs compared to decentralized systems (Behrendt et al. 2024), highlighting the complex balance required in system design. This is also backed by Kulkarni and Krejci (2023) who specifically examined the effects of mediator control in crowd-shipping platforms, finding that centralized matchmaking protects platforms from premature failure when initial participation is low and tends to outperform decentralized approaches in terms of platform revenue and participant retention.

The literature also reveals various strategies for self-organization within these systems, though often not explicitly labeled as such. Simoni and Winkenbach (2023) explored order batching and assignment algorithms that facilitate emergent coordination patterns among delivery agents. Similarly, Zou et al. (2021) investigated shortest route and nearest merchant assignment strategies, which enable delivery agents to optimize routes without centralized control. Fikar et al. (2018) focused on dynamic optimization approaches for urban last-mile distribution, illustrating how agents can adapt to changing conditions through responsive decision-making processes.

Efficiency appears as the primary KPIs in many last mile logistics studies, such as timely deliveries (Fikar et al. 2018), order costs (Simoni and Winkenbach 2023), and completion rates (Zou et al. 2021). Next to efficiency, researchers have evaluated these systems using service levels (Chen and Chankov 2017), market reach and food quality (Cramer and Fikar 2023), platform growth and performance (Mittal et al. 2021), and environmental impact (Sinha and Pandit 2021). This diversity of KPIs reflects the multifaceted nature of performance in crowdsourced food delivery systems and the industry's complex task of balancing economic, social, and environmental sustainability in last-mile logistics operations (Melkonyan et al. 2020).

Despite the growing body of literature on crowd-sourced food delivery systems, there remains a notable gap in the explicit analysis of emergent behaviors and self-organization patterns. With the exception of Mittal et al. (2021), who directly addressed feedback loops and network effects, most studies only implicitly touch upon emergent phenomena through measures such as maximum detour times (Chen and Chankov 2017) or differential urban-rural performance (Cramer and Fikar 2023). This limited focus on emergent properties represents an interesting opportunity for further research.

Our paper contributes to the existent literature by introducing a comprehensive agent-based model that explicitly includes autonomy and cooperation levels in courier decision-making. We systematically evaluate the performance implications of different levels of courier autonomy and cooperation in multiple contexts. Although our model considers real-world aspects, such as restaurant heterogeneity and time-based demand patterns, our approach considers a stylized, grid-based visual representation. Our NetLogo implementation provides an open-source platform that offers a testbed for strategies that balance courier autonomy, system efficiency, and service quality in crowd-sourced food delivery systems.

3 AN AUTONOMOUS COURIER MODEL

To control the behavior of individual autonomous couriers, we deploy an approach that allows for different levels of autonomy and cooperation. Our model consists of two main components: (i) a memory-based decision system that allows couriers to learn from past experiences, and (ii) a categorization of courier behavior based on autonomy and cooperation levels. This section describes the memory system (Section 3.1), the degree of autonomy (Section 3.2), and the degree of cooperativeness (Section 3.3).

3.1 Memory-Based Decision System

Our model includes a memory-based decision system that enables couriers to learn from past delivery experiences and adapt their behavior accordingly. Each courier maintains a historical record of rewards obtained from deliveries at different restaurants. For each restaurant, this record is capped at a certain length, controlled by a 'level-of-order' parameter. This parameter controls how much memory each courier has, influencing the degree to which courier decision-making is based on a longer history (high level-of-order) or based on the most recent memories (low level-of-order). To approximate the natural decay of human memory, the model uses a 'memory-fade' mechanism that gradually reduces the past rewards over time.

We include three distinct memory-fade mechanisms in our model: (i) linear fade, which applies a constant reduction, fading older and newer memories equally. This simplified mechanism runs counter with most models in cognitive psychology, but is included for practical reasons to ensure fairness and stability in worker-to-restaurant allocation, especially in low-frequency or high-variance environments; (ii) exponential fade, which uses a stronger decay to older memories, while preserving newer ones, similarly to Ebbinghaus' forgetting curve (Ebbinghaus 1913); and (iii) recency-weighted fade, which strongly preserves recent memories while allowing older ones to fade more rapidly, modeling a recency-bias in decision-making under time pressure.

This memory system enables couriers to recognize spatial and temporal patterns of rewarding jobs. Moreover, the memory fade mechanism allows couriers to respond to changes in the environment. With a rapid memory fade, couriers quickly adapt to changing conditions but may fail to tap into the potential of longer-term patterns. Conversely, a slow memory fade reduces the responsiveness to new opportunities.

3.2 Degree of Autonomy

Our model implements four distinct levels of courier autonomy that determine to which extent the courier is able to make independent decisions regarding job acceptance and positioning. Each level represents an increase in courier autonomy, ranging from level zero (no autonomy) to level three (full autonomy), as discussed below.

- **No Autonomy (Level 0)**. Couriers have no decision-making capabilities and are assigned to a dedicated restaurant. Couriers are only allowed to serve one restaurant, and immediately return to that restaurant after completing a delivery, regardless of any other opportunities along the way. A courier always immediately accepts a new job. This level represents a traditional delivery model where dedicated couriers operate for a single restaurant.
- **Low Autonomy (Level 1)**. This level introduces limited courier mobility within a local environment. The couriers still exhibit a strong restaurant dependency but are allowed to accept jobs in their proximity while waiting at a restaurant. This proximity is controlled by a 'neighborhood-size' parameter. This proximity-based system is chosen such as to facilitate prompt responses to new demand with minimal empty travel time. Couriers still return to the latest served restaurant. This level ensures that couriers may gradually shift their operations from one location to another within a local neighborhood. This level represents typical platforms (e.g., DoorDash, UberEats) that uses platform-imposed geographic filtering (e.g., some delivery platforms only show orders within a certain radius of the courier's current location).
- **Medium Autonomy (Level 2)**. In addition to the decision-making capabilities of level 1, couriers utilize the memory mechanism described in Section 3.1 to make strategic repositioning decisions. When the expected value of their current location falls below a 'free-moving' threshold, couriers can proactively search for restaurants outside their current neighborhood. A courier can make informed decisions on where to search, dependent on the level of available information and cooperativeness, as discussed in Section 4.3. When no information is available about restaurants outside the courier's current neighborhood (i.e., cooperation level 0), the courier resorts to a random search. With higher levels of cooperativeness, a courier can utilize information shared by other couriers to estimate where potential high-rewarding locations are. Hence, this level introduces the balance between exploitation (waiting at a known location) and exploration (searching for new opportunities elsewhere). This balance is controlled by the parameters of the memory mechanism and the 'free-moving' threshold.
- **High Autonomy (Level 3)**. This is the highest level of autonomy where couriers are allowed to actively search for opportunities while traveling. Couriers no longer have to return to the latest served restaurant, but may accept jobs along the way. Whether or not to accept a job is dependent on three elements:
  - The expected reward for each known restaurant, given by the recent memory.
  - The temporal pattern for each known restaurant. For example, a courier might remember from previous days that during lunch certain restaurants are profitable, even though these restaurants do not show up in the recent memory.
  - The distance to each restaurant, reflecting the effort it takes for a courier to move from its current location to a new one.

  The weighted average of these three elements results in a 'heatmap score' and is periodically updated per courier. While returning to a restaurant after a completed delivery or while waiting at a restaurant, the courier compares whether the expected reward of the current restaurant still outperforms other known restaurants. When this is no longer the case, the courier will strategically reposition to the restaurant with the highest known heatmap-score. When no known restaurants have a heatmap-score higher than the free-moving-threshold, the courier searches for restaurants similar to the Level 2 logic. Both Level 2 and Level 3 are extensions in terms of courier autonomy compared to current real-world platforms (which are typically Level 1).

3.3 Degree of Cooperativeness

The model also incorporates four levels of cooperation between couriers:

- **No Cooperation (Level 0)**. At the baseline level, couriers operate independently with no information sharing. Each courier bases its decision-making solely on their own experiences, making decisions in isolation from other agents. This level represents the current practice of major gig economy platforms, which centrally distributes orders and don't allow for courier-to-courier cooperation. Levels 1-3 represent theoretical forms of cooperation to move towards decentralized information sharing.
- **Low Cooperation (Level 1)**. At this level of cooperation, couriers share limited information about the job availability in their vicinity with couriers in their neighborhood. This expands the collective awareness of job opportunities within a local neighborhood. This mechanism aims to create social dynamics that balances earnings between individual couriers. Our model uses two job sharing mechanisms to introduce fairness in job allocation: (i) balanced load, which prioritizes couriers with fewer completed jobs, promoting equal sharing of profits, and (ii) proportional fairness, which assigns jobs based on the history of courier earnings, given priority to couriers with lower rewards thus far.
- **Medium Cooperation (Level 2)**. At this intermediate level of cooperation, couriers share information about restaurant occupancy conditions, allowing them to avoid overcrowded locations. Couriers observe the number of waiting couriers at restaurants within their neighborhood and share this information at a later time with other couriers within their (different) neighbourhood. When combined with autonomy level 2 or higher, this allows couriers to make strategic positioning decisions that consider not only potential rewards but also competition intensity. Level 2 cooperation enables couriers to distribute themselves more efficiently across the environment without explicit coordination. During periods of low demand, couriers use restaurant occupancy information to identify under-served locations, preventing excessive clustering at high-demand restaurants. This can help in creating a self-organizing system where couriers naturally spread to maintain appropriate coverage while avoiding counterproductive competition.
- **High Cooperation (Level 3)**. In the highest level of cooperation, couriers engage in collaborative decision-making by sharing their 'heatmap' with other couriers in their vicinity. The integration of heatmaps is controlled by an 'ego-level' parameter that determines how much weight couriers place on their history versus information received from colleagues. This level of cooperation promotes learning between couriers; e.g., a courier can share information about a region not yet visited by a colleague and vice versa.

The combination of autonomy and cooperation levels creates a matrix of possible courier behaviors that can be studied to understand their impact on system performance, as shown in Figure 1.

4 CONCEPTUAL MODEL

This section presents a conceptual model. We aim to develop a reusable, configurable simulation model to analyze how different autonomy and cooperation levels impact delivery performance. Elements include: inputs (4.1), outputs (4.2), experimental factors (4.3), and model assumptions (4.4).

4.1 Model Inputs

The simulation model incorporates inputs defining the environment and the agent behaviors, allowing flexible configuration for diverse delivery scenarios. Beyond the two-dimensional grid environment, inputs relate to couriers, restaurants, demand generation, and information sharing. Courier agents can be configured through the following input settings:

- **Courier Population**: Total number of couriers in the simulation.
- **Neighborhood Size**: Radius for detecting jobs and agent interaction.
- **Initial Courier Distribution**: Random or restaurant-based positioning.

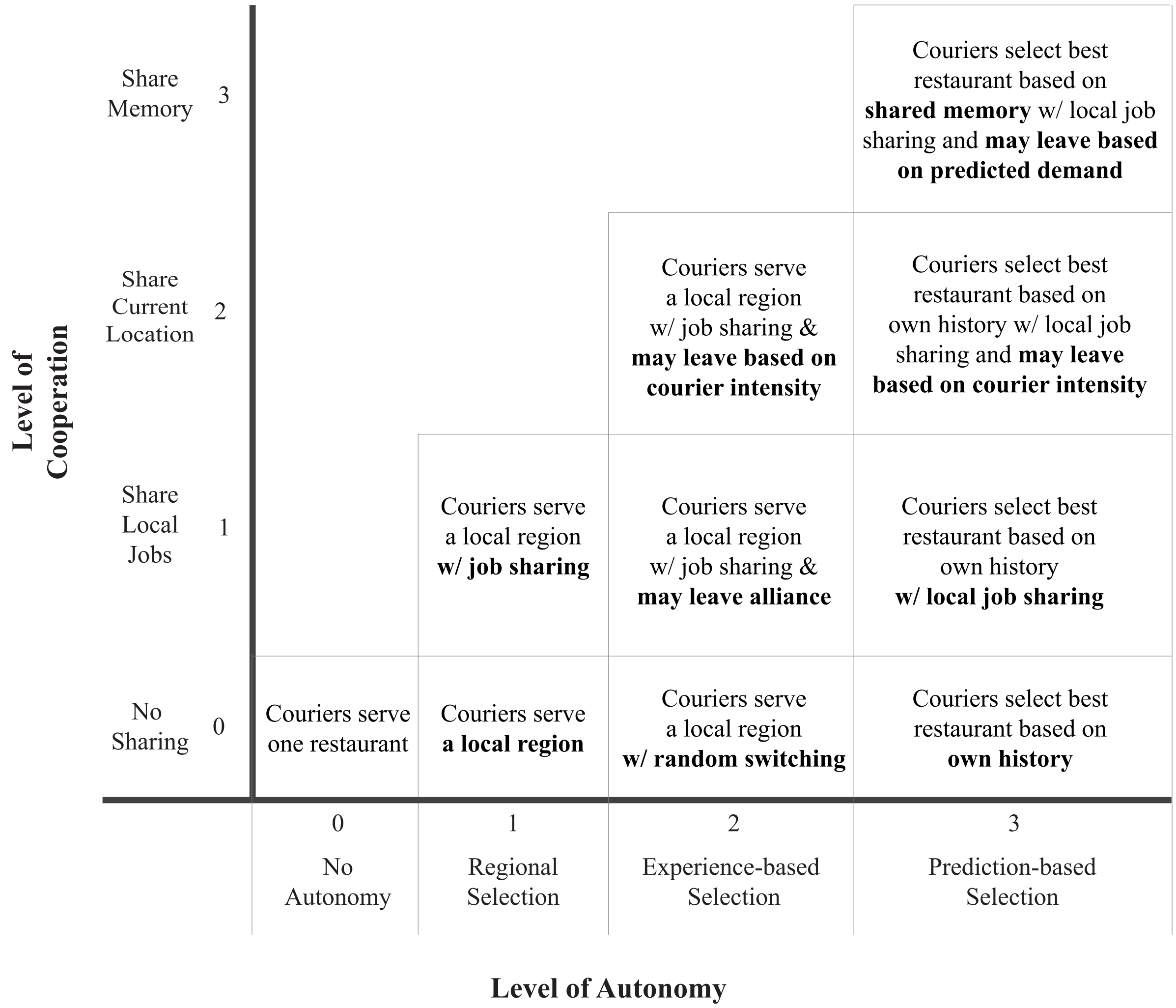

Figure 1: Self-Organizing Logistics framework presented by Gerrits (2023) applied to crowd-sourced food delivery systems. Bold-faced text indicates incremental changes compared to lower levels of autonomy or cooperativeness.

- **Autonomy Level**: Value 0-3 defining decision-making capabilities.
- **Cooperativeness Level**: Value 0-3 determining information sharing extent.
- **Memory Configuration**: Settings controlling historical information usage:
  - **Memory Usage Flag**: Enables/disables memory-based decisions.
  - **Memory Fade Rate**: Historical information diminishing percentage.
  - **Fade Strategy**: Memory decay algorithm (Linear, Exponential, Recency-weighted).
  - **Free-Moving Threshold**: Minimum expected reward to remain at location.
- **Learning Parameters**: For higher-autonomy levels:
  - **Learning Model**: Approach for behavior adaptation for autonomy level 3.
  - **Prediction Weight**: Balance between historical patterns and recent observations.

Restaurants serve as job origins and they are defined through the following input settings:

- **Restaurant Clusters**: Number of restaurant groupings.

- **Restaurants per Cluster**: Number of individual restaurants within each cluster.
- **Cluster Area Size**: Spatial radius controlling restaurant density.
- **Restaurant Types**: Distributions of categories with different operating hours.

The demand generation system creates delivery jobs, and is defined through the following input settings:

- **Job Arrival Rate**: Baseline frequency of new orders.
- **Time-Based Demand Patterns**: Parameters defining temporal demand variation:
  - **Time Window Definitions**: Non-overlapping daily periods for temporal demand segmentation.
  - **Demand Distribution**: Percentage of total daily demand per time window.
- **Reward Calculation**: Parameters for determining job rewards.

The cooperative courier behavior is defined through the following input settings:

- **Job Sharing Algorithm**: Method for job assignment (Balanced Load or Proportional Fairness).
- **Strategic Repositioning Interval**: Frequency of position reassessment.
- **Heat Map Sharing Interval**: Frequency of demand information exchange.
- **Ego Level**: Weight on personal experiences versus colleagues' information.

4.2 Model Outputs

The simulation model generates multiple output categories for comprehensive system performance analysis. We use the following performance metrics for the couriers:

- **Courier Status Distribution**: Time percentage in each state.
- **Courier Earnings**: Individual and aggregate courier rewards:
  - **Total Rewards**: Cumulative earnings per courier.
  - **Earnings Rate**: Rewards per unit time.
  - **Earnings Distribution**: Equity measures across courier fleet.

The following metrics are used to measure service quality:

- **Order Fulfillment**: Metrics capturing demand fulfillment:
  - **Open Orders**: Unfulfilled orders at any time.
  - **Orders Completed**: Successfully delivered orders.
- **Time-Based Performance**: Metrics reflecting temporal efficiency:
  - **Delivery Time**: Duration from order creation to delivery.
  - **Time-Window Performance**: Metrics for different daily periods.

4.3 Model Assumptions and Limitations

For computational tractability while preserving essential dynamics, our model incorporates simplifying assumptions:

- **Perfect Courier Reliability**: No failures, delays, or service interruptions.
- **Single-Order Delivery**: One delivery at a time, no batching or multiple pickups.
- **Proximity-Based Notification**: Couriers are only notified of deliveries within their proximity.
- **Instantaneous Pickup and Delivery**: No delays in preparation or handoff.
- **Distance-Based Rewards**: Compensation determined solely by delivery distance.
- **Homogeneous Courier Capabilities**: Identical movement capabilities.
- **Constant Restaurants and Couriers**: No dynamic entry or exit.

- **Limited External Factors**: No accounting for weather, traffic, or special events.

5 SIMULATION MODEL

Based on the autonomous courier approach and conceptual model described, an agent-based simulation model is proposed, implemented in NetLogo (Gerrits 2025). We invite researchers and practitioners to use and extend the model. Below, the main components of the simulation model are discussed: the environment (Section 4.1), the couriers (Section 4.2), and the jobs (Section 4.3).

5.1 The Spatial Environment

The environment consists of a two-dimensional grid, which is initialized with restaurant clusters that form concentrated areas of job creation, while delivery destinations (customers) can be generated at any location. The model first establishes restaurant clusters at random locations in the environment. Around each cluster, a specified number of restaurants are placed within the defined cluster radius. The environment can be visualized during simulation runs, and togglable cluster lines help visualize the relationship between restaurants and their clusters. Restaurants are color-coded orange when they have a pending job, and white otherwise.

5.2 The Courier Agents

Couriers are implemented as turtle agents in NetLogo with various properties and state variables. Each courier has a current job (if any), a next location target, a status indicator, reward history, and memory of past job rewards per restaurant. Couriers operate in one of four states:

1. **Waiting for Next Job** (orange): Waiting at a restaurant for a next job.
2. **On Job** (red): Delivering an order to a customer.
3. **Moving Back To Restaurant** (blue): Traveling back to a restaurant after completion of a job.
4. **Moving To Restaurant** (gray): Moving to a restaurant to pick-up an order.
5. **Exploring** (green): Randomly exploring the environment for a job.

The courier agents implement the decision-making logic described in Section 3. Based on their autonomy level, they use different strategies to decide which jobs to accept. For example, high-autonomy couriers (level 3) can re-evaluate their destination during transit (color-coded blue) and potentially change their decisions based on new information. Similarly, based on their cooperation level, couriers can share information and potentially coordinate their activities.

5.3 Job Generation

Jobs are created based on a configurable arrival rate parameter. Each job includes an origin (restaurant), a destination (customer), and a reward based on the distance between these points. Job assignment occurs through a combination of courier decision-making and proximity. Couriers can discover jobs within their neighborhood radius and decide whether to accept them based on their current state, and autonomy/cooperativeness level. After a job is completed, the couriers receive a reward that is added to their cumulative earnings. This reward information is also stored in the courier's memory of the restaurant, to influence future decision-making.

6 RESULTS

This section presents the simulation outcomes. Section 6.1 outlines the experimental design, followed by analyses of the efficiency and workload balance (Section 6.2) and system robustness (Section 6.3).

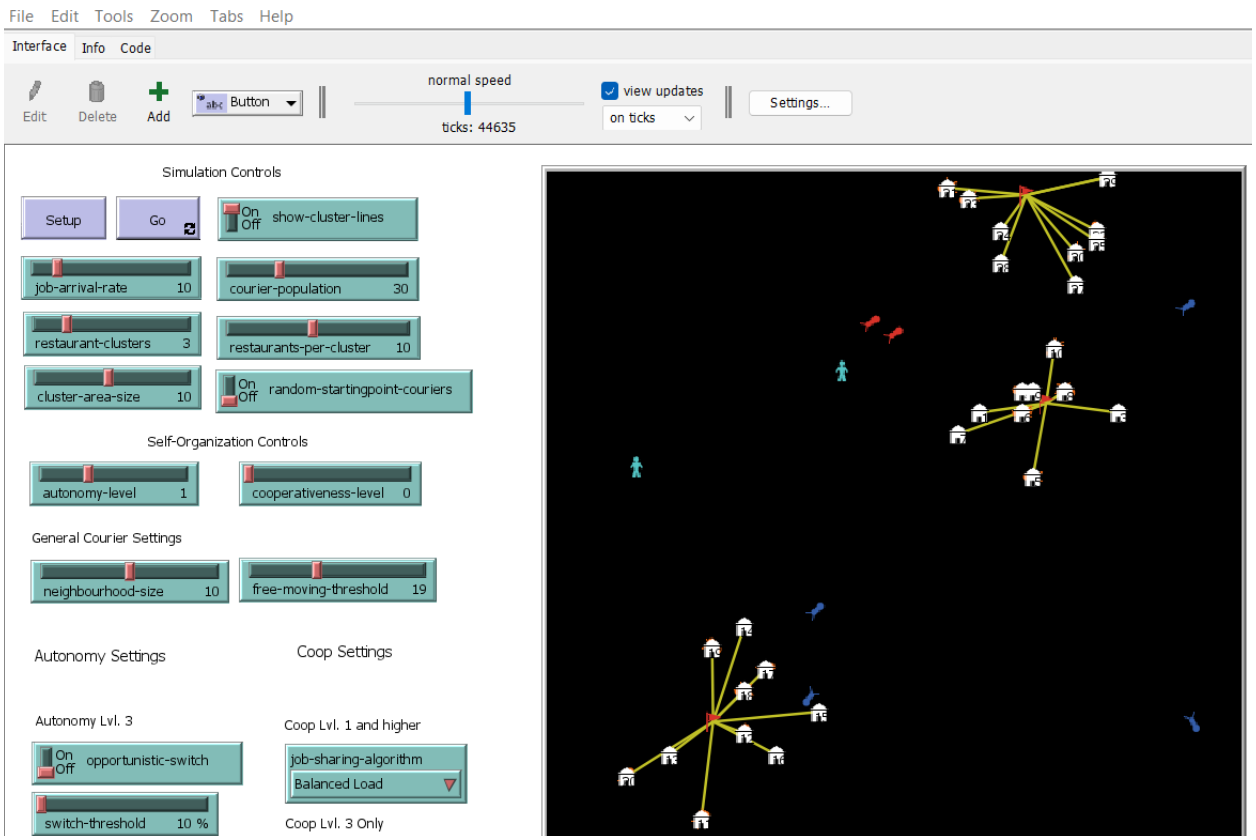

Figure 2: Screen capture of the simulation model in NetLogo.

6.1 Experimental Design

Our experimental design systematically explores autonomy and cooperativeness levels to understand performance implications. We organize experiments around 10 different autonomy/cooperativeness configurations (see Figure 1) while fixing the remaining parameters. Thirty replications are used for each experiment, resulting in a relative error of at most $\gamma = 0.1$ using a significance level $\alpha = 0.05$. The remaining parameters are set as follows:

- Environment size: 65 × 65 cell grid
- Run length: 24 hours
- Number of couriers: 30
- Number of restaurant clusters: 3
- Restaurants per cluster: 10
- Average daily demand per restaurant: 288
- Demand distribution: 6% (00:00–09:00), 41% (09:00–17:30), 33% (17:30–20:00), 20% (20:00–24:00)
- Neighborhood size: 10 cells
- Memory: Linear fade with a 5.0% decay and a maximum history 12 orders
- Job sharing algorithm (cooperation level 1 and above): Balanced Load
- Ego level (cooperation level 3): 50%
- Learning model (autonomy level 3): Demand Prediction

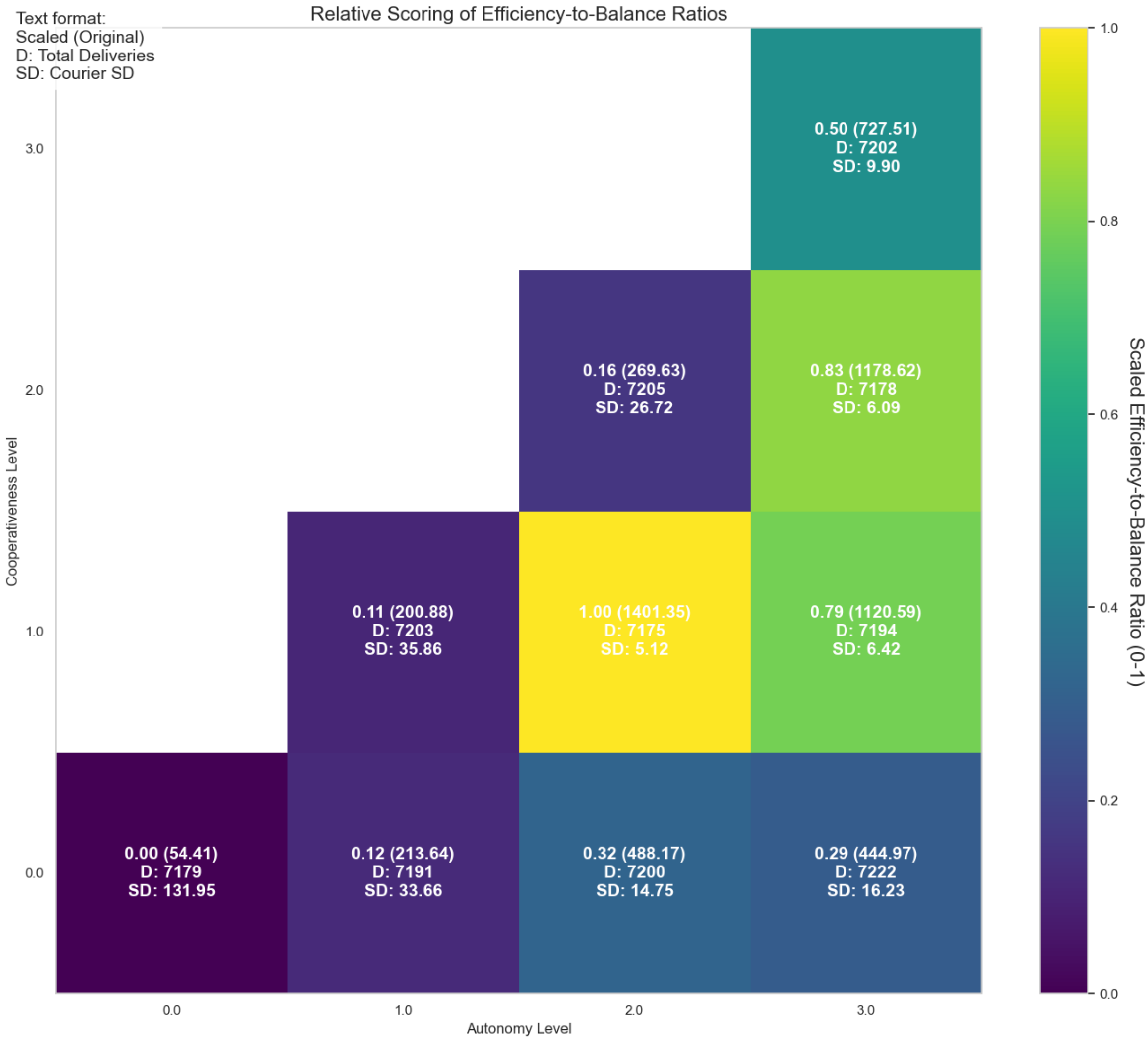

Figure 3: Efficiency-to-balance ratio across configurations.

6.2 Impact on Efficiency and Workload Balance

Figure 3 shows the (relative) efficiency-to-workload-balance ratio of the various configurations studied. It also shows the total deliveries (D), the standard deviation (SD) of the number of deliveries per courier. Efficiency was measured using the ratio of total deliveries to the SD of jobs per courier. Due to the consistently high number of couriers, total deliveries remained relatively constant across experiments (7,172-7,222 deliveries, CV = 0.2%). However, workload balance (i.e., the SD of jobs per courier) showed notable differences ranging from 5.12 to 131.95 deliveries per courier. For example, our results reveal that low cooperation and low autonomy consistently perform the worst, with the baseline configuration (0,0) achieving an efficiency-to-balance ratio of only 54.40. The relationship between autonomy and cooperation is distinctly non-linear, as evidenced by the best workload balance achieved in the configuration with autonomy level 2 and cooperation level 1 (ratio: 1,397.82), suggesting that occasional exploration across clusters and moderate cooperation enhance spatial distribution and reduce delivery disparities. Overall, the efficiency-to-balance ratio improves with higher cooperation and higher autonomy, though with diminishing returns at the highest autonomy level. Autonomy level 1 configurations average a 281% improvement in efficiency-to-balance ratio compared to level 0 (207.22 vs 54.40). The jump to autonomy level 2 provides a substantial 247% additional improvement (718.36 average ratio), while the progression to level 3 shows more modest gains (867.07 average ratio, a 21% improvement). This pattern suggests that moderate autonomy provides the greatest marginal benefit, allowing couriers sufficient flexibility without excessive random exploration. An exception to this insight that in general higher cooperation and higher autonomy lead to better performance, is the configuration with the cooperation and autonomy levels set at 2, which performs 48% worse than the optimal autonomy 2, cooperation 1 configuration. Further experimentation revealed that our relatively high courier density resulted in extreme levels of random exploration given our specific settings, resulting in diminished performance. In terms of cooperation, our results demonstrate that increasing cooperation does not necessarily improve performance. Level 1 cooperation achieves the highest average efficiency-to-balance ratio (907.61), significantly outperforming both no cooperation (300.29) and higher cooperation levels (724.13 for level 2, 727.51 for level 3). This suggests that cooperation should be balanced, where limited information sharing enhances coordination without creating increased competition or wrong directives.

Table 1: Average and maximum number of open orders (averaged across cooperation levels, memory enabled).

Metric	No Autonomy	Low Autonomy	Medium Autonomy	High Autonomy
Average Open Orders (avg)	35.5	5.3	4.3	4.0
Average Open Orders (SD)	29.4	6.2	0.7	0.4
Max Open Orders (avg)	332.6	35.5	26.0	25.0
Max Open Orders (SD)	197.6	40.2	6.6	5.6

6.3 Impact on System Robustness

Another metric of interest is the degree to which the system adapts to demand perturbations. As discussed in Section 6.1, our demand fluctuates highly over the day. To capture this metric, Table 1 shows the average and maximum number of open orders per experiment. Couriers with low autonomy are limited to a small set of restaurants, ignoring broader system needs, resulting in high open order counts averaging 35.5 orders. Allowing couriers some freedom to explore, significantly reduced both average and maximum open orders, with autonomy level 1 achieving an 85% reduction in average open orders (5.3 vs 35.5). Higher autonomy levels (2 and 3) provide additional but smaller improvements, stabilizing around 4.0-4.3 average open orders. Similar improvements were found with increased cooperation levels (see Table 2), though the effects are more nuanced. Zero cooperation across all autonomy levels averages 12 open orders, while cooperation levels 1-3 achieve much more consistent performance (4.1-5.0 average open orders). This 65-76% improvement demonstrates that information sharing mechanisms effectively complement individual courier decision-making capabilities. The combined effect of autonomy and cooperation creates a system that is significantly more resilient to demand fluctuations. The worst-performing configuration (0,0) shows high variability in open orders (SD: 19.9), while optimized configurations (2+ autonomy, 1+ cooperation) demonstrate much more stable performance (SD: 0.4-5.1), indicating not just better average performance but also more predictable system behavior under varying demand conditions. Furthermore, analysis of the maximum open orders also reveals improvements, with the baseline configuration in Table 1 experiencing peaks of 332.6 orders compared to configurations with higher autonomy, typically maintaining peaks below 35 orders — a 90% reduction in system stress during demand surges. A similar, but less drastic, reduction can be found in Table 2.

7 CONCLUSIONS AND FURTHER RESEARCH

This paper presents an agent-based simulation model for analyzing self-organization in crowd-sourced last-mile food delivery systems. By varying courier autonomy and cooperation levels, our model captures

Table 2: Average and maximum number of open orders (averaged across autonomy levels, memory enabled).

Metric	No Coop.	Low Coop.	Medium Coop.	High Coop.
Average Open Orders (avg)	12.0	5.0	4.3	4.1
Average Open Orders (SD)	19.9	5.1	0.9	0.4
Max Open Orders (avg)	102.7	31.5	25.9	24.7
Max Open Orders (SD)	165.3	32.8	7.5	5.6

the emergent behaviors that arise from decentralized decision-making. The NetLogo-based simulation environment provides a flexible and open-source testbed to study how local courier decisions, memory-based learning, and information sharing impact system-wide performance metrics. Our results suggest that increasing autonomy and cooperation among couriers improves workload balance, reduces delivery delays, and enhances system robustness to fluctuating demand. In particular, we found that medium-to-high levels of autonomy combined with low to moderate cooperation resulted in the most balanced performance, suggesting that limited but targeted decentralization can yield significant operational benefits. The model provides valuable insights into the design of decentralized logistics platforms by illustrating how simple behavioral rules and local interactions can lead to self-organized, high-performing delivery networks.

For future research, several directions are promising: (i) incorporating variable courier incentives and customer pricing mechanisms; (ii) modeling mixed fleet environments with different types of couriers and the ability to leave or join the system, and (iii) validating the model using real-world datasets from food delivery platforms. We invite researchers and practitioners to build upon our open-source framework to further explore the potential of decentralized coordination in last-mile food delivery systems as well as other delivery, ride-sharing, and taxi service systems.

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