Production and Operations Management

Smart Navigation via Strategic Communications in a Mixed Autonomous Paradigm

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Motivated by the emerging mixed autonomous paradigm in cobotic order picking operations, we investigate the optimal information design to navigate human workers (HWs) who cooperate with autonomous mobile robots (AMRs) within an intralogistics system. We incorporate asymmetric information between AMRs and HWs in a routing game where connected AMRs are informed of the congestion state while HWs rely on information provided by the system. The system designs a communication policy aiming to navigate HWs away from congestion. Without strategic communications, we show that the deployment of AMRs cannot mitigate congestion unless the automation level reaches a threshold. Interestingly, we illustrate a substitution effect between automation and strategic communications when information distortion is mild. In contrast, severe information distortion complements automation due to exacerbated congestion. Furthermore, an in-house AMR fleet is economically more efficient than a third-party logistics service. Consequently, in-house automation can be achieved with mild information distortion, while severe information distortion is required to complement the lack of efficiency in the third-party AMR fleet. With simulated numerical examples to complement the analytical results, we provide managerial insights concerning the optimal information policies under different levels of automation, guiding warehouse managers in their communications with workers to achieve the best performance of the cobotic system.

Key words: intralogistics robots, autonomous driving, routing game, information design

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1 Introduction

Enabled by the Internet of Things (IoT) technologies, one of the most promising domains for autonomous driving applications is order picking in warehouses. Order picking is traditionally performed by human workers who travel through aisles and retrieve products to fulfill customer orders, and is considered to be the most labor-intensive and time-consuming of warehouse operations (De Koster et al. 2007). To tackle the issue of rising labor costs, warehouse managers have turned to the solution of autonomous mobile robots (AMRs) which can communicate with IoT devices and navigate autonomously in intralogistics facilities. As human pickers currently remain essential for most warehouse operations, the deployment of AMRs gives rise to a *cobotic order picking system,* wherein AMRs assume the task of carrying bins/totes while human pickers focus more on value-added work, such as picking and packing orders. Improving the productivity of the cobotic system is critical for warehouse managers, especially with e-commerce retailers under pressure from soaring order volumes and customer demand for same-day delivery (Boysen et al. 2019). By developing a game-theoretical model, we hope to contribute a conceptual framework to derive optimal communication strategies and human-machine coordination within the dual context of intralogistics automation and cobotic operations.

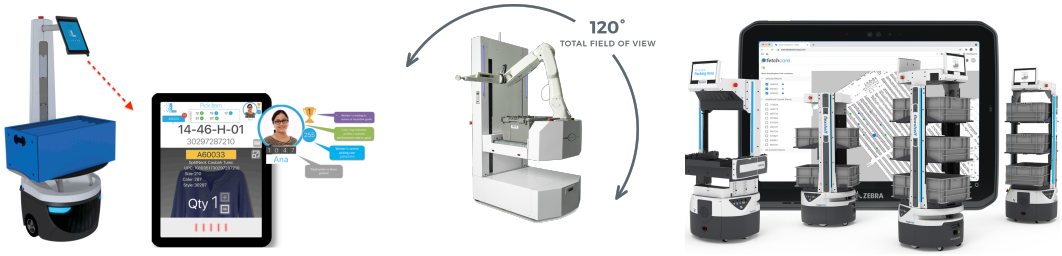
Navigating human workers (HWs) away from congestion is essential to reduce cycle time and improve productivity in cobotic order picking operations. Unlike AMRs that are programmed to avoid congestion, individual HWs may block aisles or interrupt the operation of their robotic counterparts. Because of this, a communication strategy for navigating HWs in cobotic operations is crucial for an intralogistics system to achieve optimal performance. In warehouse operations, there are multiple methods that a warehouse management system (WMS) can use to communicate with HWs, such as a voice system, handheld devices, or the screens on AMRs. A salient difference in managing human workers rather than robots is their respective compliance levels: While AMRs can be dispatched with full compliance, HWs can only be persuaded through an information system. In this paper, we study how warehouse managers can leverage communication tools to provide smart navigation to human workers in collaboration with AMRs.

1.1 Cobotic Order Picking

Human-robot collaborative order picking exemplifies cobotic operations in intralogistics systems. In this paper, we focus on a human-robot interaction known as a "swarm system", which means that each picker is assigned a zone to collaborate with multiple AMRs that visit the zone (Azadeh et al. 2020). The Locus Robotics example (see Figure 1(a)) describes such a cobotic system where a picking list is sent to an AMR which navigates to the storage area, and a nearby picker retrieves

items as instructed by the WMS. Once the work is completed, the AMR moves on to the next pick location, and the picker looks for another AMR within the zone. The AMRs are connected but independent of pickers, allowing for collective navigation decisions and greater flexibility in AMR deployment.

To deploy the AMR fleet, a warehouse manager can either make an infrastructure investment to install the automation system or subscribe to automation services from a third-party logistics (3PL) provider. Figure 1(b) describes how A.S. Watson ordered a fleet of IAM Robotics Swift AMRs for order picking in a Netherlands-based fulfillment center. These AMRs are equipped with manipulator arms and pick orders in the same way manual pickers do. The warehouse system can centrally control the operation of the in-house AMR fleet, and some AMR manufacturers offer automation solutions utilizing robots as a service (RaaS, see Figure 1(c)). While outsourced AMR fleets do not require large capital investments, they may be less efficient due to a lack of system coordination.



(a) Information on the screen (b) Swift™ (c) Platform-based Fetch Robotics

Figure 1 AMRs in real practice.

Sources: (a) https://locusrobotics.com/features/directed-picking/, (b) https://fetchrobotics.com/each-picking-robots/, (c) https://www.iamrobotics.com/products/swift/.

1.2 Research Questions and Methodology

As HWs in cobotic operations cannot be centrally controlled, their self-interested behaviors are a major source of warehouse congestion. Glock et al. (2017) and Elbert et al. (2017) find that HWs deviate from guided routes to shortcuts that save walking time because they believe their own route choices are better than those suggested by the WMS. Daily operational data from one state-of-the-art warehouse shows that only 33 out of 68 (48%) human-operated forklift trips were compliant with the routing policy provided by the WMS (Halawa et al. 2020). Such high deviation rates have been found to occur in aisles where workers are required to travel long distances but instead move in the opposite direction. When more and more workers choose the shortest route,

the subsequent crowding of certain aisles becomes a leading cause of warehouse congestion (Zhang et al. 2009).

Another salient feature of the cobotic system is AMRs' advantage in receiving, processing, and responding to information supported by IoT technology. With their seamless integration with the facility, AMRs have the capability to acquire more accurate information from the intralogistics environment (Wang et al. 2019). In practice, AMRs are integrated with the WMS to obtain synchronized information about orders and item locations. In addition, they can also collect real-time inventory data via radio frequency identification (RFID) technology, which in turn helps them make better routing decisions. In contrast to AMRs' active information acquisition, human workers rely on messages sent by the WMS to decide their movement patterns. In this paper, we characterize such stylized and representative cobotic operations wherein self-interested HWs interact with a fleet of informed AMRs. Based on the stylized cobotic operations, we raise the following research questions: (1) How to characterize the equilibrium traffic assignment in a mixed autonomous paradigm wherein uninformed HWs self-select their routes while interacting with a connected fleet of informed AMRs, and (2), How to leverage the instrument of credible information communication to navigate HWs away from congestion.

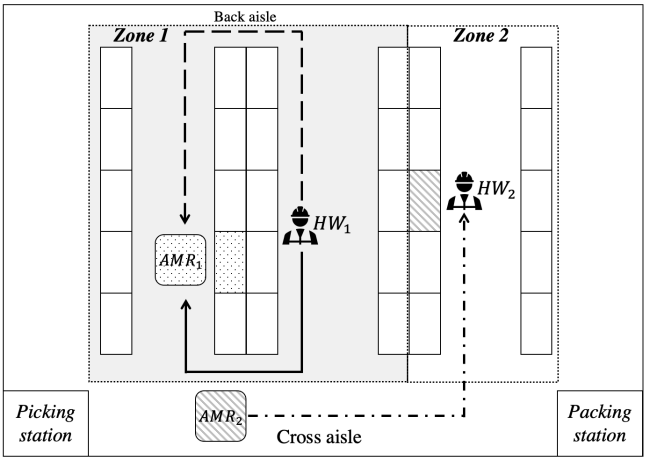


Figure 2 Warehouse layout in a cobotic system.

To address these questions, we propose a game-theoretical model based on the standard traffic routing framework. We consider a swarm order picking system in a warehouse facility as depicted in Figure 2, where there are two picking zones with HW_1 and HW_2 assigned to each zone. When AMR_1 arrives at Zone 1, HW_1 is called to meet it. HW_1 can choose the route via the cross aisle or the route via the back aisle. HW_1 prefers traveling through the cross aisle because of its shorter distance and/or wider space, but congestion may occur as AMR_2 is navigating to Zone 2. Congestion on the cross aisle is uncertain and can be further worsened when it is occupied by other

operations, such as replenishment or returning empty bins from the packing to the picking station. We characterize such uncertainty by a binary traffic state. To minimize warehouse congestion, the system can develop a communication protocol that provides HWs with information about the traffic state to navigate them away from the congested aisle. We characterize the traffic equilibrium in such a cobotic intralogistics system, and then derive the system's optimal communication policy. In this process, we also consider whether AMR operations are centrally controlled by the in-house WMS or outsourced to a 3PL service provider. When AMRs are deployed in-house, they are controlled to maximize the system's overall performance. Alternatively, when AMR solutions are outsourced to a 3PL provider, they are dispatched at the service provider's own discretion. We investigate the system's optimal communication strategies under these two operational modes.

1.3 Main Results and Contributions

We start with a manual order picking system in which HWs are provided with accurate information about the congestion state. Compared with the first-best efficiency of a centralized system, we show that HWs overcrowd the more desirable route (with a lower congestion cost), leading to a loss of efficiency as predicted by the principle of negative externalities. In a cobotic system, the deployment of an in-house AMR fleet can improve economic efficiency, but outsourcing to a third-party platform reduces this effect. AMR deployment cannot mitigate human worker overcrowding behaviors unless the fleet size is large enough, and first-best traffic efficiency can be achieved with a sufficiently large AMR fleet.

We then focus on the role of strategic communications in cobotic operations under an asymmetric information setting, where AMRs are informed of congestion conditions while HWs must rely on information provided by the system. The system strategically communicates with human workers about congestion conditions in a credible but obfuscated manner. Imperfect information accuracy can cause their expectations about congestion costs to be distorted, either upward or downward. Mild information inaccuracy can mitigate human worker overcrowding behaviors, but it can also lead to overcrowding on less desirable routes. The research sheds new light on how AMR deployment and strategic communications can work together to mitigate congestion. We find that the increase in AMR fleet size substitutes mild information distortion to navigate HWs away from overcrowding the more desirable route, while it complements strong distortion to navigate them away from overcrowding the less desirable one.

To maximize the performance of cobotic operations, we find that it is optimal for the system to implement communication policies with some extent of information distortion. When HWs have no prior information about congestion conditions in the warehouse, the system's optimal communication policy is to provide information of intermediate accuracy. With an intermediate level of

information distortion, HWs are persuaded to be more pessimistic/optimistic about congestion cost in the good/bad state, such that their selfish-routing behaviors are systematically efficient. When HWs do have prior information, intermediate information accuracy is no longer feasible due to the credibility constraint such that mild or severe information distortion is introduced. Interestingly, with a large fleet size of in-house AMRs, only mild information distortion is needed for strategic communications, while severe information distortion is required to complement the third-party AMRs' lack of efficiency in mitigating congestion. Consequently, with the in-house AMR fleet, strategic communications can reduce the number of AMRs needed to achieve the first-best performance, but it is not true for the third-party fleet. For this reason, a warehouse manager must make a trade-off between capital investment and operational efficiency in the paradigm shift towards in-house automation and RaaS integration with third-party logistics.

We simulate numerical examples to illustrate how the optimal communication strategies depend on the automation levels (measured by AMR fleet size) as well as HWs' prior beliefs about congestion conditions. The optimal information accuracy is independent with a low automation level, but then increases and plateaus in the AMR fleet size when the automation level is high. This result implies a paradigm shift in the communication protocol when the automation level of the cobotic system reaches a threshold. We then focus on the adjustment of information accuracy in response to the change in HWs' prior information. In general, as HWs expect the warehouse to be more congested, information accuracy for predicting the congested/light traffic state increases/decreases, respectively. These adjustments are monotone, given the cobotic system automation is at either a low or high level, while a non-monotone adjustment occurs when the automation level is intermediate. These results provide the warehouse manager with implementable insights into algorithm design for communicating congestion information with HWs.

Our results contribute to the operations management (OM) literature in the following respects. In terms of managerial insights, we identify the optimal number of AMRs for a cobotic intralogistics system. We show that with smart navigation, fewer AMRs are required to reduce congestion, and illustrate an interesting substitution effect between automation and strategic communications under mild information distortion. Conversely, we show how a complementary effect exists when information distortion is severe. Such managerial insights guide warehouse managers in their communications with human workers, as well as in the adoption of technology like AMRs, be they sourced from a third-party logistics provider or purchased by the facility as investments.

In terms of methodological contributions, we develop a game-theoretical framework to derive optimal communication strategies and human-in-the-loop controls within the context of intralogistics automation and cobotic operations. We fully characterize a routing game under an asymmetric information environment, wherein mixed agents (both self-interested and altruistic) are controlled

by the system's endogenous information design. We identify scenarios that perfect information is suboptimal while randomization with endogenous signal precision can assist to achieve system optimality.

The remainder of the paper is organized as follows. We review several streams of the related literature in Section 2. Our model is then formulated in Section 3 with a preliminary analysis of the first-best traffic assignment and HWs' self-interested routing. Next, we introduce complete information benchmarks to study the impacts of AMR deployment on mitigating congestion in Section 4. We derive the system's optimal information design in Section 5. We discuss the theoretical implications and managerial insights of our results in Section 6. Section 7 concludes. Proofs of lemmas and propositions are provided in the Supporting Information EC.5.

2 Literature Review

This paper is related to the literature on human-machine collaboration as disruptive technologies are introduced to operations management (Choi et al. 2022). One strand of the literature focuses on improving the productivity of order picking operations (Chen et al. 2010) via warehouse design and control (De Koster et al. 2007), such as automated storage assignment (Yuan et al. 2019) and aisle configuration (Roy et al. 2015). Inspired by human-robot collaboration in warehouses, recent studies turn to examine the optimal planning and control of AMRs (Azadeh et al. 2019). In a similar cobotic order picking system to ours, Azadeh et al. (2020) show that a dynamic zoning strategy can be used to reduce operational costs, while Žulj et al. (2022) and Wang et al. (2022) derive the optimal strategy of order batching, assignment and robot scheduling. The literature also emphasizes the importance of managing human factors (De Vries et al. 2016) in cobotic operations. Pasparakis et al. (2021) examine whether the collaboration mode with workers leading robots outperforms the mode with workers following, while Sheu and Choi (2022) examine human-robot coordination with safety concerns. Shi et al. (2022) demonstrate the congestion effect in a human-robot hybrid parcel sortation system and derive the optimal adjustment of worker capacity according to the parcel flows. Our paper also considers warehouse congestion and complements these studies by examining the optimal information provision strategy in the presence of workers' self-interested behaviors.

Our study on the underlying traffic issue within an intralogistics facility contributes to the emerging research on the application of autonomous vehicles (AVs) in logistics and transportation. Our framework is closely related to Liu and Whinston (2019), who characterize the optimal information design for a route guidance system for AVs. We also study the optimal information design problem, but we divert from their work by characterizing the advantage of AVs in acquiring information and incorporating the mixed traffic flow with human workers. In a mixed autonomous traffic system, Wang et al. (2019) provide algorithms for solving the traffic assignment problem, while we focus

on traffic navigation. The recent OM literature on the optimal operation of AVs examines facility design (Mirzaeian et al. 2021, Lu et al. 2022) and the coordination mechanism to connect individual AVs (Sun and Yin 2021). From the perspective of enhancing productivity, Reed et al. (2022) demonstrate that the deployment of AVs can improve the efficiency of last-mile deliveries, while Qi et al. (2022) examine the positive impacts of shared autonomous electric vehicles on the urban energy system. In terms of the optimal size of an AV fleet in a transportation system, Baron et al. (2022) show that partial adoption of AVs maximizes social welfare. We complement these studies by demonstrating how the fleet size of AVs and information provision interact with one another to maximize the operational efficiency of a mixed autonomous system.

This paper is based on the classic routing model extensively researched in the literature. According to Wardrop's first principle, travelers choose their routes selfishly such that the cost of each chosen route equals one another (Steinberg and Zangwill 1983). The routing game has been extended to cases where the cost of road traffic depends on the load carried on the route and information heterogeneity among travelers. Following this line of research, Acemoglu et al. (2018) study the impact of information provision on system congestion, and Liu et al. (2016) show that whether more information reduces congestion depends on the network structure and the population size of informed travelers. In a state-dependent route cost setting, Wu et al. (2017) show that information heterogeneity among travelers is beneficial to reduce congestion cost, and Wu et al. (2021) demonstrate the value of information in a Bayesian routing game. Our routing model also considers state-dependent route cost but we divert from the literature by incorporating endogenous information design in the mixed autonomous paradigm with both selfish travelers (HWs) and non-selfish travelers (AMRs).

Endogenous information design in our paper is related to the literature on Bayesian persuasion (Kamenica and Gentzkow 2011). Similar to our framework, the Bayesian persuasion approach transfers a signaling rule into a distribution of posterior beliefs and maximizes the sender's expected utility under a credibility constraint. The credibility constraint simply requires that the receiver's expected posterior informed by the sender equals the prior. Gentzkow and Kamenica (2016) extend Bayesian persuasion to cases of multiple senders and broader state space, and the information design approach has been applied to various areas. Alonso and Câmara (2016) derive the optimal rule for an individual to persuade voters via information control, while Papanastasiou et al. (2018) consider information design for an online review platform by persuading self-interested consumers to take actions that maximize total consumer surplus. In a similar spirit, we apply endogenous information design to the traffic routing environment where the system persuades self-interested HWs to make route choices that are desirable for minimizing aggregate congestion costs.

3 Basic Model

3.1 Settings

Mixed autonomous paradigm. Consider an intralogistics system of a warehouse facility depicted in Figure 2, where λ_h human workers (HWs) collaborate with λ_a robots (AMRs) in order picking operations. As AMRs use the same bin and pick orders in a way similar to HWs (Blake 2021), we assume that AMRs have the same productivity as HWs such that the penetration of AMRs does not affect the total number of AMRs and HWs needed, which can be normalized to one, i.e., $\lambda_a + \lambda_h = 1$. The traffic state of the intralogistics system i is uncertain and follows a binary distribution from the set $S = \{H, L\}$. With probability θ, the traffic is heavy ($i = H$) in the warehouse due to operations like stock replenishment. Otherwise, the traffic is light ($i = L$) with probability $1 - \theta$. The warehouse management system employs an algorithm to communicate information about the traffic state to HWs via handheld devices or AMR screens. Upon receiving information, HWs make self-interested route choices, while AMRs are centrally controlled and dispatched according to system assignment. We first consider the case of in-house AMRs in which the intralogistics system provides information to HWs while centrally controlling the assignment of AMRs as depicted in Figure 3. We also consider the warehouse manager outsourcing AMRs, in which case AMRs are assigned by a third-party platform.

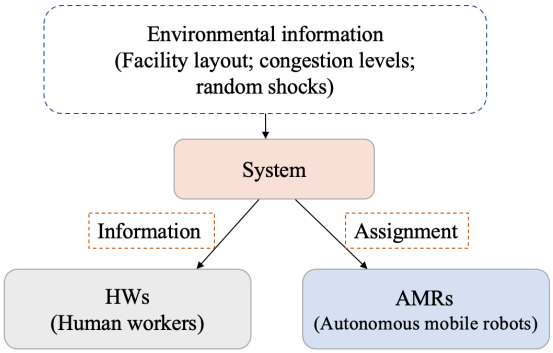


Figure 3 Information and traffic assignment structure in a cobotic system.

A routing game. There are two routes r_1 and r_2 from which HWs and AMRs can choose for their moves. As depicted in Figure 2, route r_1 represents a move that occupies the main cross aisle, while route r_2 circumvents it. Each worker receives a fixed reward V from completing a move and incurs a congestion cost that depends on the traffic load (i.e., aggregate congestion level) of the chosen route. A higher congestion cost can be regarded as longer walking time in the context of order picking operations. We abstract away from the congestion mechanism and assume that the congestion cost of each route is linear to its traffic load. More workers sharing the same route lowers

the moving speed and thus leads to a higher congestion cost. Denote the traffic load on route r_1 and r_2 by l_1 and $l_2 = 1 - l_1$, respectively. The congestion costs of the two routes are specified as follows:

$$c_1^i(l_1) = \alpha_1 l_1 + \beta^i, \text{ for } i \in \{H, L\}, \tag{1}$$

$$c_2(l_2) = \alpha_2 l_2, \tag{2}$$

where the slope coefficient α_1/α_2 measures the marginal congestion cost and the intercept β^i measures the free-flow congestion cost of route r_1, which is state-dependent. The free-flow congestion cost of route r_2 is independent of the state and normalized to zero.

ASSUMPTION 1. *$\beta^H > 0 > \beta^L$, $\alpha_2 > \beta^H$, and $\alpha_1 + \beta^L > 0$.*

We assume that the free-flow congestion cost of route r_1 is higher than that of r_2 in the "bad" state H, and the opposite is true in the "good" state L. This assumption reflects the fact that some routes in a warehouse are more prone to blocking (Halawa et al. 2020) in "bad" traffic conditions. To avoid the trivial case in which one route dominates the other, we incorporate Assumption 1 to ensure that both routes are used in either traffic state. Our linear congestion cost assumption is also common in modeling congested networks, as it is a good approximation for most nonlinear models (Steinberg and Zangwill 1983) and can be easily explained to participants (Rapoport et al. 2009). In the Supporting Information EC.2, we follow Roy et al. (2016) and provide an extension under quadratic congestion cost settings. We show that the form of congestion function does not affect how the optimal information policy is derived from the traffic equilibrium.

Smart navigation. We characterize the system's strategic communications in an endogenous information design framework. Specifically, the system communicates with HWs by designing an algorithm that predicts the traffic state i with accuracy ρ^i. For example, the system can introduce a classification algorithm to provide information about the binary traffic state, with the accuracy measured by the ratio of false positive/negative classification (i.e., Type I/II error). The algorithm sends a message to HWs announcing that "the probability of being state i is predicted as ρ^i." With this message, HWs update their posterior beliefs and make their route choices. To ensure that HWs have faith in the system's information, its algorithm design must conform to a *credibility constraint* which requires the HWs' posterior belief to be consistent with their prior on average. The credibility constraint can be written as

$$\theta\rho^H + (1-\theta)(1-\rho^L) = \theta, \tag{3}$$

where the left-hand side is the expected posterior belief for state $i = H$ and the right-hand side is the prior belief. Equation (3) also guarantees the expected posterior belief equals the prior for

state $i = L$, i.e., $\theta(1-\rho^H) + (1-\theta)\rho^L = 1-\theta$. The credibility constraint reflects the system's ability to design its algorithm to be strategically obfuscating but statistically consistent. Under this constraint, as HWs become more certain about traffic being "bad" (i.e., an increase in θ), the information accuracy for the "bad" state should be increased accordingly.

Utility functions. We introduce the micro-structures of the routing decision process by defining utility functions for the AMR fleet and HWs to measure their order picking performance. Denote $\gamma_a^i \in [0, \lambda_a]$ and $\gamma_h^i \in [0, \lambda_h]$ as the number of AMRs and HWs moving via route r_2 in state i. The aggregate traffic load on r_2 and r_1 can be derived as $l_2^i = \gamma_a^i + \gamma_h^i$ and $l_1^i = 1 - \gamma_a^i - \gamma_h^i$, respectively. Since AMRs follow system assignment explicitly, their routing decisions are decided by the system which maximizes the aggregate utility/performance of AMRs and HWs in the facility for each state i as follows:

$$U_s^i = (V - \alpha_2 l_2^i) l_2^i + [V - (\alpha_1 l_1^i + \beta^i)] l_1^i, \tag{4}$$

where $(V - \alpha_2 l_2^i) l_2^i$ is the aggregate utility of workers moving via r_2 and $[V - (\alpha_1 l_1^i + \beta^i)] l_1^i$ is the aggregate utility of workers moving via r_1. Empirical evidence has shown that individual HWs, unlike AMRs, make self-interested routing decisions in warehouse operations (Glock et al. 2017, Halawa et al. 2020). Based on the information provided by the system, each HW chooses a route with a lower expected congestion cost and obtains a utility as follows:

$$u_h^i = V - \min\{\alpha_2 l_2^i, \alpha_1 l_1^i + E\beta^i\}, \tag{5}$$

where $E\beta^i$ denotes HWs' expectation on the free-flow congestion cost in state i.

We represent the underlying transportation of an intralogistics facility in a routing model with mixed AMRs and HWs. In the Supporting Information EC.3, we extend our basic model to both a three-route network and a network with a joint edge and demonstrate that our main results remain robust, providing a foundation for our framework to be applied to more general traffic systems. For example, in a road network with a mixed traffic flow of human-driven vehicles and a fleet of autonomous taxis, human drivers make self-interested route choices while the autonomous taxi fleet makes group decisions, as they are owned and operated by a corporate entity. Our basic model provides insights to characterize how the equilibrium of traffic allocation is formed. Based on the equilibrium, a policy of optimal information provision can be designed by a benevolent information provider, such as a route guidance system, whose aim is to reduce traffic congestion.

3.2 Preliminary Analysis

We first consider a manual order picking system in which there is no automation and the system provides HWs with accurate information. We characterize the first-best traffic assignment in a

centralized intralogistics system which can control all HWs' route choices to maximize system performance. In a decentralized system where HWs make self-interested route choices, we show an efficiency loss due to HWs' selfish routing.

The "first-best". A centralized intralogistics system decides the traffic loads l_2^i and $l_1^i = 1 - l_2^i$ assigned to routes r_2 and r_1 in each state $i \in \{H, L\}$, respectively. The system's optimization problem is as follows

$$U_{FB}^i = \max_{l_2^i} V - \alpha_2 {l_2^i}^2 - [\alpha_1(1 - l_2^i) + \beta^i]\left(1 - l_2^i\right), \tag{6}$$

which results in the first-best traffic allocation with $l_{2,FB}^i \triangleq \frac{\alpha_1 + \frac{\beta^i}{2}}{\alpha_1 + \alpha_2}$ workers assigned to route r_2 and $1 - l_{2,FB}^i$ of them assigned to route r_1. Under the optimal assignment $l_{2,FB}^i$, we define the utility of the centralized system U_{FB}^i as the first-best efficiency–the highest performance a system can achieve in state i.

Selfish routing. In a decentralized system, HWs make individual choices by choosing the route with a lower cost. Their self-interested routing leads to a Wardrop equilibrium with traffic loads on the two routes l_1 and l_2 satisfying

$$c_r(l_r) \leq c_{r'}(l_{r'}) \quad \forall\ l_r, l_{r'} > 0, and\ r, r' \in \{1, 2\}. \tag{7}$$

Under Assumption 1, HWs choose both routes because neither one has a lower cost than the other when every HW uses it simultaneously. Thus, Equation (7) holds with equality, i.e., $\alpha_2 l_2^i = \alpha_1(1 - l_2^i) + \beta^i$, implying a Wardrop equilibrium characterized by $l_{2,SR}^i \triangleq \frac{\alpha_1 + \beta^i}{\alpha_1 + \alpha_2}$, the equilibrium number of HWs in transit via route r_2.

LEMMA 1. *$l_{2,SR}^H > l_{2,FB}^H$ and $l_{2,SR}^L < l_{2,FB}^L$ hold.*

Compared to the first-best traffic efficiency, Lemma 1 shows that HWs' selfish routing leads to an overcrowding problem on the route with a lower congestion cost. Specifically, in the "bad" state H, route r_1 has a higher congestion cost (i.e., $\beta^H > 0$) and HWs overcrowd route r_2 when they make self-interested route choices, i.e., $l_{2,SR}^H > l_{2,FB}^H$. Similarly, in state L, the congestion cost of r_1 is lower (i.e., $\beta^l < 0$), and HWs overcrowd r_1 with fewer workers choosing route r_2, i.e., $l_{2,SR}^L < l_{2,FB}^L$. This result indicates that a manual order picking system suffers an efficiency loss due to workers' self-interested route choices. One way to increase system performance is to replace HWs with AMRs that can also self-pick the order items, and the other tool is to implement strategic communications that navigate some HWs away from the overcrowded route. In the following analysis, we will demonstrate how these two solutions can be adopted and interact with each other to improve system performance.

Table 1 Notations.

Notation	Explanation
α_1/α_2	Coefficient of congestion cost on route r_1/r_2
β^i	State-dependent congestion cost in state i
$E\beta^i$	HWs' posterior expectation of the congestion cost in state i
λ_a/λ_h,	Number of AMRs/HWs in the system: $\lambda_a+\lambda_h=1$
γ_a^i/γ_h^i,	Number of AMRs/HWs on r_2 in state i
l_1^i/l_2^i	Traffic load on route r_1/r_2 in state i: $l_1^i+l_2^i=1$
$l_{2,FB}^i$	$l_{2,FB}^i \triangleq \frac{\alpha_1+\frac{\beta^i}{2}}{\alpha_1+\alpha_2}$, the system's first-best traffic load on r_2 in state i
$l_{2,SR}^i$	$l_{2,SR}^i \triangleq \frac{\alpha_1+\beta^i}{\alpha_1+\alpha_2}$, HWs' selfish-routing traffic load on r_2 in state i
$l_{2,ESR}^i$	$l_{2,ESR}^i \triangleq \frac{\alpha_1+E\beta^i}{\alpha_1+\alpha_2}$, HWs' selfish-routing traffic load on r_2 under expectation $E\beta^i$
$l_{2,FLT}^i$	$l_{2,FLT}^i \triangleq \frac{\alpha_1(1+\lambda_a)+\beta^i}{2(\alpha_1+\alpha_2)}$, the AMR fleet's optimal traffic load on r_2 in state i

As Equation (6) shows, traffic load l_2^i is the key variable determining the system's overall performance. When the traffic load on r_2 is $l_{2,FB}^i$, the first-best efficiency is achieved. Throughout this paper, we will focus on how the fleet size of AMRs and the system's strategic communications impact equilibrium traffic load l_2^i to show their effect on the system's overall performance. Table 1 provides the most important notations for the analysis of traffic assignment, and additional notations are given in the Supporting Information EC.6.

4 Complete Information Benchmarks

We start with a benchmark case wherein the system communicates the traffic state to HWs with accurate information. This non-strategic communication case allows us to examine the pure impact of AMRs on mitigating congestion in the cobotic intralogistics system. We characterize the equilibrium of the mixed traffic flow in separate cases, examining both in-house as well as third-party AMRs.

4.1 Benchmark 1: In-house AMR Fleet

Since the in-house AMR fleet is operated by the WMS, its goal is to maximize the overall performance of both itself and human workers. Given HWs' traffic assignment γ_h^i on route r_2, the system assigns γ_a^i AMRs to route r_2 in state i to maximize the system performance:

$$\max_{\gamma_a^i\in[0,\lambda_a]} U_s^i = [V-\alpha_2(\gamma_a^i+\gamma_h^i)](\gamma_a^i+\gamma_h^i)+[V-\alpha_1(1-\gamma_a^i-\gamma_h^i)-\beta^i](1-\gamma_a^i-\gamma_h^i), \tag{8}$$

indicating the optimal assignment of the AMR fleet to route r_2 as given by Equation (9).

$$\gamma_a^i = \begin{cases} 0, & \gamma_h^i \geq l_{2,FB}^i \\ l_{2,FB}^i-\gamma_h^i, & l_{2,FB}^i-\lambda_a \leq \gamma_h^i < l_{2,FB}^i \\ \lambda_a, & \gamma_h^i < l_{2,FB}^i-\lambda_a \end{cases}. \tag{9}$$

The system's optimal assignment of the AMR fleet is to sustain the total traffic load on r_2 at the first-best level $l^i_{2,FB}$. Specifically, given the number of HWs on route r_2 is intermediate, the number of AMRs assigned to r_2 is such that the total traffic load on r_2 reaches the first-best level. Given the HWs' traffic assignment on r_2 exceeds the first-best level, no AMR is dispatched to r_2 in order to maintain the traffic load on r_2 close to the optimum. Similarly, given the low number of HWs assigned to r_2, the entire AMR fleet is dispatched there in order to increase the traffic load.

With accurate information, HWs are informed of the traffic condition β^i in each state. Given AMRs' traffic assignment γ^i_a on route r_2, the utility of each HW in state i is as follows:

$$u^i_h = V - \min\{\alpha_2(\gamma^i_a + \gamma^i_h), \alpha_1\left(1 - \gamma^i_a - \gamma^i_h\right) + \beta^i\}. \tag{10}$$

Each HW makes a self-interested route choice, resulting in a Wardrop equilibrium wherein the chosen routes have equal congestion costs and the unchosen route has a higher cost than the chosen. Given route r_2 is crowded with AMRs (i.e., $\gamma^i_a \geq l^i_{2,SR} = \frac{\alpha_1+\beta^i}{\alpha_1+\alpha_2}$), the Wardrop equilibrium indicates that there is no HW choosing r_2. In contrast, given route r_1 is crowded with AMRs (i.e., $\gamma^i_a < l^i_{2,SR} - \lambda_h$), all HWs choose r_2. Given an intermediate γ^i_a, HWs make route choices such that the congestion costs of the two routes are equal. In Wardrop equilibrium, the number of HWs assigned to r_2 is summarized as follows:

$$\gamma^i_h = \begin{cases} 0, & \gamma^i_a \geq l^i_{2,SR} \\ l^i_{2,SR} - \gamma^i_a, & l^i_{2,SR} - \lambda_h \leq \gamma^i_a < l^i_{2,SR} \\ \lambda_h, & \gamma^i_a < l^i_{2,SR} - \lambda_h \end{cases}. \tag{11}$$

In contrast to the AMRs dispatched to sustain the first-best traffic assignment, HWs' self-interested choices in Equation (11) divert the traffic assignment on r_2 to the selfish-routing level $l^i_{2,SR}$. The equilibrium traffic assignment can be derived by the combination of AMRs' and HWs' traffic assignments in Equations (9) and (11).

PROPOSITION 1. *Denote* $l^i_{2,FB} = \frac{\alpha_1+\frac{\beta^i}{2}}{\alpha_1+\alpha_2}$ *and* $l^i_{2,SR} = \frac{\alpha_1+\beta^i}{\alpha_1+\alpha_2}$. *The equilibrium traffic assignment of HWs and in-house AMRs on* r_2 *is given by Table 2.*

Table 2 Traffic equilibrium with in-house AMRs under complete information.

State i	Condition	γ^i_a	γ^i_h	l^i_2
L	$\lambda_a \leq l^L_{2,SR}$	λ_a	$l^L_{2,SR} - \lambda_a$	$l^L_{2,SR}$
	$l^L_{2,SR} < \lambda_a \leq l^L_{2,FB}$	λ_a	0	λ_a
	$\lambda_a > l^L_{2,FB}$	$l^L_{2,FB}$	0	$l^L_{2,FB}$
H	$\lambda_a \leq 1 - l^H_{2,SR}$	0	$l^H_{2,SR}$	$l^H_{2,SR}$
	$1 - l^H_{2,SR} < \lambda_a \leq 1 - l^H_{2,FB}$	0	λ_h	λ_h
	$\lambda_a > 1 - l^H_{2,FB}$	$l^H_{2,FB} - \lambda_h$	λ_h	$l^H_{2,FB}$

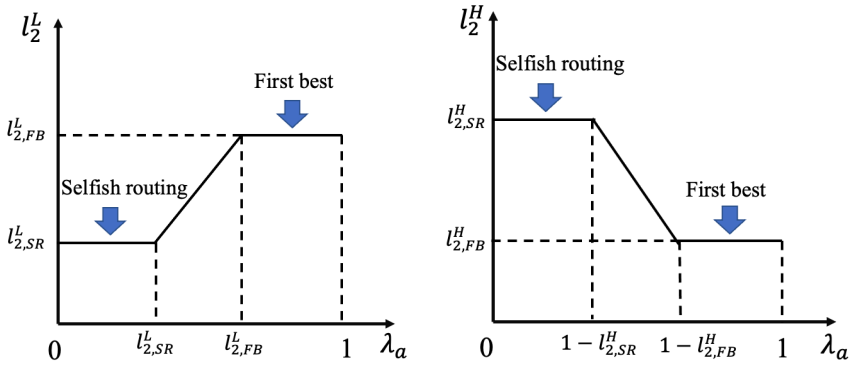
Proposition 1 indicates that in either state H or L, the equilibrium of traffic assignment depends on the number of AMRs in the cobotic system. Intuitively, when the number of AMRs is insignificant, the equilibrium outcome is dominated by HWs' selfish-routing behaviors. They overcrowd the more desirable route r_1/r_2 which has a lower congestion cost in state L/H. In contrast, when the fleet size is sufficiently large, the equilibrium can be centrally controlled by the system's assignment of AMRs such that the first-best traffic allocation is achieved. Interestingly, given an intermediate-sized AMR fleet, the entire AMR fleet is assigned to the less desirable route, allowing all HWs to use the good route. Based on the equilibrium traffic allocation, we have the following finding:

COROLLARY 1.

1. *In state L, in-house AMRs mitigate human overcrowding* r_1 *when* $\lambda_a \geq l^L_{2,SR}$*, and system optimization is achieved when* $\lambda_a \geq l^L_{2,FB}$.

2. *In state H, in-house AMRs mitigate human overcrowding* r_2 *when* $\lambda_a \geq 1 - l^H_{2,SR}$*, and system optimization is achieved when* $\lambda_a \geq 1 - l^H_{2,FB}$.

3. *The first-best traffic assignment in both states is achieved when* $\lambda_a \geq max\{l^L_{2,FB}, 1 - l^H_{2,FB}\}$.



(a) State L (b) State H

Figure 4 The equilibrium traffic assignment with in-house AMRs in states L and H.

Corollary 1 presents the impact of AMR fleet size on mitigating the overcrowding problem caused by HWs' selfish-routing behaviors. As shown in Figure 4, introducing AMRs does not mitigate the overcrowding problem unless the fleet size reaches the thresholds $l^L_{2,SR}$ and $1 - l^H_{2,SR}$ in states L and H, respectively. As the fleet size further increases, the overcrowding problem is further mitigated. When the overcrowding problem disappears, the first-best traffic assignment is achieved once fleet size reaches the thresholds $l^L_{2,FB}$ and $1 - l^H_{2,FB}$ in the two states. Thus, for the system to maximize overall efficiency in both states, it needs to purchase an amount of AMRs over the threshold $max\{l^L_{2,FB}, 1 - l^H_{2,FB}\}$. These results shed light on how many AMRs should be purchased to improve the performance of a cobotic order picking system. When automation is under-invested,

order picking efficiency cannot be improved under an insufficiently sized fleet of AMRs. Conversely, full automation may also be unnecessarily expensive since the first-best can be achieved by a moderate-sized fleet.

4.2 Benchmark 2: Third-party AMR Fleet

When AMR operations are outsourced to a third-party platform, the platform maximizes the AMR fleet's performance rather than the overall system performance. Given HWs' traffic assignment γ_h^i on route r_2, the platform dispatches γ_a^i AMRs to route r_2 to maximize fleet performance as follows:

$$\max_{\gamma_a^i \in [0,\lambda_a]} U_a^i = [V - \alpha_2(\gamma_a^i + \gamma_h^i)]\gamma_a^i + [V - \alpha_1(1 - \gamma_a^i - \gamma_h^i) - \beta^i](\lambda_a - \gamma_a^i). \tag{12}$$

The platform's optimal assignment of AMRs can be derived as follows:

$$\gamma_a^i = \begin{cases} 0, & \frac{\gamma_h^i}{2} \geq l_{2,FLT}^i \\ l_{2,FLT}^i - \frac{\gamma_h^i}{2}, & l_{2,FLT}^i - \lambda_a \leq \frac{\gamma_h^i}{2} < l_{2,FLT}^i \\ \lambda_a, & \frac{\gamma_h^i}{2} < l_{2,FLT}^i - \lambda_a \end{cases}, \tag{13}$$

where $l_{2,FLT}^i \triangleq \frac{\alpha_1(1+\lambda_a)+\beta^i}{2(\alpha_1+\alpha_2)} \leq l_{2,FB}^i$ is the third-party AMR fleet's preferred traffic load on r_2. Intuitively, given the number of HWs on route r_2 is sufficiently large/small, the third-party platform's optimal assignment is to dispatch all/no AMRs to r_2. Given an intermediate number of HWs on route r_2, the optimal assignment of third-party AMRs is such that the traffic load $\gamma_a^i + \frac{\gamma_h^i}{2}$ is constant at $l_{2,FLT}^i$. In other words, increasing one unit of HWs on route r_2 induces the third-party platform to reduce only a half unit of AMRs on the same route. As a comparison, the assignment of in-house AMRs fully internalizes human performance by decreasing the same amount to allow HWs to benefit from a lower traffic load on r_2 (i.e., $\gamma_a^i = l_{2,FB}^i - \gamma_h^i$ in Equation (9)). Therefore, without fully internalizing HW performance, the assignment of third-party AMRs is less responsive to human route choices. Together with HWs' traffic assignment in Equation (11), we can derive the equilibrium traffic assignment on r_2.

PROPOSITION 2. *Denote* $l_{2,FLT}^i = \frac{\alpha_1(1+\lambda_a)+\beta^i}{2(\alpha_1+\alpha_2)}$ *and* $l_{2,SR}^i = \frac{\alpha_1+\beta^i}{\alpha_1+\alpha_2}$. *The equilibrium traffic assignment of HWs and third-party AMRs on* r_2 *is given by Table 3.*

Table 3 Traffic equilibrium with third-party AMRs under complete information.

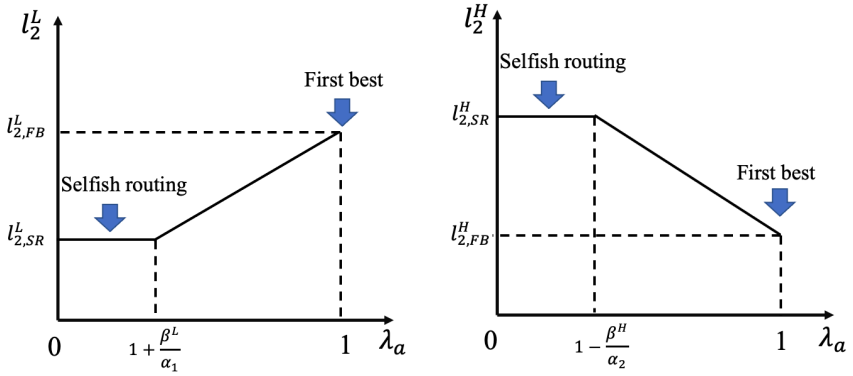
State i	Condition	γ_a^i	γ_h^i	l_2^i
L	$\lambda_a \leq 1 + \frac{\beta^L}{\alpha_1}$	$\frac{\alpha_1\lambda_a}{\alpha_1+\alpha_2}$	$\frac{\alpha_1\lambda_h+\beta^L}{\alpha_1+\alpha_2}$	$l_{2,SR}^L$
	$\lambda_a > 1 + \frac{\beta^L}{\alpha_1}$	$l_{2,FLT}^L$	0	$l_{2,FLT}^L$
H	$\lambda_a \leq 1 - \frac{\beta^H}{\alpha_2}$	$\frac{\alpha_1\lambda_a}{\alpha_1+\alpha_2}$	$\frac{\alpha_1\lambda_h+\beta^H}{\alpha_1+\alpha_2}$	$l_{2,SR}^H$
	$\lambda_a > 1 - \frac{\beta^H}{\alpha_2}$	$l_{2,FLT}^H - \frac{\lambda_h}{2}$	λ_h	$l_{2,FLT}^H + \frac{\lambda_h}{2}$

Proposition 2 shows that the equilibrium traffic assignment depends on the size of the AMR fleet. In state L/H, when the fleet size is small, HWs' selfish routing to the more desirable route r_1/r_2 dominates the equilibrium (i.e., $l_2^i = l_{2,SR}^i$). In contrast, when the fleet size is large enough, its optimal assignment dominates the equilibrium, leading to the traffic load $l_2^L = l_{2,FLT}^L$ in state L and $l_2^H = l_{2,FLT}^H + \frac{\lambda_h}{2}$ in state H. In equilibrium, the third-party platform never dispatches the entire AMR fleet to the less desirable route, resulting in a sharp contrast to Proposition 1 where the whole fleet is in fact dispatched there. In other words, a third-party fleet of AMRs will not fully concede the more desirable route to their human collaborators, such that the positive externality of AMR deployment is less salient when robotic operations are outsourced to a third-party company seeking to maximize its own profit.

Corollary 2.

1. *In state L, third-party AMRs mitigate HWs' overcrowding r_1 when $\lambda_a \geq 1 + \frac{\beta^L}{\alpha_1} > l_{2,SR}^L$, and system optimization is achieved when $\lambda_a = 1$.*

2. *In state H, third-party AMRs mitigate HWs' overcrowding r_2 when $\lambda_a \geq 1 - \frac{\beta^H}{\alpha_2} > 1 - l_{2,SR}^H$, and system optimization is achieved when $\lambda_a = 1$.*



(a) State L (b) State H

Figure 5 The equilibrium traffic assignment with third-party AMRs.

Given the size of the robotic fleet is instrumental in mitigating congestion, Corollary 2 shows that it requires at least $1 + \frac{\beta^L}{\alpha_1}$ third-party AMRs to improve the performance of cobotic operations in state L (see Figure 5). Compared to Corollary 1, where the result is $l_{2,SR}^L$ for in-house AMRs, we find that it requires more AMRs to correct human overcrowding behaviors when the fleet is operated by a third-party platform (i.e., $1 + \frac{\beta^L}{\alpha_1} > l_{2,SR}^L$). First-best system performance is also more difficult to achieve with third-party AMRs: With in-house AMRs, the first-best is achieved when $\lambda_a \geq l_{2,FB}^L$, while it requires $\lambda_a = 1$ for the third-party. These findings also hold for state H. Our

result implies that deploying in-house AMRs is more operationally efficient than using a third-party RaaS provider. There is a trade-off between the two options when we further consider their cost difference. While RaaS can save upfront costs, the third-party AMR fleet may have routing inefficiencies and require a larger fleet size to achieve optimal system performance.

So far, we have demonstrated that regardless of whether AMRs are in-house or outsourced, they can mitigate selfish routing only when the fleet size reaches a threshold. Furthermore, the first-best traffic assignment on the two routes can be achieved when there are sufficient AMRs in the cobotic system. When it comes to the impact of the ownership, we show that in-house AMRs can mitigate HWs' self-interested routing more efficiently as the entire fleet can be dispatched to the less desirable route. Nevertheless, as long as HWs have full knowledge of the congestion state, it always requires a minimum robotic fleet size to resolve the overcrowding problem. To reduce the minimum number of AMRs required, it is necessary for the system to strategically design information to navigate some HWs from the more desirable route to the less desirable one.

5 Information Design

To further improve system performance, we consider the system providing smart navigation to HWs. In this section, we model a persuasion process in which the system designs a communication rule which reveals information with imperfect accuracy but remains statistically credible. Upon receiving the information from the system, HWs update their posterior beliefs about the traffic state. In contrast, AMRs can collect accurate information from the facility as both the integration with the WMS and the application of IoT provide the robots with up-to-date access to data for orders, inventory, item locations, etc. With this in mind, we construct a heterogeneous information structure in the cobotic system, wherein HWs passively receive information sent by the system while AMRs can actively and accurately receive real-time information from the facility.

5.1 Information Design with In-house AMR Fleet

Given the system's information accuracy ρ^i for the traffic state i, HWs update the expected congestion cost to $E\beta^i = \rho^i\beta^i + (1-\rho^i)\,\beta^{-i}$ in state $i \in \{H, L\}$. Based on their belief $E\beta^i$ and given AMRs' traffic assignment γ_h^i, each HW's utility in state i is as follows:

$$u_h^i = V - \min\{\alpha_2(\gamma_a^i + \gamma_h^i), \alpha_1\left(1 - \gamma_a^i - \gamma_h^i\right) + E\beta^i\}. \tag{14}$$

Each HW makes a self-interested route choice, leading to a Wardrop equilibrium where the expected congestion costs of the chosen routes are equal, with the unchosen having a higher expected cost than the chosen one. Denote $l_{2,ESR}^i \triangleq \frac{\alpha_1 + E\beta^i}{\alpha_1+\alpha_2}$ as the traffic load on r_2 in state i resulting from HWs' selfish routing behaviors under the expectation $E\beta^i$. Given the number of AMRs assigned to r_2 or

r_1 is sufficiently large (i.e., $\gamma_a^i \geq l_{2,ESR}^i$ or $\gamma_a^i < l_{2,ESR}^i - \lambda_h$), all HWs choose the other route (i.e., $\gamma_h^i = 0$ or $\gamma_h^i = \lambda_h$). Given an intermediate number of AMRs on route r_2, the human workers choose both routes and the expected costs of the two routes are equal, i.e., $\gamma_h^i = l_{2,ESR}^i - \gamma_a^i$. Thus, the number of HWs on r_2 under Wardrop equilibrium is summarized as follows:

$$\gamma_h^i = \begin{cases} 0, & \gamma_a^i \geq l_{2,ESR}^i \\ l_{2,ESR}^i - \gamma_a^i, & l_{2,ESR}^i - \lambda_h \leq \gamma_a^i < l_{2,ESR}^i \\ \lambda_h, & \gamma_a^i < l_{2,ESR}^i - \lambda_h \end{cases}. \tag{15}$$

Given HWs' traffic assignment γ_h^i on r_2, the in-house AMR fleet's optimal traffic assignment is identical to Equation (9). Along with Equation (15), we derive the equilibrium traffic assignment of in-house AMRs and HWs on r_2 for each state i.

PROPOSITION 3. *Denote $l_{2,FB}^i = \frac{\alpha_1 + \frac{\beta^i}{2}}{\alpha_1 + \alpha_2}$ and $l_{2,ESR}^i = \frac{\alpha_1 + E\beta^i}{\alpha_1 + \alpha_2}$. The equilibrium traffic assignment of HWs and in-house AMRs on r_2 under the expectation $E\beta^i$ in state $i \in \{H, L\}$ is given by Table 4.*

Table 4 Traffic equilibrium with in-house AMRs in state i under posterior expectation $E\beta^i$.

Condition		γ_a^i	γ_h^i	l_2^i
$E\beta^i \leq \frac{\beta^i}{2}$	$\lambda_a \leq l_{2,ESR}^i$	λ_a	$l_{2,ESR}^i - \lambda_a$	$l_{2,ESR}^i$
	$l_{2,ESR}^i < \lambda_a \leq l_{2,FB}^i$	λ_a	0	λ_a
	$\lambda_a > l_{2,FB}^i$	$l_{2,FB}^i$	0	$l_{2,FB}^i$
$E\beta^i > \frac{\beta^i}{2}$	$\lambda_a \leq 1 - l_{2,ESR}^i$	0	$l_{2,ESR}^i$	$l_{2,ESR}^i$
	$1 - l_{2,ESR}^i < \lambda_a \leq 1 - l_{2,FB}^i$	0	λ_h	λ_h
	$\lambda_a > 1 - l_{2,FB}^i$	$l_{2,FB}^i - \lambda_h$	λ_h	$l_{2,FB}^i$

Denote $\underline{\lambda} = l_{2,ESR}^i$ and $\overline{\lambda} = l_{2,FB}^i$ for $E\beta^i \leq \frac{\beta^i}{2}$; $\underline{\lambda} = 1 - l_{2,ESR}^i$ and $\overline{\lambda} = 1 - l_{2,FB}^i$ for $E\beta^i > \frac{\beta^i}{2}$. The following statements hold for $\lambda_a \leq \underline{\lambda}$:

(1) Strategic communications mitigate HWs' overcrowding problem on the more desirable route, i.e., $l_{2,ESR}^L \geq l_{2,SR}^L$, and $l_{2,ESR}^H \leq l_{2,SR}^H$.

(2) If $E\beta^i \leq \frac{\beta^i}{2}$, then $l_{2,ESR}^i \leq l_{2,FB}^i$ such that HWs overcrowd r_1. If $E\beta^i > \frac{\beta^i}{2}$, then $l_{2,ESR}^i > l_{2,FB}^i$ such that HWs overcrowd r_2.

Under strategic communications, Proposition 3 shows that the equilibrium traffic assignment depends on both HWs' posterior belief $E\beta^i$ and the number of AMRs λ_a. For ease of demonstration, we focus on the traffic equilibrium in state L with a similar analysis applied to state H. We depict the space of $(E\beta^L, \lambda_a)$ in Figure 6 which is divided into four regions, representing four equilibrium outcomes. Firstly, when the automation level of the cobotic system is high (i.e., a large robotic fleet is available, corresponding to region Ω_{IV}), traffic equilibrium is dominated by the WMS's central control of the AMR fleet, such that the first-best traffic assignment $l_{2,FB}^L$ is achieved regardless

of the system's strategic communications with the human workers. This result is consistent with Corollary 1 in the case of complete information provision. Thus, in a cobotic order picking system automated by a large robotic fleet, there is no need for the warehouse manager to navigate HWs via strategic communications.

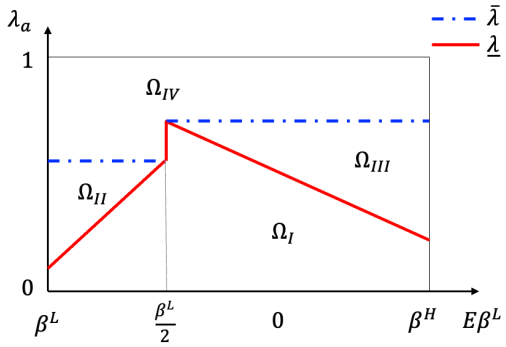
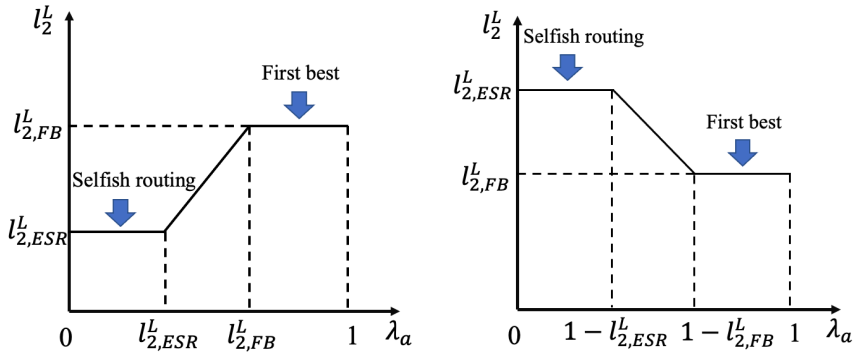


Figure 6 The interaction of in-house AMRs (λ_a) and information design ($E\beta^L$) in state L.

Secondly, when the size of the AMR fleet is insignificant to the cobotic system (i.e., region Ω_I), the equilibrium traffic assignment $l^L_{2,ESR}$ depends only on HWs' posterior expectation $E\beta^L$. Compared with the benchmark without strategic communications (see Corollary 1), the first statement in Proposition 3 indicates that strategic communications can be leveraged to resolve the overcrowding problem even without the deployment of AMRs. The reason is that strategic communications nudge workers to the less desirable route r_2 by upwardly distorting their expectations about congestion conditions (i.e., $E\beta^L \geq \beta^L$). The first-best efficiency is achieved by strategic communications only when information distortion is intermediate with $E\beta^L = \frac{\beta^L}{2}$. Otherwise, if the system provides mildly distorted information (i.e., $E\beta^L < \frac{\beta^L}{2}$), the overcrowding problem on the more desirable route r_1 is mitigated. In contrast, if the system provides information with severe distortion (i.e., $E\beta^L > \frac{\beta^L}{2}$), HWs overcrowd the less desirable route r_2. Therefore, when the cobotic order picking system contains a small AMR fleet, the information accuracy requires fine-tuning to avoid deteriorating congestion.

Finally, we analyze the interaction between strategic communications and AMR fleet size in shaping the traffic equilibrium when the automation level is intermediate, i.e., $\underline{\lambda} < \lambda_a \leq \bar{\lambda}$. If the system communicates information with mild distortion (i.e., $E\beta^L \leq \frac{\beta^L}{2}$ in region Ω_{II}), the entire AMR fleet is dispatched to the less desirable route r_2 while all HWs choose the more desirable route r_1. As λ_a increases, Figure 7(a) shows that the traffic load on route r_2 increases and approaches the first-best result, indicating that the increase in the number of AMRs substitutes for mild information distortion in mitigating congestion on the more desirable route r_1. In contrast, if the



(a) $E\beta^L \leq \frac{\beta^L}{2}$ (b) $E\beta^L > \frac{\beta^L}{2}$

Figure 7 The equilibrium traffic assignment with strategic communications and in-house AMRs.

system designs information with strongly upward distortion (i.e., region Ω_{III}), the entire fleet is sent to the more desirable route r_1 while all HWs are navigated to the less desirable r_2. In this region, the severe information distortion induces HWs to overcrowd the less desirable route r_2 while the overcrowding problem is mitigated as the number of AMRs increases (see Figure 7(b)). Thus, the increase in robotic fleet size complements severe information distortion to mitigate congestion on the less desirable route. As has been made evident, our research sheds novel light on the substitution and complementary interactions between AMR penetration and information provision in a cobotic system with an intermediate level of automation.

COROLLARY 3. *With in-house AMRs, there are four potential outcomes of traffic assignment on* r_2*:* $l_2^i \in \{l_{2,ESR}^i, l_{2,FB}^i, \lambda_a, \lambda_h\}$*, with only* $l_{2,ESR}^i$ *dependent on HWs' posterior belief* $E\beta^i$*.*

The aforementioned interactions lead to four potential equilibrium outcomes of traffic assignment as summarized in Corollary 3. The system's information design has an impact on the equilibrium outcome only when the fleet size of AMRs is small. In this case, a delicate policy design is needed to complement AMR deployment to achieve traffic efficiency. Otherwise, large fleet size is sufficient to mitigate congestion and improve traffic efficiency without information design. In the following analysis, we show how the system determines its communication policy according to the fleet size of AMRs.

Based on the equilibrium traffic assignment in both states, the system decides its information rule by solving the following optimization problem:

$$\begin{aligned} \min_{\rho^H,\rho^L} \quad & TC = \theta TC^H + (1-\theta)TC^L \\ s.t. \quad & \theta\rho^H + (1-\theta)(1-\rho^L) = \theta, \end{aligned} \tag{P-1}$$

where $TC^i = \alpha_2 {l_2^i}^2 + [\alpha_1(1-l_2^i) + \beta^i](1-l_2^i)$ is the aggregate congestion cost on the two routes in state i and l_2^i is given by Proposition 3. Governed by the equality $E\beta^i = \rho^i\beta^i + (1-\rho^i)\beta^{-i}$, there is

one-to-one mapping between (ρ^H, ρ^L) and $(E\beta^H, E\beta^L)$. The credibility constraint $\theta\rho^H + (1-\theta)\rho^L = \theta$ is equivalent to $\theta E\beta^H + (1-\theta)E\beta^L = \bar{\beta}$. Thus, both (ρ^H, ρ^L) and $(E\beta^H, E\beta^L)$ can represent the system's information policy. As the traffic equilibrium l_2^i is conditioned on $E\beta^i$, we will focus on the optimal $(E\beta^H, E\beta^L)$, then derive the corresponding result of (ρ^H, ρ^L).

LEMMA 2. *Without credibility constraint, the system's optimal information design is* $\rho^{L*} \triangleq \frac{2\beta^H - \beta^L}{2\left(\beta^H - \beta^L\right)} \in (0,1)$ *and* $\rho^{H*} \triangleq \frac{\beta^H - 2\beta^L}{2\left(\beta^H - \beta^L\right)} \in (0,1)$*, such that HWs' posterior belief is distorted to an intermediate level* $E\beta^i = \frac{\beta^i}{2}$*, and the first-best* $l_2^i = l_{2,FB}^i$ *is achieved in both states* $i = H, L$.

We first consider the case in which HWs have no prior information about the traffic state such that they accept any information provided by the system. In this case, the system can design its communication policy with arbitrary information accuracy. Lemma 2 shows that the system can achieve the first-best traffic assignment by persuading HWs with intermediate information accuracy (ρ^{H*}, ρ^{L*}) for both states. With intermediate information distortions, HWs are persuaded to be more pessimistic about the congestion cost (i.e., $E\beta^L = \frac{\beta^L}{2} > \beta^L$) in the good state L and more optimistic (i.e., $E\beta^H = \frac{\beta^H}{2} < \beta^H$) in the bad state H such that their selfish routing behaviors are systematically efficient.

LEMMA 3. *Denote* $\bar{\beta} \triangleq \theta\beta^H + (1-\theta)\beta^L$ *as the prior expectation. The unconstrained optimal information design rule* (ρ^{H*}, ρ^{L*}) *is credible, i.e.,* $\theta\rho^{H*} + (1-\theta)(1-\rho^{L*}) = \theta$ *if and only if* $\bar{\beta} = 0$.

In long-term order picking operations, HWs develop prior beliefs about congestion conditions. For example, they expect the warehouse to be more congested in peak sales seasons, and so only accept the information provided by the system if its information accuracy for the congestion state is sufficiently high. Otherwise, they find the information not credible and thus of value for their routing decision-making. Lemma 3 shows that information design with intermediate accuracy (ρ^{H*}, ρ^{L*}) is not credible unless HWs' expectation about the congestion state is neutral (i.e., $\bar{\beta} = 0$). When the congestion cost is expected to be zero, distorting the posterior belief to the same extent in each state does not alter its prior expectation. In this case, information design is powerful enough to restore traffic efficiency without the deployment of AMRs. However, whenever HWs expect that a good/bad traffic state is more likely (i.e., $\bar{\beta} \neq 0$), the unconstrained optimal information design (ρ^{H*}, ρ^{L*}) is no longer credible.

PROPOSITION 4. *Given* $\bar{\beta} \neq 0$*, there are three potentially optimal information policies that minimize the aggregate congestion cost in the optimization problem (P-1):*
Policy 1. $\rho_1^L \triangleq \rho^{L*} - \frac{\bar{\beta}}{2\left(\beta^H - \beta^L\right)}$ *and* $\rho_1^H \triangleq \rho^{H*} + \frac{\bar{\beta}}{2\left(\beta^H - \beta^L\right)}$ *such that* $E\beta^L = \frac{\beta^L + \bar{\beta}}{2}$ *and* $E\beta^H = \frac{\beta^H + \bar{\beta}}{2}$.
Policy 2. $\rho_2^L \triangleq \rho^{L*} - \frac{\bar{\beta}}{2(1-\theta)(\beta^H - \beta^L)}$ *and* $\rho_2^H \triangleq \rho^{H*}$ *such that* $E\beta^L = \frac{\beta^L}{2} + \frac{\bar{\beta}}{2(1-\theta)}$ *and* $E\beta^H = \frac{\beta^H}{2}$.
Policy 3. $\rho_3^L \triangleq \rho^{L*}$ *and* $\rho_3^H \triangleq \rho^{H*} + \frac{\bar{\beta}}{2\theta\left(\beta^H - \beta^L\right)}$ *such that* $E\beta^L = \frac{\beta^L}{2}$ *and* $E\beta^H = \frac{\beta^H}{2} + \frac{\bar{\beta}}{2\theta}$.

When information design with intermediate distortion is unfeasible in both states, Proposition 4 shows that there are three ways that the system can adjust the unconstrained optimal rule to minimize the aggregate congestion cost while satisfying the credibility constraint. As HWs expect a bad/good traffic state to be more likely, the credibility constraint implies that the system has to (1) increase information accuracy for the more likely state and/or (2) decrease information accuracy for the less likely state. Policy 1 simultaneously adjusts information accuracy for both states, implying mild information distortion in the more likely state and severe distortion in the less likely one. Policy 2/3, on the other hand, adjusts information accuracy for only one state L/H while maintaining intermediate information distortion to achieve the first-best efficiency in the other state. As none of these three policies can be leveraged to achieve the first-best performance in both states, the warehouse manager of a cobotic system cannot fully eliminate workers' overcrowding behaviors solely through strategic communications.

PROPOSITION 5. *Under the credibility constraint, the system's optimal information design with in-house AMRs is given by Table 5. With information accuracy ρ^{L*} and ρ^{H*}, the first-best efficiency is achieved in states L and H. The cutoff λ_1 is implied by $TC_2(\lambda_1) = TC_1$, and λ_2 is implied by $TC_3(\lambda_2) = TC_1$, where TC_1, TC_2, and TC_3 are presented in the proof.*

Table 5 Optimal information design policy with in-house AMRs.

Condition		Information accuracy
Optimistic prior: $\frac{\theta}{1-\theta} \leq \frac{-\beta^L}{\beta^H}$	$\lambda_a \leq \lambda_1$	Policy 1: (ρ_1^L, ρ_1^H)
	$\lambda_a > \lambda_1$	Policy 2: (ρ_2^L, ρ^{H*})
Pessimistic prior: $\frac{\theta}{1-\theta} > \frac{-\beta^L}{\beta^H}$	$\lambda_a \leq \lambda_2$	Policy 1: (ρ_1^L, ρ_1^H)
	$\lambda_a > \lambda_2$	Policy 3: (ρ^{L*}, ρ_3^H)

Proposition 5 identifies which information policy the system should implement according to the number of in-house AMRs and the prior belief θ. When the fleet size is insignificant in the cobotic system, only strategic communications can be used to alter HWs' route choices. Information distortion is needed in both states to mitigate HWs' overcrowding behaviors, and thus the optimal policy is to simultaneously adjust information accuracy for both states (Policy 1). When the fleet size is relatively large, AMR deployment substitutes for strategic communications to mitigate the overcrowding problem, and thus only mild information distortion is needed to achieve the first-best efficiency in at least one state. Specifically, when HWs are relatively certain of a good traffic state (optimistic prior), Policy 2 provides mild information distortion (i.e., $\rho_2^L > \rho^{L*}$) for state L, while restoring efficiency in state H. Similarly, Policy 3 with mild information distortion for state H is optimal given a pessimistic prior. Therefore, with sufficient in-house AMRs, mild information distortion with relatively higher accuracy is needed in strategic communications.

Corollary 4.

1. *Given $\bar{\beta} < 0$, for $\lambda_a \geq l^L_{2,FB}$, the system can achieve the first-best in both states by information design Policy 2.*

2. *Given $\bar{\beta} > 0$, for $\lambda_a \geq 1 - l^H_{2,FB}$, the system can achieve the first-best in both states by information design Policy 3.*

We have demonstrated that as the number of AMRs exceeds a certain threshold, strategic communications can be leveraged to achieve the first-best efficiency in one state. Corollary 4 further shows that the system can achieve the first-best in both states as the fleet size reaches a sufficiently high level. When there is no strategic communication, Corollary 1 shows that it requires $\lambda_a \geq max\{l^L_{2,FB}, 1 - l^H_{2,FB}\}$ to achieve the first-best efficiency in both states. With strategic communication, the number is decreased to $l^L_{2,FB}$ or $1 - l^H_{2,FB}$ depending on the prior expectation about the warehouse congestion state. In other words, strategic communications can be leveraged to strengthen limited AMR deployment to save on capital investments, decreasing the purchasing number of AMRs to attain optimal performance of the cobotic system.

5.2 Information Design with Third-party AMRs

We further analyze the system's optimal strategic communications with HWs in a cobotic system with AMR operations delegated to a third-party platform. As the AMR fleet is informed of the traffic conditions in the warehouse, its optimal traffic assignment is given by Equation (13). Provided the system's information provision such that HWs' posterior expectations about the congestion cost is $E\beta^i$ in state i, their optimal traffic assignment is given by Equation (15). The interaction between the AMR fleet and its human collaborators results in the warehouse's equilibrium traffic assignment. We have transferred the analysis of traffic equilibrium to the Supporting Information EC.1, and focus on the system's optimal information design in this section.

Based on the traffic equilibrium in each state, the system's goal is to minimize the expected aggregate congestion costs in both states, as shown in optimization problem (P-1). We show in the Supporting Information EC.1 that Policies 1, 2, and 3 characterized in Proposition 4 are also the potential policies for the system to minimize the congestion cost with third-party AMRs. This result indicates that no matter whether AMRs are in-house or outsourced from a third party, the optimal information policies from which the system can choose are the same.

Proposition 6. *Under the credibility constraint, the system's optimal information design with third-party AMRs is given by Table 6. The cutoffs $(\lambda_3, \lambda_4, \lambda_5, \lambda_6)$ are implied by $TC'_2(\lambda_3) = TC_1$, $TC'_3(\lambda_4) = TC_1$, $TC''_2(\lambda_5) = TC_1$, and $TC''_3(\lambda_6) = TC_1$, respectively, where $TC'_2(\lambda_a)$, $TC'_3(\lambda_a)$, $TC''_2(\lambda_a)$, and $TC''_3(\lambda_a)$ are presented in the proof.*

Table 6 Optimal information design policy with third-party AMRs.

Condition		Information accuracy
Extremely optimistic: $\frac{\theta}{1-\theta} < \frac{-\beta^L}{2(\beta^H-\beta^L)}$	$\lambda_a \le \lambda_3$	Policy 1: (ρ_1^L, ρ_1^H)
	$\lambda_a > \lambda_3$	Policy 2: (ρ_2^L, ρ^{H*})
Mildly optimistic: $\frac{-\beta^L}{2(\beta^H-\beta^L)} \le \frac{\theta}{1-\theta} < 1$	$\lambda_a \le \lambda_4$	Policy 1: (ρ_1^L, ρ_1^H)
	$\lambda_a > \lambda_4$	Policy 3:(ρ^{L*}, ρ_3^H)
Mildly pessimistic: $1 \le \frac{\theta}{1-\theta} < \frac{2(\beta^H-\beta^L)}{\beta^H}$	$\lambda_a \le \lambda_5$	Policy 1: (ρ_1^L, ρ_1^H)
	$\lambda_a > \lambda_5$	Policy 2: (ρ_2^L, ρ^{H*})
Extremely pessimistic: $\frac{\theta}{1-\theta} \ge \frac{2(\beta^H-\beta^L)}{\beta^H}$	$\lambda_a \le \lambda_6$	Policy 1: (ρ_1^L, ρ_1^H)
	$\lambda_a > \lambda_6$	Policy 3: (ρ^{L*}, ρ_3^H)

The main results in Proposition 6 echo our findings in Proposition 5. By adjusting information accuracy simultaneously over both traffic states, Policy 1 is optimal when the size of the robotic fleet is insignificant. Similar to in-house AMRs, a large fleet of third-party AMRs substitute with strategic communications to mitigate congestion and achieve the first-best in at least one state. The difference with a third-party AMR fleet is that it is not as efficient as the in-house one in mitigating the overcrowding problem (as fewer third-party AMRs concede the good route to HWs). As a result, when the prior belief is relatively neutral (i.e., mildly optimistic/pessimistic), the system relies on strategic communications with severe information distortion (i.e., Policy 3/2) to achieve the first-best efficiency. In contrast, in-house AMRs are efficient in resolving the overcrowding problem such that the system can implement mild information distortion only. That is, when deploying third-party AMRs, severe information distortion with lower information accuracy is used to minimize congestion due to a weak substitution effect. When HWs are relatively certain about the traffic state (i.e., extremely optimistic/pessimistic prior), severe distortion is no longer feasible due to the credibility constraint such that the choice of mild information distortion (i.e., Policy 2/3) coincides with the case of in-house AMRs.

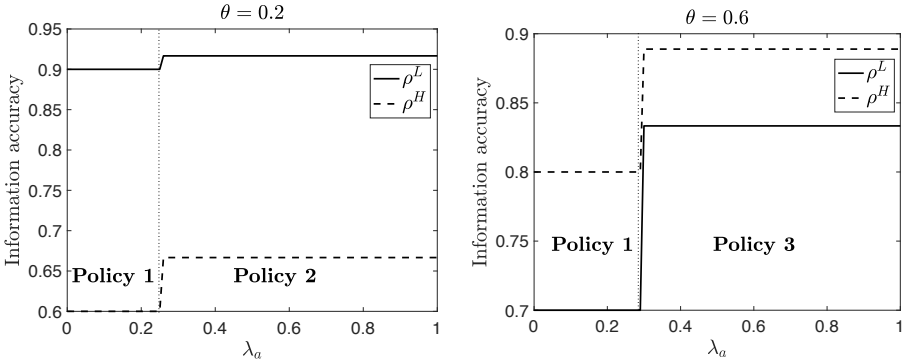
Corollary 5. *With third-party AMRs, the system cannot achieve the first-best efficiency in both states by information design for* $\lambda_a < 1$.

Corollary 5 shows that the cobotic system with third-party AMRs cannot achieve the first-best efficiency in both states as long as $\lambda_a < 1$. The intuition here is that as long as the cobotic system is not entirely operated by third-party AMRs, the AMR fleet's objective is not completely aligned with the system. The comparison to Corollary 4 shows that it requires a smaller AMR fleet to achieve the first-best traffic assignment if it is in-house. For the same reason, information design does not reduce the minimum number of third-party AMRs necessary to fully restore the first-best traffic assignment. So far, we have identified the optimal number of AMRs in the cobotic system, which in practice may also depend on the throughput requirements of the warehouse. In our model,

throughput requirements are assumed to be fulfilled by a unit mass of workers (including both robotic and human workers). When throughput requirements increase such that the total number of workers also increases, the systemwide congestion cost grows quadratically, deteriorating the overcrowding problem in the cobotic system. Consequently, if the total number of workers doubles due to the increase in throughput requirements, the optimal fleet size of AMRs should more than double for an in-house cobotic system. However, the change in throughput requirements does not alter the result that full automation is needed for third-party AMRs to achieve system optimization.

5.3 Simulated Numerical Examples

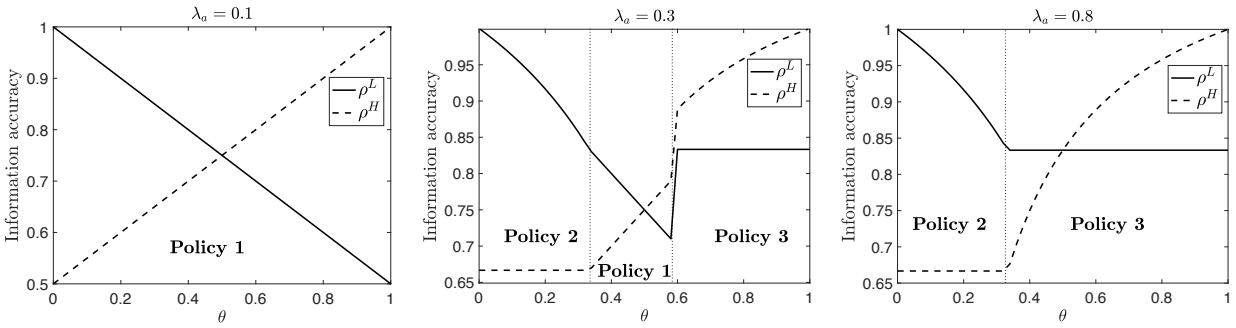
With the aim of providing implementable managerial insights for cobotic order picking in e-commerce, we simulate numerical examples to illustrate how the system implements the optimal communication policies by fine-tuning an algorithm for traffic predictions. The information accuracy ρ^H/ρ^L corresponds to the complementary probability of a false positive/negative prediction (i.e., Type I/II error) in a classification algorithm. In the simulations, we vary the number of AMRs to reflect the automation level in the cobotic system. We also vary the HWs' prior beliefs to reflect their dynamic assessment of warehouse congestion conditions. For ease of demonstration, we focus on the case of in-house AMRs, and the simulation results for third-party AMRs are provided in the Supporting Information EC.1.



Note: Exogenous parameters include $\beta^L = -1$, $\beta^H = 2$, $\alpha_1 = 2$, and $\alpha_2 = 3$.

Figure 8 Adjustment of information accuracy to the fleet size of in-house AMRs.

We first show the adjustment of information accuracy in response to the number of in-house AMRs deployed in the cobotic system. As shown in Figure 8, the system should maintain relatively low information accuracy when the fleet size is small. When the automation level is high enough, the system can increase information accuracy as the overcrowding problem is partially mitigated by replacing HWs with AMRs. This adjustment pattern is robust over HWs' prior beliefs on



Note: Exogenous parameters include $\beta^L = -1$, $\beta^H = 2$, $\alpha_1 = 2$, and $\alpha_2 = 3$.

Figure 9 Adjustment of information accuracy to the prior belief.

the congestion condition. In the case of third-party AMRs, the adjustment with a decrease in information accuracy can be seen as predicted by Proposition 6.

Secondly, we show in Figure 9 how the system adjusts its information accuracy according to HWs' prior beliefs (θ). In general, as the traffic condition in the warehouse is expected to be more congested (i.e., an increase in θ), such as in peak seasons, information accuracy for predicting the congested traffic state (ρ^H) increases while the accuracy for predicting the light traffic state (ρ^L) decreases. The diverging trends in accuracy are monotone when the automation level of the cobotic system is low. When the automation level is high, the accuracy ρ^H plateaus when the prior belief is relatively optimistic, while ρ^L plateaus when the prior is pessimistic. Interestingly, given an intermediate automation level, the information accuracy ρ^L first decreases then increases and plateaus. The non-monotone change is because when the congestion state is relatively certain (i.e., a high θ), the system becomes sure that the deployment of AMRs can mitigate HWs' overcrowding behaviors, and thus only mild information distortion is needed (i.e., an increase in information accuracy). This non-monotone pattern also occurs in the case of third-party AMRs.

6 Discussion

This paper addresses the value of strategic communications in a cobotic intralogistics system. On the theoretical front, we develop a game-theoretical framework to derive optimal communication strategies and human-in-the-loop controls within the context of emerging OM literature on intralogistics automation and cobotic operations. Our results also provide actionable managerial insights for warehouse managers to coordinate human-robot collaboration.

6.1 Theoretical Implications

We extend the ongoing research on robotized and automated warehouse systems (Azadeh et al. 2019). There are extensive studies on automated storage and retrieval systems (AS/RS) (Roodbergen and Vis 2009, Roy et al. 2015) and autonomous guided vehicle (AGVs) (Žulj et al. 2022)

as they have been widely used in practice. The emerging application of AMRs to warehouse operations represents a new generation of warehouse automation. Different from AGVs that require dedicated pathways, AMRs can cooperate with human workers in the same workspace. While there is emerging research on cobotic operations, e.g., Fragapane et al. (2022), Pasparakis et al. (2021) and Azadeh et al. (2020), they typically emphasize the control and planning of AMRs. We highlight a conceptual framework for the strategic level decisions in the context of human-robot interactions, including the fleet size of AMRs deployment and smart navigation for workers. We fully characterize a routing game under an asymmetric information environment, wherein mixed agents (both self-interested and altruistic) are controlled by the system's endogenous information design. We identify scenarios that perfect information is suboptimal while randomization with endogenous signal precision can assist to achieve system optimality. Under such a theoretical framework, our result implies that AMRs cannot improve system efficiency unless the automation level is sufficiently high. We further discuss the impacts of the ownership of AMR operations and the warehouse manager's communication strategy with workers on the optimal deployment of AMRs. Our proposed theoretical foundation is a first step in understanding the strategic interactions in human-robot collaborative operations.

These insights are novel to the literature, narrowing the gap between theoretical research and the practice of cobotic operations. Our focus on mitigating workers' overcrowding behaviors is related to studies on the design of incentive schemes to motivate workers and enhance productivity. De Vries et al. (2016) show that a competition-based incentive scheme increases the productivity of parallel picking while a cooperation-based scheme should be used in a zone picking method. Similar to our information tool, Zhang et al. (2022) study the impact of information feedback to workers on the speed and quality of order picking, while we focus on the role of information in coordinating cobotic operations. Our endogenous information design approach is also related to the rising debate on the impact of information provision on system congestion. Exogenously given an asymmetric information structure, Wu et al. (2021) and Acemoglu et al. (2018) demonstrate that more accurate information can be harmful to system performance due to the congestion effect. In contrast, our paper allows the system to endogenously design the information structure and explicitly formulates the system's design of information accuracy to mitigate congestion.

6.2 Managerial Insights

We briefly highlight managerial insights for warehouse managers concerning AMRs deployment and communication strategies in intralogistics operations. To overcome the financial hurdle in AMRs adoption, we advise a moderate-sized fleet of in-house AMRs. Such gradualism in order picking automation implies a more cautious view of technology evolution towards autonomous driving

and smart navigation. Furthermore, when the warehouse manager subscribes to RaaS from 3PL providers, our results imply a trade-off between capital investment and operational efficiency in the paradigm shift towards RaaS integration with 3PL.

Our results also suggest that subtle information policy design is needed to complement warehouse automation. The optimal communication policies are implementable by fine-tuning the prediction accuracy of a machine learning algorithm. As e-commerce platforms, such as Amazon and JD.com, are embracing advanced data analytics technologies in warehouse management, our strategic communications shed light on how warehouse managers can use algorithm design to provide smart navigation to workers. We show that the information accuracy of an algorithm should be fine-tuned according to the automation level of the cobotic system as well as warehouse conditions. With carefully designed information accuracy, strategic communications can be leveraged to improve human-robot coordination under a limited deployment of AMRs.

7 Conclusion

In this paper, we model a cobotic intralogistics system wherein uninformed HWs self-select their routing decisions while interacting with a fleet of informed AMRs. We address the system's information design problem to reduce congestion and restore economic efficiency in the context of a stylized routing game, synergizing warehouse automation with information provision. Our study has limitations as our analysis is based on the assumption that AMRs are fully informed of the congestion state regardless of their ownership. The third-party AMR fleet's access to warehouse information can be controlled by the facility operator. In the Supporting Information EC.4, we provide an extension with information design targeted for third-party AMRs and show that the insight about the three optimal policies remains unchanged. It would be an interesting research direction to further explore the economic benefit for a warehouse facility to strategically share information with the third-party AMR fleet. Based on a stylized model with two routes, this paper reveals some basic principles of how information design cooperates with the deployment of AMRs to improve warehouse operations. Future research is needed to study the interaction between warehouse automation and information provision in a general network setting.

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