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Matching daily home health-care demands with supply in service-sharing platforms

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A R T I C L E I N F O

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A B S T R A C T

The availability of innovative technologies (e.g., the Internet of Things, big data analytics, blockchain, the cloud, and applications) has led to a shift in the provision of home health-care (HHC) services from traditional institutions to service-sharing platforms. In the HHC context, one main challenge faced by service-sharing platforms is the matching of demand with supply, while considering the heterogeneity of care requests and service providers. From a centralized perspective of service-sharing platforms regarding three stakeholders (i.e., platform, caregiver, and customer), different matching strategies are used, including the “self-interested”, “customer-first”, “hard-work-happy-life”, and “social-welfare” strategies. When addressing the matching problem at an operational level, the platforms must comply with various requirements and rules, including break requirements, temporal dependencies, and flexible service durations. In this study, mixed-integer linear programming models and a branch-and-price approach are designed to match demand with supply using different matching strategies while satisfying all of the requirements and rules. The effects of key factors on performance indicators (e.g., platform revenue, caregiver profit, and customer surplus) are examined, and the matching strategies are compared. The results indicate that the “customer-first” and “self-interested” strategies benefit more from flexible service durations, however they are more and less negatively affected by break requirements and temporal dependencies, respectively, as compared to the “social-welfare” and “hard-work-happy-life” strategies. A comparison between the “social-welfare” strategy and the other three strategies indicates that the former strategy is beneficial for all three stakeholders of the service-sharing platforms as well as the government. Another comparison between the service-sharing platforms and traditional HHC institutions indicates the sharing economy has a positive impact on caregiver profit and customer surplus.

1. Introduction

The coronavirus disease 2019 (COVID-19) outbreak (CVO) has severely affected many long-term care facilities. For example, 167 confirmed COVID-19 cases have been epidemiologically linked to a skilled nursing facility in King County, Washington in the United States of America (US), which reported a resident case-fatality rate of 33.7% (McMichael et al., 2020). In disaster scenarios such as the CVO, innovative “bring-service-near-your-home” mobile service operations can provide help and enable such service providers to

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survive (Choi, 2020). Home health-care (HHC) is a type of mobile service operation that provides healthcare services to elderly people in home settings. HHC is becoming an indispensable and integral part of healthcare systems because of the availability of technology-based health-care products for home-centered disease management, such as smart homes and home health-monitoring technologies (Liu et al., 2016). HHC offers various short- or long-term services intended to meet the health- or personal-care needs of elderly individuals, such as medical and paramedical services, rehabilitation services, social services, psychological support, and other personal-care services. These services enable the elderly to live as independently and safely as possible when they can no longer perform daily activities by themselves. However, the provision of HHC services requires large amounts of resources.

To enable HHC service delivery, traditional institutions must guarantee a certain level of service at a low cost, caregivers require a fair workload assignment, and the elderly demand high-quality care (Carello et al., 2018). The daily delivery procedure must satisfy all operational rules and requirements. Caregivers can reduce transit time by traveling directly between their homes and the locations of their activities, and can be assigned to perform tasks within their available time windows. However, although a break requirement is common in real-life care applications, it is difficult to formulate and address this requirement in models and algorithms (Liu et al., 2017). Each task is performed once or cancelled. Tasks are allocated based on firm time windows, service-duration ranges, caregiver preferences, and qualification requirements. A flexible service duration enables tasks to be completed more quickly and, ultimately, more tasks to be scheduled (Mosquera et al., 2019). However, this attribute also increases the level of difficulty when attempting to address it in an exact algorithm. Furthermore, temporal dependency among tasks occurs in real-life applications of HHC delivery procedures, and must be considered when designing models and algorithms (Rasmussen et al., 2012). To meet increasing HHC demands, particularly in the context of fewer available resources, daily operational delivery activities in traditional HHC institutions are typically optimized with three main objectives, namely the minimization of travel-related costs (Liu et al., 2017), a guaranteed workload balance for caregivers (Cappanera and Scutellà, 2015), and the maximization of customer satisfaction in terms of their preferences (Braekers et al., 2016).

The availability of innovative technologies has enabled a shift in HHC provision from traditional institutions to service-sharing platforms. Value is derived from the fact that many resources are acquired to satisfy the HHC demand but are otherwise poorly utilized due to factors such as high risks, low trust levels, and difficulty with access. Thus, service-sharing enable the use of these resources by the application of exciting new technologies such as blockchain (Sun et al., 2016) and applications (apps). Blockchain has been shown to provide useful support for various platform operations, as exemplified by Everledger, Tripago, Fmeimei, and Walmart-IBM blockchains (Choi et al., 2020). Apps take the form of innovative technologies, including Internet of Things, big data analytics, blockchain, and the cloud, and enable single click mobile device-based access to sharing services. App-based service-sharing platforms cover various sectors that support the delivery of HHC services to the elderly. For example, time banks provide escort services, holiday celebration services, and psychological support (Nansha Timebank in Guangzhou, China), Amazon Home Services and TaskRabbit provide home-care and personal-care services, and Meituan and Ele.me provide meal services and Homeincare and AliHealth provide medical and rehabilitation services.

Although the form of service organization is shifting from traditional HHC institutions to service-sharing platforms, the ability to match demand with supply remains a key problem in the HHC service-delivery process. Different service-sharing platforms may have different aims, and thus use different matching strategies. Here, four matching strategies that are defined according to the aims of three stakeholders and used in practice are summarized: the "self-interested", "customer-first", "hard-work-happy-life", and "social-welfare" strategies. For example, time banks often aim to maximize either the proportion of matched tasks or social welfare. The former aim can be described as a "self-interested" strategy, while the latter can be described as a "social-welfare" strategy. Many time banks are non-profit platforms that target socially and economically marginalized populations, such as the young, elderly, poor, or disabled. Caregivers associated with these time banks are often volunteers, who receive rewards for their efforts. For-profit platforms may use matching procedures that can maximize the number of matched demands (i.e., a "self-interested" strategy), social welfare (i.e., a "social-welfare" strategy), the preferences of consumers (i.e., a "customer-first" strategy), or the profit of caregivers (i.e., a "hard-work-happy-life" strategy). For example, a for-profit platform such as TaskRabbit offers customers two options to hire a service provider on a future date, based on two typical matching models: the distribution-matching model and the assignment-matching model (Li et al., 2020). In the distribution-matching model, the service platform distributes the demand requests to all service providers, who then decide whether to respond to the request. This type of platform cannot guarantee matching efficiency in terms of platform revenue, service-provider profit, or customer surplus (Li et al., 2020). Therefore, this study focuses on the assignment-matching model, in which the service platform matches the demand requests with service providers based on certain objectives related to revenue and service quality. This study focuses specifically on platforms that assign tasks to caregivers using well-designed matching criteria.

An exchange of services between peers involves an intangible encounter between a peer provider and at least one peer consumer. Consequently, there is a requirement to meet in time and place, which implies that temporal and spatial aspects are key factors in service-sharing platforms. Despite increasing media attention, care-service sharing through peer-to-peer platforms is not yet a widespread practice. A key reason for this is that the matching and coordination of peer providers and consumers is challenging due to the heterogeneity of service requests and service providers. Therefore, it is important for peer-to-peer care-service sharing platforms to develop matching strategies that enable efficient management. This need raises several questions. First, how do the matching strategies affect performance indicators such as the platform revenue, customer surplus, and caregiver profit when addressing daily care demands and supply in the HHC context? Second, can peer-to-peer service-sharing platforms outperform traditional HHC institutions in terms of these three performance indicators? Third, how do operational rules such as flexible service durations, break requirements, and temporal dependencies among tasks affect these three performance indicators, when using different matching strategies? To answer these questions, models with different matching strategies have been developed to match the daily demands with supplies, and have been validated using instances provided online. The effects of various key factors have also been examined.

The first contribution of this study relates to practice. To the best of our knowledge, this study is the first to design and compare matching strategies at an operational level from the centralized perspective of service-sharing platforms. Four matching strategies inspired by practice, namely the "self-interested", "customer-first", "hard-work-happy-life", and "social-welfare" strategies, are designed with different aims regarding the maximization of platform revenue, customer surplus, caregiver profit, or all three of these indicators. A comparison of the four matching strategies concludes that the "social-welfare" strategy is beneficial for all three stakeholders involved in the service-sharing platform and for the government. This strategy can maximize social welfare by sacrificing some of the profit of each stakeholder, and these sacrifices can be recompensed by subsidies from the government via tax decreases or other benefits (e.g., coupons). Additionally, a comparison between service-sharing platforms and traditional HHC institutions demonstrates the positive effect of sharing economy on indicators.

The second contribution to the literature is derived from the novel models and approach used in this study. To the best of our knowledge, this is the first paper in this field to simultaneously address attributes such as flexible service durations, break requirements, and temporal dependencies. These three important attributes are common in the context of HHC but are not considered simultaneously in the literature, due to the difficulty and complexity of modeling and designing algorithms. This study proposes the use of multi-objective mixed-integer linear programming models to formulate matching strategies that maximize the profits of the three stakeholders, while also considering factors such as time windows, flexible service durations, temporal dependencies, break requirements, qualifications, and preferences. A branch-and-price (B&P) approach is additionally designed to address these attributes. In the pulse algorithm for sub-pricing problem with break requirements and flexible service durations, pulses are derived with consideration of break activity and flexible service duration, rollback with break rules, and the dominance rules of partial paths. Three branching strategies, namely branching on the time window, on uncovered tasks, and on assignment variables, are developed to ensure the constraints of temporal dependency and integrity of solutions are met. The effects of these key factors on the above-identified performance indicators (i.e., platform revenue, caregiver profit, and customer surplus) are also examined when using different matching strategies. The results indicate that the "customer-first" and "self-interested" strategies benefit more from flexible service durations, however they are more and less negatively affected by break requirements and temporal dependencies, respectively, as compared to the "social-welfare" and "hard-work-happy-life" strategies.

The remainder of the paper is organized as follows. A literature review on the daily matching problem faced by service-sharing platforms in the HHC context is presented in Section 2. The models with different strategies are proposed and analyzed in Section 3. The design of the B&P method to address the problem is described in Section 4. The effects of key factors and matching strategies on performance are further assessed in Section 5. Finally, conclusions are given and possible future avenues of research are discussed in Section 6.

2. Literature review

Appropriate, high-quality HHC services are provided by service-sharing platforms to satisfy the health and social needs of the elderly. The daily matching of demand and supply in the HHC context is a variant of the HHC routing and scheduling problem (HHCRSP) described in the literature. This work is closely related to two streams of research. The first stream involves the emerging research on service-sharing platforms, and the second stream is relevant to studies of HHCRSP.

2.1. Service-Sharing platforms

This work is closely related to the new environment of the peer-to-peer service-sharing economy (Wirtz et al., 2019). The exchange of services is one of four broad categories used to classify activities in a sharing economy (Schor, 2016). This category differs from file sharing, trading, and goods sharing in two main respects: the object of sharing and physical coordination, wherein the peer provider and peer consumer collaborate simultaneously at the same place to produce a mutually beneficial intangible encounter (Andersson et al., 2013).

Several platform types are used in the service-sharing economy (see Table 1), as described and inspired by Taylor (2018). Non-profit service-sharing is rooted in time banks, which allow users to provide and request services in exchange for time currency. Time banking highlights the principle of equal contribution, wherein both high-skill and low-skill offerings by providers are treated equally, using time spent as the benchmark (Collom and Lasker, 2016). This principle differs from that used by for-profit service-sharing platforms. The categories of services that are most frequently exchanged in time banks in the US are "construction, installation, maintenance, and repair", "transportation and moving", "tutoring, consultation, and personal services", and "cleaning, light tasks, and errands" (Collom and Lasker, 2016). Thus, time banks provide many types of services to participants and require service providers with

Table 1
Service-sharing platforms.

Platform type	Market orientation	Price-setting party	Nature of offering	
			Differentiation	Timing
Time bank	Non-profit	Platform	Agent specific	Scheduled
On-demand service	For-profit	Platform	Undifferentiated	On-demand
Freelancing	For-profit	Skilled agent	Agent specific	On-demand
Scheduled service	For-profit	Skilled agent	Agent specific	Scheduled

different skills.

Monetized service-sharing platforms, such as on-demand service platforms, freelancing platforms, and scheduled service platforms, are exemplified by TaskRabbit, Upwork, and Zaarly. These on-demand service platforms differ from scheduled service platforms in several respects. Particularly, their offering to delay-sensitive customers exhibits homogeneity, and the platforms determine prices based on different concerns. Taylor (2018) examines the effects of two defining features of an on-demand service platform—delay sensitivity and agent independence—on the platform's optimal per-service price and wage. Choi et al. (2020) focus on uncovering the effects of risk attitudes of customers on the optimal service-pricing decisions, consumer surplus, and expected profits and profit risks of the platform. Liu et al. (2019) analyze the effects of the threshold participating quantity, value-added-service, and matching ability of the provider on the pricing decisions of service platforms. All of these researchers ignore how the platform determines the matching ability and the related mechanisms.

Boysen et al. (2019) use a classification scheme to describe any matching problem in service-sharing platforms by summarizing the heterogeneity of supply and demand with many attributes, such as resource type, preference, and individual sharing duration. When heterogeneity is considered, a key role of a platform such as a time bank, freelancing platform (Moreno and Terwiesch, 2014), or scheduled-service platform is to adequately match customers with service providers, in terms of the customer's needs and the service providers' capabilities. In the literature, matching-mechanism design is mostly strategic and is described at a tactical level. A distinct set of demand or supply characteristics is integrated as a "type", which can be differentiated horizontally or vertically (Hu and Zhou, 2018). The matching rewards differ according to this differentiation. For example, under horizontal differentiation, the matching reward between a demand type and a supply type is determined by their idiosyncratic "taste" for each other. Under vertical differentiation, a particular type (e.g., a high-quality provider) is always considered superior to a different type (e.g., a low-quality provider) when generating matching rewards (Tunc et al., 2019). Three degrees of platform involvement, namely no-intervention, operational efficiency, and enabling communication, have been distinguished and characterized using various game-theoretic queuing models based on a service marketplace where the objective of both the individual customers and service providers is to maximize their own utility (Allon et al., 2012). When focusing on the design of a matching strategy at an operational level, Li et al. (2020) have formulated matching and pricing strategies using a freight O2O platform, which charges a delivery price depending on the total route distance. Their strategies use mixed-integer nonlinear programming based on vehicle routing and pricing-process selection to assign orders effectively and efficiently to drivers, thereby optimizing the platform revenue. In contrast to the literature, this study focuses on the design of matching strategies at an operational level without considering pricing. Rather, it considers a set of characteristics of demand and supply, such as the time window, the temporal dependency of demand, break requirements, the available working-time window, and the skills of the supplier.

Due to the characteristics of elderly customers, such as regular care-service demands and delay-insensitivity, the service-sharing platforms in this study are closely related to time banks and scheduled service platforms (e.g., Amazon Home Services), as they share offering characteristics such as heterogeneity and advance scheduling/matching. Many of these sharing platforms manage matching centrally. This study focuses on the assignment-matching model (Li et al., 2020).

2.2. HHCRSP

Our work is closely related to the HHCRSP and must address several characteristics of rules, including those that are time-related and task-caregiver-related. The time- and visit-related factors considered in the main studies published since 2012 are summarized in **Appendix A**, which also presents the differences between this study and those studies.

In practice, the **travel cost/time** between two locations differs due to the transportation mode, peak-hour traffic, available route choices, and departure time (Grenouilleau et al., 2019). Hiermann et al. (2015) consider a multimodal transportation network that may involve car travel, walking, and public transportation. Caregivers start and finish their activities at their own homes (i.e., multi-depots) (Bard et al., 2014; Fathollahi-Fard et al., 2020; Trautsamwieser et al., 2011). Each task is necessarily performed for a certain duration, which can be requested using either a fixed constant (Cappanera et al., 2018; Gomes and Ramos, 2019; Liu et al., 2017; Maya Duque et al., 2015) or a flexible range (Mosquera et al., 2019). Yuan et al. (2018) and Shi et al. (2018) assume that the **service duration** is a random variable with known probability distributions, while Shi et al. (2019) describe an uncertainty set for the service duration. Mosquera et al. (2019) define the lower and upper bound of the duration (p_t^-, p_t^+) for each visit t, such that a visit always has a minimum and maximum duration of p_t^- and p_t^+ time units, respectively. A task starts within a **time window** $[t^-, t^+]$, which is considered as either a soft (Gamst and Jensen, 2012; Maya Duque et al., 2015) or hard constraint (Grenouilleau et al., 2019; Mosquera et al., 2019; Yuan et al., 2018). When caregivers work as full-time employees at traditional institutions, a **lunch break** is generally necessary and can happen during a time window $[e_B, l_B]$ with a regular duration τ (Gomes and Ramos, 2019; Liu et al., 2017). A caregiver can also take a break if the maximum consecutive working time exceeds a threshold during the workday (Rest and Hirsch, 2016; Trautsamwieser and Hirsch, 2014). **Overtime** should be minimized to mitigate burnout syndrome in caregivers who work as employees at traditional institutions, and to reduce the overtime costs at these institutions (Bard et al., 2014; Braekers et al., 2016; Nickel et al., 2012; Rest and Hirsch, 2016).

The matching procedure cannot guarantee that all tasks will be matched with capable caregivers, and this results in **unmatched tasks** (Grenouilleau et al., 2019; Liu et al., 2017; Mosquera et al., 2019; Nickel et al., 2012; Rasmussen et al., 2012; Trautsamwieser and Hirsch, 2014; Yuan et al., 2018). It is important to ensure that as few tasks as possible remain unmatched when performing matching at a traditional institution, as unmatched tasks are generally delayed or subcontracted to another institution at a higher cost (Liu et al., 2017). This is also an important goal of "self-interested" platforms, as their revenues are derived from matched tasks. These matched tasks may have different priorities (Cinar et al., 2019; M. Lin et al., 2016). Each caregiver has a predefined **qualification** that is a function of the caregiver, sex constraints, or language skills (Braekers et al., 2016; Cappanera and Scutellà, 2015; Cappanera et al., 2018; Eveborn et al., 2009; Grenouilleau et al., 2019; Lin et al., 2018; Maya Duque et al., 2015; Mosquera et al., 2019; Nickel et al., 2012; Rest and Hirsch, 2016; Yalçındağ et al., 2016). The caregiver's qualification must match the required qualification for each task that the caregiver is required to perform (Braekers et al., 2016; Lin et al., 2018; Maya Duque et al., 2015; Mosquera et al., 2019). Customers can indicate their **preferences** regarding caregivers based on the information posted on platforms. The indication of a caregiver as preferred, moderately preferred, or not preferred for a task results in different penalties (e.g., 0, 1, 2) when this caregiver is assigned to the task (Braekers et al., 2016). **Temporal dependency** (Frifita and Masmoudi, 2020; Rasmussen et al., 2012) may exist among tasks requested by the same customer. Dohn et al. (2011) describe five types of temporal dependencies between two different visits/customers, including synchronization (Bachouch et al., 2011; En-nahli et al., 2016; Redjem and Marcon, 2016), precedence (minimum/maximum difference, and minimum plus maximum difference) (Mankowska et al., 2014; Rasmussen et al., 2012; Redjem and Marcon, 2016), and overlap (Kergosien et al., 2009).

The HHCRSP has three objectives, namely maximizing the platform revenue, maximizing the customer surplus, and maximizing the caregiver profit. According to a summary by Fikar and Hirsch (2017), maximizing revenue for traditional institutions means minimizing costs associated with travel, overtime, and the number of unscheduled tasks. The customer surplus and caregiver profit derive from the preferences of both stakeholders and fairness. Few studies consider a single objective such as fairness (Cappanera and Scutellà, 2015; Cappanera et al., 2018) or cost control (Yalçındağ et al., 2016). Rather, most studies implement multiple objectives with weighted objective functions (Grenouilleau et al., 2019; Lin et al., 2018; Liu et al., 2017; Rest and Hirsch, 2016; Trautsamwieser and Hirsch, 2014; Yuan et al., 2018). Only a few studies have addressed multi-objective optimization using either a lexicographic approach (Maya Duque et al., 2015; Mosquera et al., 2019; Gomes and Ramos, 2019) or a Pareto-related approach (Braekers et al., 2016).

This literature review shows that sufficient attention has been given to matching the care demand with supply in the context of traditional institutions, but not in the context of service-sharing platforms. Therefore, in this study, the problem of matching faced by service-sharing platforms is investigated and analyzed. Several aspects of this problem are shared by traditional institutions and service-sharing platforms, such as task factors (e.g., service-start time window, service-duration time window, temporal dependency, preference for caregivers, and qualification requirement) and caregiver factors (e.g., maximum daily workload, available time window, and qualification).

Traditional institutions and service-sharing platforms differ with respect to caregivers' contracts. Caregivers are employees at traditional institutions but are independent contractors on service-sharing platforms (Taylor, 2018). Overtime is meaningless for caregivers on service-sharing platforms, as they have the right to decide whether to take a break during their daily delivery procedure. For example, a caregiver may always prefer to work when the average income is higher than the average cost. Traditional institutions and service-sharing platforms also differ in terms of their objectives. In the business model used by service-sharing platforms, revenue is produced from the average value of matched tasks, customer surplus typically refers to the ability to satisfy customers' preferences for caregivers, and caregiver profit is mainly derived from the difference between a caregiver's income (related to his/her service load) and costs (related to his/her travel load). Different aims lead to different matching strategies being used (e.g., "self-interested", "social-welfare", "customer-first", and "hard-work-happy-life"), and hence to different concerns regarding objectives. To the best of our knowledge, no previous work has focused on the problem of matching from the perspective of the daily scheduling and routing of caregivers on service platforms, proposed matching strategies for such platforms, and discussed the effects of these strategies on the profits of the three parties connected to the platforms.

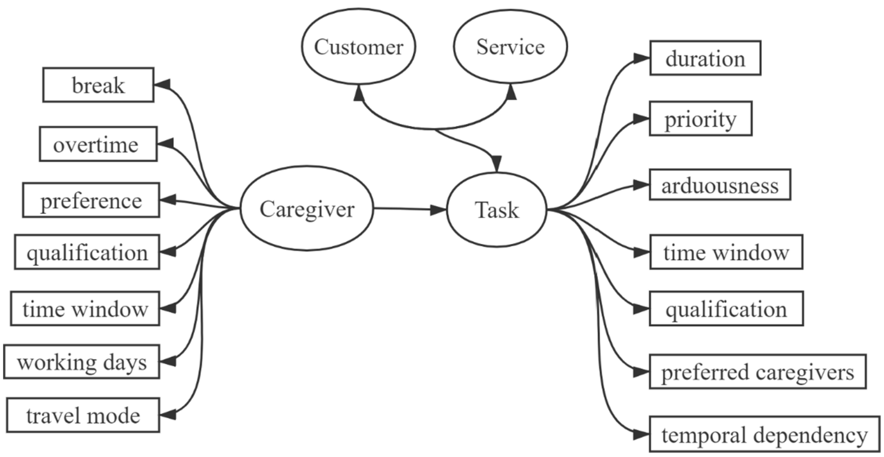

Fig. 1. The attributes of task demand and caregiver supply.

3. Matching demand with supply at the operational level

3.1. Problem description

Given a set of caregivers (supply) and a set of tasks (demand) for a future working day, the goal of a service platform is to match a series of care demands with each caregiver and to indicate when the tasks must be conducted. The resulting problem is described from the caregiver's perspective, the tasks, and the rules governing both of these factors.

Various types of services, such as medical and paramedical services, rehabilitation services, social services, psychological support, and personal-care services, are provided to patients registered on peer-to-peer service-sharing platforms. To simplify the description of the model, each visit during which a type of service s is provided to a customer p is called a task j. The attributes of a task consisting of a duration $[d_j^-, d_j^+]$, a hard time-window $[t_j^-, t_j^+]$, and a qualification level k_j are presented in Fig. 1. The duration of task j should have a minimum of d_j^- time units and a maximum of d_j^+ time units. When $d_j^- = d_j^+$, the duration of task j is a constant value. A customer who requests a task j states his/her preference for caregiver c. This preference is represented by a value contributing to the parameter p_{cj}, which represents the customer-side evaluation of the caregiver's information, including whether the caregiver is punctual, professional, and experienced, the appropriateness of his/her hourly rate and a rated review. The arduousness level of task j, α_j, is a weight that indicates the level of difficulty of the task relative to the associated travel. A positive correlation exists between α_j and the price of task j. The travel time between tasks i and j for caregiver c is described as t_{ij}^c. Tasks i and j may involve five types of temporal dependencies, as indicated by the value δ_{ij}; these comprise synchronization, overlap, minimum difference, maximum difference, and min–max difference (please refer to Table 2). These tasks are added to the set Δ. If task j must be conducted by n caregivers at the same time, then n-1 copies $(j_1, j_3, \cdots, j_{n-1})$ of the task with the same attributes (time window and fixed service duration) are added to the set Δ^{share}. The indices of these copies are redefined.

Caregivers on peer-to-peer care-service-sharing platforms work as independent contractors (Selloni, 2017), and are denoted service providers. A caregiver has an available time window $[a_c^-, a_c^+]$ during a workday and a qualification level $k_c^{'}$. A caregiver is sufficiently qualified to perform task j only if his/her qualification level $k_c^{'}$ is not less than the qualification requirement k_j for task j. He/she also has a maximum allowed daily workload, m_c, to avoid burnout syndrome. A break with a regular duration τ generally occurs during a time window $[t_B^-, t_B^+]$. A caregiver can choose whether to take a break, work overtime, and accept or decline the tasks sent to them. The tendency of the caregiver to accept or decline a task is based on the caregiver-side evaluation of the task information that comprises the price, level of arduousness, time window, location, duration of service, and the customer. Each side prefers to be matched with the stakeholder on the other side who offers him/her the greatest profit (Tunc et al., 2019). From a centralized perspective, a caregiver will always choose to accept an assigned task when the profit is positive. The attributes of a caregiver and a task are summarized in Fig. 1.

3.2. Matching strategies

The operational-level matching procedure for the service-sharing platforms is described as follows. First, demand information about all posted tasks that need to be performed on the next workday and supply information about all caregivers who are available on the next workday are collected. Second, a proper matching strategy is selected to achieve the optimal matches of demands and supplies while satisfying all of the operational rules/constraints.

3.2.1. Feasible matching

The types of demand/supply are differentiated horizontally according to the detailed characteristics of the tasks and the caregivers mentioned above (Hu and Zhou, 2018). The satisfaction of the rules/constraints between a task and a caregiver indicates a feasible match.

The match of a daily demand with a daily supply in the context of HHC is formulated using the HHCRSP model, a mixed-integer linear programming model built on directed graphs. A directed graph $\mathcal{G}_c = (V_c, A_c)$ is denoted for caregiver c, where V_c is the set of vertices and A_c is the set of arcs. Given a set of home caregivers $C = \{1, 2, \ldots, |C|\}$ and a set of tasks $J = \{1, 2, \ldots, |J|\}$, each task is represented by a separate vertex in our graph, where o_c^- and o_c^+ respectively represent two artificial start and end tasks for caregiver c. Parameter q_{jc} indicates whether a caregiver c is sufficiently qualified ($q_{jc} = 1$) or not ($q_{jc} = 0$) to perform a task j. Thus, $V_c = J_c \cup \{o_c^-, o_c^+\}$, where J_c is the set of tasks that caregiver c is qualified to perform, and $J_c = \left\{j | q_{jc} = 1\right\}$, $J_c \subset J$. Note that

Table 2
Parameter values for the five temporal dependencies (Dohn et al., 2011), where $0 < diff_{min} < diff_{max}$.

Temporal dependency	δ_{ij}	δ_{ji}
Synchronization	0	0
Overlap	$-d_j^-$	$-d_i^-$
Minimum difference	$diff_{min}$	N/A
Maximum difference	N/A	$-diff_{max}$
Minimum and maximum	$diff_{min}$	$-diff_{max}$

$d_{o_c^-,c} = d_{o_c^+,c} = 0; q_{o_c^-c} = q_{o_c^+c} = 1$. The arc set is defined as follows: $A_c = \{$. M is a large constant value in the model. C_j represents the set of capable caregivers who can perform task j. $M_c = 0$ if caregiver c, who works as an independent contractor, uses a public/shared transportation tool, such as Uber.

To formulate the model, the following binary decision variables are defined:

$$x_{ij}^c = \begin{cases} 1, & \text{if caregiver } c \text{ travels along } (i,\ j), \\ 0, & \text{otherwise.} \end{cases} \qquad \forall c \in C, (i,\ j) \in A_c$$

$$\theta_{jc} = \begin{cases} 1, & \text{if caregiver } c \text{ takes a break before task } j, \\ 0, & \text{otherwise.} \end{cases} \qquad \forall c \in C,\ j \in V_c$$

$$\vartheta_{jc} = \begin{cases} 1, & \text{if caregiver } c \text{ takes a break after task } j, \\ 0, & \text{otherwise.} \end{cases} \qquad \forall c \in C,\ j \in V_c$$

$$\mu_j = \begin{cases} 1, & \text{if task } j \text{ is not scheduled}, \\ 0, & \text{otherwise.} \end{cases} \qquad \forall j \in J$$

$$z_c = \begin{cases} 1, & \text{if caregiver } c \text{ is selected}, \\ 0, & \text{otherwise.} \end{cases} \qquad \forall c \in C$$

The continuous variables are defined as follows:

φ_{jc}: Start time of task j performed by caregiver c,$\forall c \in C, j \in V_c$. $\varphi_{jc} = 0$ if caregiver c is not assigned to task j.

ϕ_{jc}: Duration of task j performed by caregiver c, $\forall c \in C, j \in V_c$. $\phi_{jc} = 0$ if caregiver c is not assigned to task j or if j is the start/end task of caregiver c.

φ_{Bc}: Start time of break of caregiver c,$\forall c \in C$

The constraints are formulated as follows:

$$\sum_{j|(o_c^-,j)\in A_c} x_{o_c^-j}^c = 1, \forall c \in C \tag{1}$$

$$\sum_{j|(j,o_c^+)\in A_c} x_{jo_c^+}^c = 1, \forall c \in C \tag{2}$$

$$\sum_{i|(i,h)\in A_c} x_{ih}^c = \sum_{j|(h,j)\in A_c} x_{hj}^c, \forall c \in C, h \in J_c \tag{3}$$

$$t_i^- \sum_{j|(i,j)\in A_c} x_{ij}^c \le \varphi_{ic} \le t_i^+ \sum_{j|(i,j)\in A_c} x_{ij}^c, \forall c \in C, i \in J_c \tag{4}$$

$$t_i^- \le \varphi_{ic} \le t_i^+, \forall c \in C, i \in \{o_c^-, o_c^+\} \tag{5}$$

$$\varphi_{ic} + \phi_{ic} + t_{ij}^c \le \varphi_{jc} + M\left(1 - x_{ij}^c\right), \forall c \in C, (i,j) \in A_c \tag{6}$$

$$d_j^- \sum_{h|(j,h)\in A_c} x_{jh}^c \le \phi_{jc} \forall c \in C, j \in J_c \tag{7}$$

$$\phi_{jc} \le d_j^+ \sum_{h|(j,h)\in A_c} x_{jh}^c, \forall c \in C, j \in J_c \tag{8}$$

$$\phi_{jc} = 0, \forall c \in C, j \in \{o_c^-, o_c^+\} \tag{9}$$

$$\sum_{j\in J_c} \left(\theta_{jc} + \vartheta_{jc}\right) \le M_c{*}z_c, \forall c \in C \tag{10}$$

$$\theta_{ic} + \vartheta_{ic} \le \sum_{j|(i,j)\in A_c} x_{ij}^c, \forall c \in C, i \in J_c \tag{11}$$

$$\theta_{o_c^-c} + \vartheta_{o_c^+c} = 0, \forall c \in C \tag{12}$$

$$\varphi_{Bc} + \tau \le \varphi_{jc} + M\left(1 - \theta_{jc}\right), \forall c \in C, j \in J_c \tag{13}$$

$$\varphi_{ic} + \phi_{ic} + t_{ij}^{c} \leq \varphi_{Bc} + M\left(2 - x_{ij}^{c} - \theta_{jc}\right), \forall c \in C, (i,j) \in A_c \tag{14}$$

$$\varphi_{Bc} + \tau + t_{ij}^{c} \leq \varphi_{jc} + M\left(2 - x_{ij}^{c} - \vartheta_{ic}\right), \forall c \in C, (i,j) \in A_c \tag{15}$$

$$\varphi_{ic} + \phi_{ic} \leq \varphi_{Bc} + M(1 - \vartheta_{ic}), \forall c \in C, i \in J_c \tag{16}$$

$$t_B^{-} z_c \leq \varphi_{Bc} \leq t_B^{+} z_c, \forall c \in C \tag{17}$$

$$\varphi_{o_c^{+}c} - \varphi_{o_c^{-}c} \leq m_c, \forall c \in C \tag{18}$$

$$t_i^{-}\mu_i + \sum_{c \in C_i} \varphi_{ic} + \delta_{ij} \leq \sum_{c \in C_j} \varphi_{jc} + t_j^{+}\mu_j, \forall (i,j) \in \Delta \tag{19}$$

$$\mu_i = \mu_j, \forall (i,j) \in \Delta^{share} \tag{20}$$

$$z_c \geq \sum_{j|(i,j) \in A_c} x_{ij}^{c}, \forall c \in C, i \in J_c \tag{21}$$

$$\sum_{c \in C_i} \sum_{j|(i,j) \in A_c} x_{ij}^{c} + \mu_i = 1, \forall i \in J \tag{22}$$

$$\mu_j \in \{0,1\}, \forall j \in J \tag{23}$$

$$x_{ij}^{c} \in \{0,1\}, \forall c \in C, (i,j) \in A_c \tag{24}$$

$$\varphi_{jc}, \phi_{jc} \in \mathbb{R}_{+}, \theta_{jc}, \vartheta_{jc} \in \{0,1\}, \forall c \in C, j \in V_c \tag{25}$$

$$z_c \in \{0,1\}, \varphi_{Bc} \in \mathbb{R}_{+}, \forall c \in C \tag{26}$$

Constraints (1) and (2) ensure that each caregiver leaves and returns to the depot once. Constraint (3) ensures that each task's location is entered and left. Constraints (4)–(9) ensure that the time variables associated with each task are correctly set, and that each task starts within its time window and is performed for the correct duration within its duration range. Constraints (7) and (8) restrict the service duration to the duration time window. Constraint (7) is similar to the formulation in the work (Mosquera et al., 2019), and is used to enforce the minimum task duration. Constraints (10)–(17) state the break requirements, which are modified from a previous work (Liu et al., 2017) in which the authors considered a lunch break in their model. Constraints (10)–(12) claim that caregivers can only take a break during task i if it is performed, but cannot take a break before the start or after the end depot. Constraints (13)–(16) guarantee the correct start times of the breaks, during which caregivers rest before or after starting tasks. Constraint (17) ensures that a break is taken within the break-time window. Constraint (18) guarantees the total working time of a caregiver. Constraint (19) defines the general temporal dependencies formulated in the work (Rasmussen et al., 2012). The u-variable terms ensure that the generalized precedence constraints are respected, even when the tasks are uncovered by allowing one of the shared visits $(i,j) \in \Delta^{share}$ to be assigned and the other to be uncovered. Therefore, Constraint (20) is added to guarantee that the tasks in Δ^{share} must be visited by different caregivers at the same time or uncovered. Constraint (21) ensures that tasks can only be assigned to caregivers who are on duty and capable. Constraint (22) guarantees that each task is performed once or uncovered. Constraints (23)–(26) define the domains of the variables.

The operational rules/constraints include time-related rules, such as the time consumption and the travel- and service-time windows [formulated as Constraints (4)–(9)], the temporal dependency among the tasks [formulated as Constraints (19)–(20)], the break requirements [formulated as Constraints (10)–(17)], and the visit-related rules, such as task–caregiver matching [formulated as Constraints (21)–(22)]. The travel cost and travel time differ among different transportation modes. In the business model of a peer-to-peer service-sharing platform, a break requirement for caregivers who work as independent contractors is not mandatory, and it therefore depends on the transportation mode. That is, a break is necessary when a caregiver drives by himself/herself. In contrast, he/she can rest while traveling by public transportation (e.g., bus, subway) or via a shared-mobility tool (e.g., DiDi, Uber). Therefore, it is assumed that he/she does not take a break when using public transportation or a shared-mobility tool, which is represented by a parameter M_c value equal to 0 in Constraint (10). Although there is no overtime cost associated with caregivers on service-sharing platforms, they may choose to work harder to increase their earnings. Therefore, the operational rules/constraints governing breaks and overtime on service-sharing platforms differ from those in traditional HHC institutions, where a lunch break is a mandatory type of employee benefit for full-time caregivers, and where a bonus may be given to caregivers who work overtime to finish their daily tasks.

3.2.2. Optimal matching

A feasible match of demand with supply generates matching rewards that benefit the three stakeholders, that is platform revenue,

Table 3
Optimal matching strategies.

Organization	Strategy objective	max f_1	max f_2	max f_3	min f_4, f_6,f_8, max f_7
Service-sharing platforms	"self-interested" strategy	Level 1	Level 2	Level 2	
	"customer-first" strategy	Level 2	Level 2	Level 1	
	"hard-work-happy-life" strategy	Level 2	Level 1	Level 2	
	"social-welfare" strategy	Level 1	Level 1	Level 1	
Traditional HHC institutions					Levels 1 ~ 3, 5, and 4

caregiver profit, and customer surplus. The maximization of the platform revenue, the caregiver profit, and the customer surplus are therefore the three objectives that are considered when designing matching strategies. On for-profit service-sharing platforms, it is assumed that the average hourly rate of the caregiver and the price per hour for each task can be estimated and calculated using the hourly rate set by each caregiver, and the price and service duration of each task requested and needed by the customer. In a time bank, all caregivers set the same hourly rate, and therefore, the average hourly rate of a caregiver and price per hour for each task can be assumed as 1. The customer surplus, the caregiver profit, and the platform revenue can then be formulated as follows. First, Objective (27) maximizes the proportion of matched tasks, which represents the platform revenue. Objective (28) then maximizes the difference between the caregiver's received income and spent costs, which represents the average caregiver profit. Let $p_{cj}^{'} = p_{cj}/\sum_{c\in C_j} p_{cj}$ represent the standardized preference between caregiver c and task j. Objective (29) maximizes the average preference of the customer between the caregiver and task, and thus indicates the average customer surplus.

Objectives (27)–(29) differ from those of traditional HHC institutions, which mainly aim to minimize their daily operational costs, such as outsourced visits (related to the number of unmatched tasks), overtime, and travel costs, and to maximize customers' preferences and balance the caregivers' workloads as follows. First, Objective (30) minimizes the number of unmatched tasks. Then, Objective (31) minimizes the total overtime costs, Objective (32) minimizes the total travel cost and Objective (33) maximizes the customer's preference. Objective (34) minimizes the maximum utilization among caregivers to balance the caregiver's workload. Finally, Formulations (35)–(39) are used to calculate the overtime cost and maximize workload utilization among caregivers.

$$\mathbf{max}\, f_1 = \left(|J| - \sum_{i\in J} u_i\right) /|J| \tag{27}$$

$$\mathbf{max}\, f_2 = \left(\sum_{c\in C}\left(\sum_{i\in J_c}\alpha_i\phi_{ic} - \sum_{(i,j)\in A_c} t_{ij}^c x_{ij}^c\right)/m_c\right)/|c| = \sum_{c\in C}\left(\sum_{i\in J_c}\alpha_i\phi_{ic} - \sum_{(i,j)\in A_c} t_{ij}^c x_{ij}^c\right)/(m_c|c|) \tag{28}$$

$$\mathbf{max}\, f_3 = \sum_{j\in J}\left(\sum_{c\in C_j}\sum_{i|(i,j)\in A_c} p_{cj}x_{ij}^c \Big/ \sum_{c\in C_j} p_{cj}\right)/|J| = \left(\sum_{j\in J}\sum_{c\in C_j} p_{cj}^{'} \sum_{i|(i,j)\in A_c} x_{ij}^c\right)/|J| \tag{29}$$

$$\mathbf{min}\, f_4 = \sum_{i\in J} u_i \tag{30}$$

$$\mathbf{min}\, f_5 = \sum_{c\in C} \omega_c \tag{31}$$

$$\mathbf{min}\, f_6 = \sum_{c\in C}\sum_{(i,j)\in A_c} v_{ij}^c x_{ij}^c \tag{32}$$

$$\mathbf{max}\, f_7 = \sum_{c\in C}\sum_{(i,j)\in A_c} p_{cj} x_{ij}^c \tag{33}$$

$$\mathbf{min}\, f_8 = m \tag{34}$$

$$w_c \geq \varphi_{o_c^+ c} - \varphi_{o_c^- c} - r_c, \forall c \in C \tag{35}$$

$$w_c \times ot_c \leq \omega_c + M(1 - z_c), \forall c \in C \tag{36}$$

$$0 \leq \omega_c + Mz_c, \forall c \in C \tag{37}$$

$$\left(\sum_{(i,j)\in A_c} t_{ij}^c x_{ij}^c + \sum_{i\in J_c}\alpha_i\phi_{ic}\right)/r_c <= m, \forall c \in C \tag{38}$$

$$w_c, \omega_c, m \in \mathbb{R}_+ \tag{39}$$

Objectives (27)–(29) guide the searching algorithm to identify the optimal matches among the feasible searching spaces for service-sharing platforms. Therefore, the different levels of importance of the objectives lead to different optimal matches, which are summarized as different matching strategies. For service-sharing platforms, each matching strategy represents a lexicographic rule regarding the three types of objectives, within which a multi-level hierarchy reflects the importance of each objective. Level 1 refers to the most important objective function on a service-sharing platform. This study defines and investigates the following four matching strategies, which differ from each other according to the objective(s) of Level 1, as summarized in Table 3. The first matching strategy, the "self-interested" strategy, seeks first to maximize the platform revenue, and then maximizes the caregiver profit and the customer surplus. Objective (27) is thus the most important objective (Level 1), while Objectives (28) and (29) are classified as Level 2. The second matching strategy, the "customer-first" strategy, first maximizes the customer surplus [Objective (29): Level 1], and then maximizes the platform revenue and the caregiver profit [Objectives (27) and (28): Level 2]. Customers of a platform that uses this matching strategy may be willing to pay higher prices for their preferred caregivers when their surplus is maximized. The third matching strategy, the "hard-work-happy-life" strategy, first maximizes the caregiver profit [Objective (28): Level 1], and then maximizes the platform revenue and the customer surplus [Objectives (27) and (29): Level 2]. This strategy aims to attract more caregivers who will remain loyal to the platform. The fourth matching strategy, the "social-welfare" strategy, places equal importance on maximizing the platform revenue, caregiver profit, and customer surplus.

3.2.3. Analysis of models

There are two classical methods to solve the multi-objective matching problem, a lexicographic method and a weighted-sum method. The lexicographic method comprising two phases. Phase I achieves an optimal matching solution in terms of the Level-1 objective, while Phase II achieves an optimal matching solution in terms of the Level-2 objectives, where this solution does not degrade the values of the Level-1 objective obtained during Phase I. For the "social-welfare" strategy, wherein each objective receives the same constant weight (assumed as 1), only Phase I is needed. The other three matching strategies must be subjected to Phases I and II to obtain the final optimal matching solution. The objective value obtained in Phase I becomes a constraint in Phase II. In the weighted-sum method, the multi-objective matching problem is transferred into a single-phase weighted-sum single-objective matching problem.

Proposition 3.1. *Given a level for each objective, a weight set exists such that the optimal values obtained using the lexicographic method are equal to the corresponding parts obtained using the weighted-sum method.*

For example, F_1 presents the maximum value of the objective obtained in Level 1 by the lexicographic method, while F_2 presents the optimal value of the objectives obtained in Level 2. It is assumed that the objectives at the same level have the same weight. According to the lexicographic method, the final optimal solution is obtained in Phase II. In Phase I, F_1 is obtained by solving the model for the maximization of $f_i, i \in \{1,2,3\}$, while satisfying Constraints (1)–(26). In Phase II, F_2 is obtained by solving Model I with Objective (40) and Constraints (1)–(26) and (41). Model I can be transferred to Model III with Objective (42) and Constraints (1)-(26) by setting a large enough penalty ρ to ensure that $f_i = F_1$. For the weighted-sum method, Model II with Objective (43) and Constraints (1)–(26) is solved to obtain the final solution. This leads to a question about the existence of w_1 and w_2, and makes the objective function of Model III equal to f_{122} in Model II. Let $w_1 = \rho$; then, w_1 and w_2 satisfy Equation (44), where LB_1 and UB_1 are the lower and upper bounds of the objective in Level 1 (i.e., f_i), respectively, and LB_2 and UB_2 are the lower and upper bounds of the objectives in Level 2 (i.e., f_{22}), respectively. Let $w_2 = 0.5$; then, w_1 satisfies Equation (45). Let ϖ_i denote the weight for objective function f_i, as presented in Table 4.

$$\max f_{22} = \sum_{j \in \{1,2,3\} \setminus \{i\}} f_j \tag{40}$$

s.t. $f_i \geq F_1$ (41)

$$\max f_{22} - \rho(F_1 - f_i) \tag{42}$$

$$\max f_{122} = w_1 f_i + w_2 f_{22} \tag{43}$$

$$LB_2/UB_1 \leq w_1/(1 - w_2) = f_{22}/F_1 \leq UB_2/LB_1 \tag{44}$$

$$LB_2/2UB_1 \leq w_1 \leq UB_2/2LB_1 \tag{45}$$

More computational time is required to identify the optimal solution if a lexicographic exact method rather than a weighted-sum exact approach is applied to solve the matching problem. Therefore, the exact method for determining the optimal matching problem is reformulated as a weighted-sum minimization problem.

4. B&P approach

A B&P approach is introduced to solve the optimal matching problem mentioned above. The B&P approach is a branch-and-bound method in which a column generation algorithm is used at each node of the search tree.

4.1. Overview of the B&P approach

In the B&P framework, as shown in a flowchart inspired by Liu et al. (2017) (refer Fig. 2), a Dantzig–Wolfe decomposition is applied to naturally decompose the matching problem into a set-partitioning problem with side constraints (i.e., the master problem) and a pricing sub-problem. In the master problem, one schedule for each caregiver is chosen from a large set of feasible schedules. The sub-problem generates these feasible schedules, which are subsequently combined feasibly in the master problem. Because the master problem contains exponential variables (i.e., all possible feasible routes/schedules for each caregiver), the restricted master problem (RMP), which consists of a subset of decision variables (i.e., feasible routes presented to caregivers) and constraints (columns), is introduced to replace the master problem. By taking the values of the dual variables of the RMP, the pricing sub-problem is solved to identify columns with negative reduced costs for a minimization problem. If such a column exists, it is then added to the RMP. This column generation procedure is repeated until no new column can be identified. The B&P approach initializes a root node of the search tree by adding a set of initial columns to the RMP. Then, the RMP is solved in child node by column generation, using the set of feasible columns inherited from the parent node. If the optimal solution of the RMP violates the precedence or/and integrality constraints, the branching strategies are adopted to generate new child nodes. Otherwise, the best choice between this feasible solution and the existing upper bound is selected as the new upper bound, and is used to guide a pruning operation. These child nodes are then added to the search tree. The search process ceases when all of the nodes in the tree have been explored using a priority–queue strategy, in which the node with the smallest lower bound is selected for processing.

4.2. Master problem and pricing problem

A feasible schedule/route r for a caregiver c is defined as a route starting at o_c^- and ending at o_c^+. t_{jr}^c and s_{jr}^c are the service-start time and the service duration of task j in schedule r for caregiver c, respectively, if j is included in r for caregiver c. If j is not included in schedule r for caregiver c,$t_{jr}^c = s_{jr}^c = 0$. Assume that the total travel and service load with arduousness level and the standardized preference score of schedule r for caregiver c are tl_r^c, sl_r^c, and p_r^c, respectively. A binary parameter and a binary variable are respectively defined:

$$a_{jr}^c = \begin{cases} 1, & \textit{if task } j \textit{ is included in schedule } r \textit{ for caregiver } c, \\ 0, & \textit{otherwise} \end{cases} \qquad \forall c \in C, j \in J_c, r \in R^c$$

$$\Lambda_r^c = \begin{cases} 1, & \textit{if schedule } r \textit{ is chosen for caregiver } c, \\ 0, & \textit{otherwise.} \end{cases} \qquad \forall c \in C, r \in R^c$$

$$\min F^{'} = \varpi_1 \left(|J| - \sum_{i \in J} u_i\right) / |J| + \varpi_2 \sum_{c \in C} \left(\sum_{r \in R^c} sl_r^c \Lambda_r^c - \sum_{r \in R^c} tl_r^c \Lambda_r^c\right) / (m_c |c|) + \varpi_3 \sum_{c \in C} \sum_{r \in R^c} p_r^c \Lambda_r^c / |J| \tag{46}$$

Subject to

$$\sum_{c \in C} \sum_{r \in R^c} a_{jr}^c \Lambda_r^c + \mu_j = 1, \forall j \in J \tag{47}$$

$$\sum_{r \in R^c} \Lambda_r^c \le 1, \forall c \in C \tag{48}$$

$$t_i^- \mu_i + \sum_{c \in C} \sum_{r \in R^c} t_{ir}^c \Lambda_r^c + \delta_{ij} \le \sum_{c \in C} \sum_{r \in R^c} t_{jr}^c \Lambda_r^c + t_j^+ \mu_j, \forall (i,j) \in \Delta \tag{49}$$

$$\mu_i = \mu_j, \forall (i,j) \in \Delta^{share} \tag{50}$$

$$\Lambda_r^c \in \{0,1\}, \forall c \in C, r \in R^c \tag{51}$$

$$\mu_j \in \{0,1\}, \forall j \in J \tag{52}$$

Objective (46) minimizes the negative weighted sum of the platform revenue, caregiver profit, and customer surplus for the selected matching solutions, where $\varpi_1, \varpi_2,$ and ϖ_2 are less than 0. Constraint (47) has the same meaning as Constraint (22), which ensures that all tasks are either included in exactly one schedule or are considered to be uncovered. Constraint (48) ensures that each caregiver selects a maximum of one schedule. Constraint (49) respects the generalized precedence constraints. Constraint (50) ensures that tasks in the set of shared visits are assigned or uncovered simultaneously. Constraints (51) and (52) represent the binary nature of all decision variables. The ability to solve the master problem in the B&P framework requires the relaxation of the integrality constraints on the decision variables and the precedence Constraint (49), which yields a simpler pricing problem. The relaxed precedence and integrality constraints are addressed in the branching part of the B&P algorithm by applying two branching strategies, namely a time-window branching strategy based on the ideas proposed by Rasmussen et al. (2012) and an integer-branching strategy based on the ideas proposed by Liu et al. (2017). The relaxed and restricted master problem is abbreviated as RMP, as noted earlier.

Let π_j and λ_c represent the dual vectors associated with Constraints (47) and (48), respectively. Using the column generation technique, the dual variables are applied to generate new schedules that improve the solution to the RMP. The reduced cost of schedule r (i.e., the objective function of the pricing sub-problem) as adhered to by caregiver c is computed using Equation (53). In the pricing sub-problem, the route with the minimum reduced cost satisfies constraints (1)–(18), (21), and (24)–(26). The pricing problem is solved using a novel pulse algorithm based on the ideas proposed by Lozano et al. (2016) and Liu et al. (2017), and by extending the label definition with one more parameter, namely a set that contains the service duration of tasks that have already been served along the route. If the optimal value of the pricing problem is less than 0, then better matching solutions exist and a new column is added to the RMP.

$$min\ F^{''} : \varpi_2\left(sl_r^c - tl_r^c\right)\Big/(m_c|c|) + \varpi_3 p_r^c\Big/|J| - \sum_{j\in J} a_{jr}^c \pi_j - \lambda_c \tag{53}$$

4.3. *Novel pulse algorithm for the pricing Sub-problem*

Given the directed graph $\mathscr{G}_c = (V_c, A_c)$ defined in section 3.2.1, each task has a service time $d_i \in [d_i^-, d_i^+]$ and preference p'_{ci} for caregiver c. Let $\varpi'_{2c} = \varpi_2/(m_c|c|)$ and $\varpi'_{3c} = \varpi_3/|J|$. Let $\pi_{o_c^-} = \lambda_c, p'_{c,o_c^-} = p'_{c,o_c^+} = 0, s_{o_c^-} = s_{o_c^+} = 0$ to represent the artificial dual values, preference, and service duration, respectively, associated with nodes o_c^- (noted by v_s) and o_c^+(noted by v_e) for caregiver c. Each arc $(i, j) \in A_c$ has a travel time t_{ij} and a reduced cost contribution $r_{ij} = \varpi'_{2c}(s_i - t_{ij}) + \varpi'_{3c} p'_{ci} - \pi_i$, where $s_i = \alpha_i d_i$. A path from start node v_s to end node v_e corresponds to a column (variable) in the RMP and represents route k with a reduced cost $r_k = \sum_{(v_i,v_j)\in k} r_{ij}$. The sub-problem aims to identify an elementary path from the start node to the end node that minimizes the reduced cost with respect to the time-window constraints and the break constraint over the nodes, if required.

To solve the sub-problem, an elementary short-path problem with resource constraints (ESPPRC), flexible service durations and break requirements, the pulse algorithm developed by Lozano et al. (2016) is modified as shown in Algorithm 1, to address the flexible service durations and break requirements. The bound stage, which identifies the lower bounds of the reduced cost according to the amount of time consumed, is similar to that in the original algorithm. The pulse algorithm for the ESPPRC with flexible service durations and break requirements comprises two stages. The first is a bound stage that identifies the lower bounds according to a given amount of time consumed, and the second is a recursive exploration stage that identifies an optimal solution. The recursive exploration is triggered by sending a pulse that initiates at the start depot and propagates throughout the outgoing arc of each visited vertex. At each vertex, different pruning strategies (e.g., an infeasibility pruning strategy, a bound pruning strategy, and a rollback pruning strategy) attempt to stop the pulse propagation by using various forms of information, such as the partial path $\mathscr{P}$ with the service duration $\mathscr{S}$, the cumulative reduced cost $r(\mathscr{P})$, the cumulative time consumption $t(\mathscr{P})$, and the break-taking statuses ℓ_a and ℓ_b. Any pulse that initiates at the start depot and reaches the end depot contains all of the information pertaining to a feasible path. Lines 1–6 of Algorithm 1 initialize the values for the partial path from the start depot. Line 7 calculates the lower bounds for all vertexes and is detailed in Algorithm 4. Line 8 invokes the recursive procedure pulse initiating at the start depot, which is detailed in Algorithm 3.

Algorithm 1. (*Novel Pulse Algorithm*)

Input: $\mathscr{G}_c$, directed graph; v_s, start node; v_e, end node; Δ, bound step size; $[\underline{t}, \bar{t}]$, bounding time limits

Output: $\mathscr{P}^*, \mathscr{S}^*$, optimal path, with service start time and duration
1. $\mathscr{P} \leftarrow \{\}$
2. $\mathscr{S} \leftarrow \{\}$
3. $r(\mathscr{P}) \leftarrow 0$
4. $t(\mathscr{P}) \leftarrow 0$
5. $\ell_a \leftarrow 0$
6. $\ell_b \leftarrow 0$
7. bound $(\mathscr{G}, \Delta, \left[\underline{t}, \bar{t}\right])$ // see Algorithm 4
8. pulse $(v_s, r(\mathscr{P}), t(\mathscr{P}), \ell_a, \ell_b, \mathscr{P}, \mathscr{S})$ // see Algorithm 3
9. return $\mathscr{P}^*, \mathscr{S}^*$

The main difference from the pulse algorithm developed by Lozano et al. (2016) is identified using the recursive-exploration stage pulse procedure, as indicated in Algorithm 3. Lines 1–3 use the pruning, bound pruning, and rollback pruning strategies to prune the incoming pulse. If the pulse is not pruned, Lines 4–34 propagate the pulse by invoking the pulse procedure over all outgoing vertexes of the current vertex. The pulse ceases its propagation when it reaches the end depot, and information about the best-known path is updated. When the pulse attempts to propagate throughout the outgoing arcs (v_i, v_j) of each visited node v_i, different service durations d_i are tested, and three break rules are considered. Only those service durations that feasibly reach to the outgoing vertex v_j are attempted, and the bound of the service duration is calculated using Lines 5–9, 15–19, and 24–28 of Algorithm 3. The break rules are described as follows. **Rule 1**: no break is taken during arc (v_i, v_j), which corresponds to Lines 5–13. **Rule 2**: a break is taken after serving task i, with reference to Lines 14 and 23. **Rule 3**: a break is taken before serving task j, with reference to Lines 24 and 32. The pulse state based on these three rules is calculated by Algorithm 2, which adds the current vertex v_i to the partial path being explored and a break vertex to the partial path, if necessary. Lines 2–7 updates the state of vertex v_i with break rule 1. Lines 9–14 update the state with break rule 2. Lines 16–21 update the state with break rule 3.

Algorithm 2. (*pulseState* $(v_i, v_j, r(\mathscr{P}), t(\mathscr{P}), \mathscr{k}, \mathscr{b}_a, \mathscr{b}_b, \mathscr{P}, \mathscr{S}, d_i)$)

Input: v_i, current node; v_j, next node; $r(\mathscr{P})$, path reduced cost; $t(\mathscr{P})$, path time; $\mathscr{k}$, break rule; $\mathscr{b}_a$, flag of break after servicing v_i; $\mathscr{b}_b$, flag of break before servicing v_j; $\mathscr{P}$, current path; $\mathscr{S}$, service start time and duration of the current path; d_i, service duration of current node. v_B : break flag in path

Output: $(r(\mathscr{P}'), t(\mathscr{P}'), \mathscr{b}'_a, \mathscr{b}'_b, \mathscr{P}', \mathscr{S}')$, next state

$r(\mathscr{P}') \leftarrow r(\mathscr{P}) + r_{ij}$
if $\mathscr{k} = 1$ **then do**
  $\mathscr{P}' \leftarrow \mathscr{P} \cup \{v_i\}$
  $t(\mathscr{P}') \leftarrow t(\mathscr{P}) + d_i + t_{ij}$
  $\mathscr{b}'_a \leftarrow \mathscr{b}_a$
  $\mathscr{b}'_b \leftarrow \mathscr{b}_b$
  $\mathscr{S}' \leftarrow \mathscr{S} \cup \{(t(\mathscr{P}), d_i)\}$
else if $\mathscr{k} = 2$ **then do**
  $\mathscr{P}' \leftarrow \mathscr{P} \cup \{v_i, v_B\}$
  $\tau^B \leftarrow max\{a_B, t(\mathscr{P}) + d_i\}$
  $t(\mathscr{P}') \leftarrow \tau^B + d_B + t_{ij}$
  $\mathscr{b}'_a \leftarrow 1$
  $\mathscr{b}'_b \leftarrow \mathscr{b}_b$
  $\mathscr{S}' \leftarrow \mathscr{S} \cup \{(t(\mathscr{P}), d_i), (\tau^B, d_B)\}$
else if $\mathscr{k} = 3$ **then do**
  $\mathscr{P}' \leftarrow \mathscr{P} \cup \{v_i, v_B\}$
  $\tau^B \leftarrow max\{a_B, t(\mathscr{P}) + d_i + t_{ij}\}$
  $t(\mathscr{P}') \leftarrow \tau^B + d_B$
  $\mathscr{b}'_a \leftarrow \mathscr{b}_a$
  $\mathscr{b}'_b \leftarrow 1$
  $\mathscr{S}' \leftarrow \mathscr{S} \cup \{(t(\mathscr{P}), d_i), (\tau^B, d_B)\}$
endif
return $r(\mathscr{P}'), t(\mathscr{P}'), \mathscr{b}'_a, \mathscr{b}'_b, \mathscr{P}', \mathscr{S}'$

Algorithm 3. (*pulse* $(v_i, r(\mathscr{P}), t(\mathscr{P}), \mathscr{b}_a, \mathscr{b}_b, \mathscr{P}, \mathscr{S})$)

Input: v_i, current node; $r(\mathscr{P})$, path reduced cost; $t(\mathscr{P})$, path time; $\mathscr{b}_a$, flag of break after service; $\mathscr{b}_b$, flag of break before service; $\mathscr{P}$, current path; $\mathscr{S}$, service start time and duration of the current path

Output: void

if isFeasible $(v_i, t(\mathscr{P}))$=false **then** return; // see section 4.1 in the work by Lozano et al. (2016)
if checkBounds $(v_i, t(\mathscr{P}), r(\mathscr{P}))$ =true **then** return; // see section 4.2 in the work by Lozano et al. (2016)
if rollback $(v_i, r(\mathscr{P}), t(\mathscr{P}), \mathscr{b}_a, \mathscr{b}_b, \mathscr{P})$ = true **then** return;
for $v_j \in \Gamma^+(v_i)$ **do**
  $d_i \leftarrow d_i^-$
  do
    $d_i \leftarrow d_i + \Delta^d$
  while $(t(\mathscr{P}) + d_i + t_{ij} \le a_j \&\& d_i \le d_i^+)$
  $d_i \leftarrow d_i - \Delta^d$
  while $t(\mathscr{P}) + d_i + t_{ij} \le b_j \&\& d_i \le d_i^+$ **do**
    pulse $(v_j, \text{pulseState}(v_i, v_j, r(\mathscr{P}), t(\mathscr{P}), 1, \mathscr{b}_a, \mathscr{b}_b, \mathscr{P}, \mathscr{S}, d_i))$ // see Algorithm 2
    $d_i \leftarrow d_i + \Delta^d$
  end while
  if $\mathscr{b}_a + \mathscr{b}_b = 0$ **then**
    $d_i \leftarrow d_i^-$
    do
    $d_i \leftarrow d_i + \Delta^d$
    while $t(\mathscr{P}) + d_i \le a_B \&\& d_i \le d_i^+$
    $d_i \leftarrow d_i - \Delta^d$
    while $t(\mathscr{P}) + d_i \le b_B \&\& d_i \le d_i^+$ **do**
      pulse $(v_j, \text{pulseState}(v_i, v_j, r(\mathscr{P}), t(\mathscr{P}), 2, \mathscr{b}_a, \mathscr{b}_b, \mathscr{P}, \mathscr{S}, d_i))$
      $d_i \leftarrow d_i + \Delta^d$
    end while
    $d_i \leftarrow d_i^-$
    while $t(\mathscr{P}) + d_i + t_{ij} \le a_B \&\& d_i \le d_i^+$ **do**
      $d_i \leftarrow d_i + \Delta^d$
    end while
    $d_i \leftarrow d_i - \Delta^d$
    while $t(\mathscr{P}) + d_i + t_{ij} \le b_B \&\& d_i \le d_i^+$ **do**

(*continued on next page*)

(*continued*)

```
30.         pulse (v_j, pulseState(v_i, v_j, r(P), t(P), 3, ℓ_a, ℓ_b, P, S, d_i))
31.       d_i ← d_i + Δ^d
32.     end while
33.   end if
34. end for
```

The infeasibility pruning (Line 1 in Algorithm 3) and bound pruning (Line 2 in Algorithm 3) are similar to those presented in Sections 4.1 and 4.2 of the work by Lozano et al. (2016). The infeasibility pruning strategy uses time-window and cycle constraints, and determines whether a cycle is created or a time window is violated whenever a partial path reaches a vertex. If any of these events occur, the partial path will be pruned safely because of its infeasibility. The bound-pruning strategy uses the bounds that store the minimum reduced cost achieved by any partial path that reaches vertex v_i at a given value of the consumed resource $t(\mathscr{P})$. The bounds are calculated by Algorithm 4, where $\bar{t}$ represents the upper time-window of the end depot and Δ represents a nonnegative time-step (e.g., four-time units). Every optimal solution identified using Lines 5–14 acts as a lower bound on the minimum reduced cost that can be achieved by any partial path that reaches vertex v_i, given a time consumption $t(\mathscr{P})$. By using the previously computed bounds, the algorithm continues in a backward mode by repeating the same procedure until a given time-limit is reached, as shown in Lines 1–3. The bound-pruning function checkBounds in Line 2 of Algorithm 3 prunes a partial path if $r(\mathscr{P}) + r_{-}(v_i, t(\mathscr{P})) \leq \bar{r}$, where $\bar{r}$ is a primal upper bound that is constantly updated with the value of the best solution identified at any time during the exploration.

Algorithm 4. (*Bounding Algorithm*)

Input: $\mathscr{G}_c$, directed graph; Δ, bound step size; $[t_{-}, \bar{t}]$, bounding time limits

Output: $B = \left[r_{-}(v_i, \tau)\right]$, upper bound matrix

```
1. τ ← t̄
2. while τ > t_ do
3.   τ ← τ − Δ
4.   for v_i ∈ J_c do
5.     P − {}
6.     r(P) ← 0
7.     t(P) ← τ
8.     ℓ_a ← 0
9.     ℓ_b ← 0
10.    pulse (v_i, r(P), t(P), ℓ_a, ℓ_b, P, S)
11.    if P* = {} then
12.    r_(v_i, τ) ← ∞
13.   else
14.    r_(v_i, τ) ← r(P*)
15.   end if
16. end for
17. end while
18. returnB
```

The main difference is attributable to the rollback pruning, compared to the pruning strategy by Lozano et al. (2016). Consider a partial path $\mathscr{P}_{si}$ from v_s to v_i that is extended to node v_k and then reaches node v_j. Let partial path $\mathscr{P}_{sj} = \mathscr{P}_{si} \cup \{v_k\} \cup \{v_j\}$, which reaches node v_j through v_k, and $\mathscr{P}'_{sj} = \mathscr{P}_{si} \cup \{v_j\}$ represent an alternative partial path to node v_j that does not visit node v_k. According to Liu et al. (2017), if $\mathscr{P}'_{sj} \subseteq \mathscr{P}_{sj}, r(\mathscr{P}'_{sj}) \leq r(\mathscr{P}_{sj}), t(\mathscr{P}'_{sj}) \leq t(\mathscr{P}_{sj}), \ell'_a + \ell'_b \geq \ell_a + \ell_b$, and at least one of the four previous conditions holds strictly (e.g.,$\mathscr{P}'_{sj} \subset \mathscr{P}_{sj}$ or $r(\mathscr{P}'_{sj}) \langle r(\mathscr{P}_{sj}))$, then path $\mathscr{P}_{sj}$ is dominated by path $\mathscr{P}'_{sj}$. Because $\mathscr{P}'_{sj} \subset \mathscr{P}_{sj}$, the rollback pruning strategy must confirm that $r(\mathscr{P}'_{sj}) \leq r(\mathscr{P}_{sj}), t(\mathscr{P}'_{sj}) \leq t(\mathscr{P}_{sj}), \ell'_a + \ell'_b \geq \ell_a + \ell_b$ to prune path $\mathscr{P}_{sj}$. The condition $\ell'_a + \ell'_b \geq \ell_a + \ell_b$ contains three cases, as shown in Fig. 3, where υ_B represents the break activity. (1) No break is taken at both paths, thus $\ell'_a + \ell'_b = \ell_a + \ell_b = 0$. (2) A break is taken at both paths, thus$\ell'_a + \ell'_b = \ell_a + \ell_b = 1$. In this case, if a break is taken in $\mathscr{P}_{si}$, no break is taken in partial paths $\mathscr{P}'_{ij} = \{v_i, v_j\}$ and $\mathscr{P}_{ij} = \{v_i, v_k, v_j\}$. Otherwise, a break is taken in partial paths $\mathscr{P}'_{ij}$ and $\mathscr{P}_{ij}$. (3) A break is taken at $\mathscr{P}'_{sj}$, but not $\mathscr{P}_{sj}$, $\ell'_a + \ell'_b = 1; \ell_a + \ell_b = 0$. In this case, no break is taken in $\mathscr{P}_{si}$ **and** $\mathscr{P}_{ij}$, but is taken in $\mathscr{P}'_{ij}$.

Table 4
The weights associated with objective under different matching strategies.

Strategy Weight	"self-interested"	"customer-first"	"hard-work-happy-life"	"social-welfare"
Setting	$\varpi_1 = -w_1$ $\varpi_2 = \varpi_3 = -w_2$	$\varpi_3 = -w_1$ $\varpi_1 = \varpi_2 = -w_2$	$\varpi_2 = -w_1$ $\varpi_1 = \varpi_3 = -w_2$	$\varpi_2 = -w_1 = -1$ $\varpi_1 = \varpi_3 = -w_1 = -1$

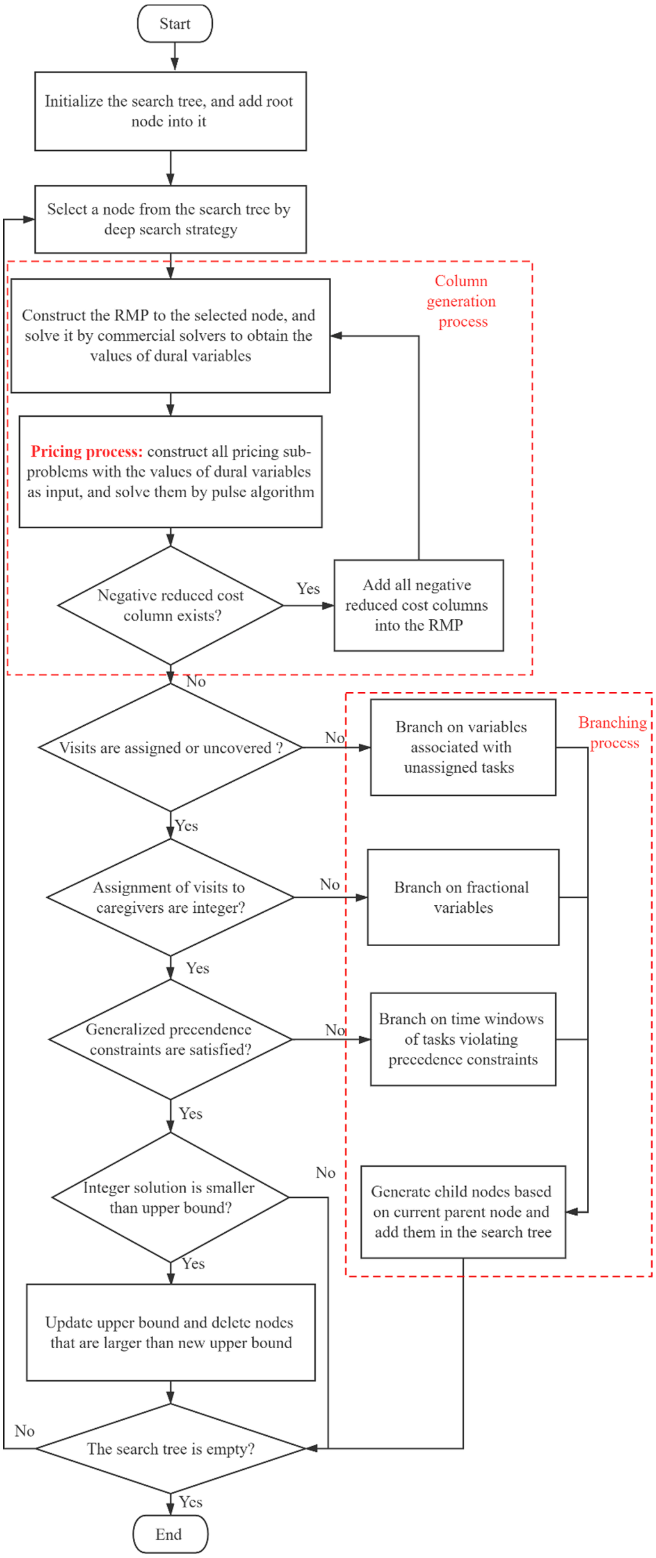

Fig. 2. Flowchart of branch & price approach for the matching problem.

4.4. Branching strategies

In the search tree, branching is required when the relaxed RMP of each node is solved optimally but the precedence Constraints (49) and (50) are violated, or the corresponding solution is not an integer.

(a) Time-window branching

A simple reduction technique is adopted, based on the generalized precedence Constraint (49) (Dohn et al., 2011). For any two tasks, i and j with $(i,j) \in \Delta$, it is possible to reduce the time-windows in Table 5. This reduction technique is essential when applying time-window branching.

Suppose that the generalized precedence Constraint (49) for $(j,i) \in \Delta$ is violated. Given a split time t^s of task i, the resulting time-windows are branched as shown in Table 5. A reduction procedure is applied to the time-window through all revenant precedence constraints, and the new time-window of task i is used to reduce the time-window. The candidates of the split time for task i are identified by traversing all of the routes with the positive values that are included in the solution. If task i is included in one of these routes, the start time of the task i is a candidate. If task j is included in one of these routes where$(j,i) \in \Delta$, the sum of the start time of task j and δ_{ji} is a candidate of the split time for task i. Branching candidates that exclude paths as much as possible in the least effective branch are preferred, and the detailed selection of the best split time among candidates is based on the strategy presented by Dohn et al. (2011).

(b) Integer branching

Two integer-branching strategies are designed, based on the work of Liu et al. (2017), namely (1) branching on uncovered tasks and (2) branching on the assignment of caregivers to tasks.

The first branching strategy addresses the constraints related to uncovered tasks. If some values of μ_i are fractional, the value farthest from an integer is chosen to generate two child nodes, that is $\mu_i = 1$ and $\mu_i = 0$. The constraint $\mu_i = 1$ for a task that is not included in the shared set (or the constraint $\mu_i = \mu_j = 1$ for tasks included in the shared set) can be satisfied implicitly by removing the columns with task i (also j) from the column sets of the RMP, and deleting the ingoing and outgoing arcs of task i (also j) in the networks of all capable workers. The constraint $\mu_i = 0$ (or $\mu_i = \mu_j = 0$) is added directly to the model of the RMP.

If Constraint (50) is satisfied, and all values of μ_j are integers but some values of $\mathscr{Y}_{jc} = \sum_{r \in R^c} a^c_{jr} \Lambda^c_r, j \in J_c, c \in C$ are fractional, the $\mathscr{Y}_{jc}$ that is farthest from an integer is chosen to branch to two nodes. If $\mathscr{Y}_{jc} = 1$ in one child node, task j must be assigned to caregiver c in the solution. Subsequently, the columns that contain task j for other caregivers are deleted, and the ingoing and outgoing arcs of task

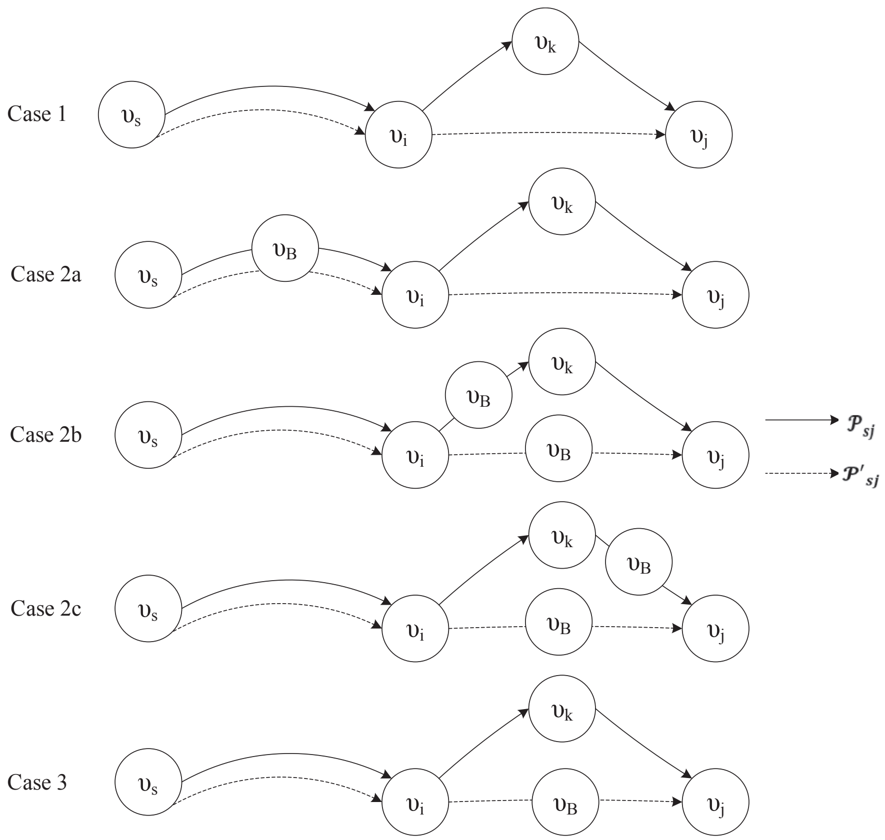

Fig. 3. Graphical representation of paths $\mathscr{P}_{sj}$ and $\mathscr{P}'_{sj}$ used in the rollback pruning strategy.

j in the networks of other capable caregivers are removed. If $\mathscr{Y}_{jc} = 0$ in the other node, task j must not be assigned to caregiver c in the solution. Then, the columns associated with task j in the column set of caregiver c in the RMP are removed, and the ingoing and outgoing arcs of task j in the network of the caregiver are removed.

5. Experimental results

In this section, the results from three experiments are examined, based on the modified instances as described in Section 5.1. One experiment examines the effects of key factors, namely the arduousness level, the service duration, the break requirement, and the temporal dependency, on performance indicators (the platform revenue, caregiver profit, and customer surplus). One experiment examines the effectiveness of the B&P approach. One experiment compares the performances of four matching strategies in the context of peer-to-peer service-sharing platforms.

5.1. Test instances

As no benchmark data are available for our problem, the set of instances is modified from the instances (bihcrsp_1-bihcrsp_30), an overview of which refers to the work by Braekers et al. (2016). First, the preferred starting times of tasks are ignored, while other information is reserved. Given the data above, the temporal dependencies, overtime, break-time window and duration are added, as explained below. The modified instances are adopted to validate the above-developed models and approach. Only the first 30 instances are selected, because these are small and can be solved quickly to yield optimal results (most can be solved within 1800 s, while a few are stopped when the computational-time reaches 1800 s), and because this study aims to analyze the effects of matching strategies on performance.

The arduousness level $\alpha_j$is set at an average constant for all tasks. For the break time, the setting proposed by Liu et al. (2017) is used as follows. The length of the lunch break for each full-time caregiver equals the average service time of the tasks. The earliest start-time of this lunch break is half of the latest service start-time of the artificial task a_c^- minus the length of the break, while the latest start-time is half of the latest service start-time of the artificial task a_c^+ plus the length of the break. However, there is no lunch break for part-time caregivers. The service time-window $[d_j^-, d_j^+]$ is generated according to the situation: $d_j^- = d_j^+$, when the service duration is fixed to the service time given in posted instances, or $d_j^- = 0.8d_j^+$ when the service duration is flexible, where d_j^+ equals the service time given in posted instances.

A random combination of the temporal dependency constraints, namely the synchronization, overlap, minimum difference, and minimum–maximum difference, is generated. The numbers of temporal dependency constraints are approximately 10%, 20%, and 40% of the number of tasks. The numbers of shared visit constraints are approximately 0%, 10%, and 20% of the number of tasks. The sets of generalized precedence constraints are generated using the algorithm proposed by Dohn et al. (2011). That is, if $t_i^+ < t_j^-$ or $t_j^+ < t_i^-$, synchronization cannot exist between tasks i and j. If $t_i^+ + d_i^- < t_j^-$ or $t_j^+ + d_j^- < t_i^-$, overlap between tasks i and j cannot occur. If $t_j^+ < t_i^-$, a minimum difference in time from tasks i and j cannot be achieved. When a minimum difference exists, $t_j^- - t_i^+ < diff_{min} \le t_j^+ - t_i^-$. If $t_j^+ < t_i^-$, the maximum difference in time between tasks i and j is meaningless. If $t_i^+ + diff_{max} < t_j^-$, the maximum difference in time between tasks i and j is impossible. When a maximum difference exists, then $t_j^- - t_i^+ < diff_{max} \le t_j^+ - t_i^-$. Note that when the temporal dependency is generated randomly, the maximum and minimum differences are actually identical. Therefore, the maximum difference is omitted.

5.2. Effects of key factors

The first experiment is conducted to examine the effects of key factors in the HHCRSP models, such as the arduousness level, service duration, break requirement, and temporal dependency, on performance indicators such as the platform revenue, customer surplus,

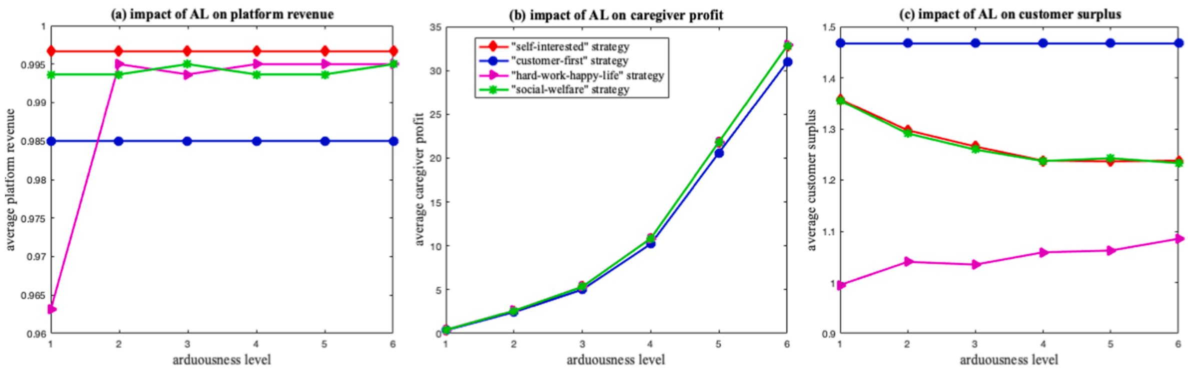

Fig. 4. Effect of arduousness on the platform revenue, caregiver profit, and customer surplus.

and caregiver profit. The y-axis of each figure in this section represents the average platform revenue (caregiver profit, and customer surplus), which is calculated over all test instances using Eq. (27) (Eqs. (28)-(29) respectively). The models that consider each task with a fixed service duration, each caregiver without a break requirement, and a lack of temporal dependency among the tasks serve as the base models. For each task, different arduousness levels are set to examine the effect of this factor on the performance indicators. A consideration of the effect of the service duration compares two cases, namely the base models wherein each task is considered with a fixed or with a flexible service duration. When discussing the effect of the break requirement, the base models with and without a caregiver break requirement are examined. To evaluate the effect of temporal dependency, base models with and without temporal dependency among the tasks are examined.

(a) Arduousness Level (AL)

A few preliminary runs are conducted to fine-tune the value of the arduousness level α_j (e.g., 1, 5, 10, 20, 40, 60), which indicates the ratio of the service load to the travel load based on the online instances. Each x-axis in Fig. 4 presents the respective values of the arduousness levels (1, 5, 10, 20, 40, and 60). In Fig. 4, Sub-figure (a) shows that α_j has a limited effect on the platform revenue when the "self-interested" and "customer-first" strategies are used, whereas α_j has a noticeable effect on the platform revenue when the "hard-work-happy-life" and "social-welfare" strategies are used. In particular, the "hard-work-happy-life" strategy significantly improves the platform revenue when α_j increases from 1 to 5, and slightly improves the revenue when α_j increases from 5 to 60. The caregiver profit increases with increasing α_j for all matching strategies, as indicated in Sub-figure (b) of Fig. 4. As α_j increases, the customer surplus increases when the "hard-work-happy-life" strategy is used but decreases when the "self-interested" and "social-welfare" strategies are used, as indicated in Sub-figure (c) of Fig. 4.

Briefly, the use of the "self-interested" strategy maintains the platform revenue and increases the caregiver profit as the arduousness level increases, but decreases the customer surplus. In other words, proper arduousness level of service can balance caregiver profit and customer surplus without harms to platform revenue when using the "self-interested" strategy. When the "customer-first" strategy is used, only the caregiver profit increases as the arduousness level increases, and the platform revenue and customer surplus are maintained. When the "hard-work-happy-life" strategy is used, the platform revenue, caregiver profit, and customer surplus all increase according to different trends as the arduousness level increases. When the "social welfare" strategy is used, an increasing arduousness level has a limited effect on the platform revenue (similar to that of the "self-interested" strategy), while increasing the caregiver profit and decreasing the customer surplus. Thus, the arduousness level should be tuned accordingly when using different strategies. Here, α_j is set to 10 for all tasks, to accommodate trade-offs among the platform revenue, caregiver profit, and customer surplus.

(b) Service Duration (SD)

Each x-axis in Fig. 5 uses the values 1, 2, 3, and 4 to represent the "self-interested", the "customer-first", the "hard-work-happy-life", and the "social-welfare" strategies, respectively. The graphs demonstrate that a flexible service duration help to increase the platform revenue, caregiver profit, and customer surplus when all matching strategies are used. The positive impact of flexible service duration is also drawn in the prior literature (Mosquera et al., 2019).

Fig. 5 also indicates that a flexible service duration affects the platform revenue, caregiver profit, and customer surplus differently when different matching strategies are used. A flexible service duration yields the greatest increase in the platform revenue when the "customer-first" strategy is used, while successively smaller increases are gained by use of the "social-welfare" strategy, the "self-interested" strategy, and the "hard-work-happy-life" strategy. A flexible service duration increases the caregiver profit to the greatest extent when the "self-interested" strategy is used, while successively smaller increases are obtained from the "hard-work-happy-life" strategy, the "social-welfare" strategy or the "customer-first" strategy. A flexible service duration also increases the customer surplus to the greatest extent when the "customer-first" strategy is used, while successively smaller increases are obtained from the "self-interested" strategy, the "social-welfare" strategy, or the "hard-work-happy-life" strategy.

Briefly, the "customer-first" strategy yields the greatest benefit in terms of the platform revenue and customer surplus, and the least benefit in the caregiver profit when the service duration is flexible. The "hard-work-happy-life" strategy yields the least benefits in the

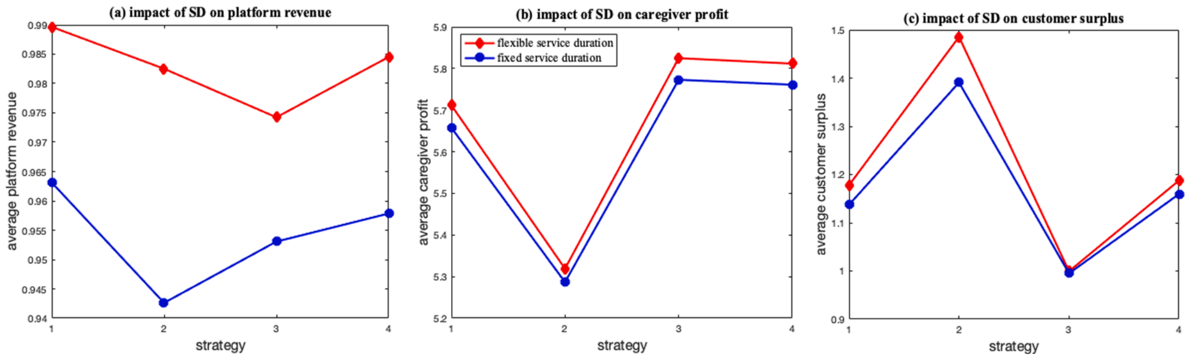

Fig. 5. Effect of service duration on the platform revenue, caregiver profit, and customer surplus.

context of flexible service duration. The “self-interested” strategy and the “social-welfare” strategy yield similar benefits in the context of a flexible service duration. These variations in benefits associated with a flexible service duration may be attributable to the maximization of the number of matched tasks, both directly and indirectly, in the “customer-first” and “self-interested” strategies, which can be achieved by slightly reducing the service duration of each matched task. In contrast, the “hard-work-happy-life” strategy mainly aims to maximize the difference between the service load and travel load and the service duration of each matched task. The “social-welfare” strategy benefits less than the “self-interested” strategy from a flexible service duration because of the trade-off between the platform revenue and caregiver profit when both are maximized simultaneously.

(c) Break Requirement (BR)

The break requirement for caregivers is a key difference between service-sharing platforms and traditional HHC institutions. Therefore, it is necessary to examine the effect of a break requirement on traditional HHC institutions. Each x-axis in Fig. 6 uses the values 1, 2, 3, 4, and 5 to represent the “self-interested”, “customer-first”, “hard-work-happy-life”, and the “social-welfare” strategies and the traditional HHC institutions, respectively. Here, the break requirement slightly reduces the platform revenue and customer surplus, but has a limited effect on the caregiver profit in the context of a traditional HHC institution. For service-sharing platforms, the break requirement has a limited effect on the platform revenue, caregiver profit, and customer surplus, regardless of the applied matching strategy. This latter observation is attributed to the typical caregiver practice of taking a break when all tasks are completed, or between two tasks when the difference in the start times of the tasks is sufficiently large.

Specifically, a break requirement inflicts the greatest harm on the platform revenue in the context of a traditional HHC institution, compared to any of the matching strategies in the context of a service-sharing platform. This observation is attributed to the mandatory nature of the break requirement for caregivers who work as employees. As more caregivers take breaks, less work time is available for visits and task performance, leading to an increase in unmatched tasks. In the context of a service-sharing platform, the break requirement affects performance differently when different matching strategies are used. Specifically, the break requirement reduces the platform revenue to the greatest extent when the “customer-first” strategy is used, while successively smaller reductions are obtained when the “self-interested” or “hard-work-happy-life” strategies are used. This requirement also decreases the caregiver profit to the greatest extent when the “social-welfare” strategy is used, while successively smaller decreases are obtained by using the “self-interested” strategy, the “hard-work-happy-life” strategy, or the “customer-first” strategy. The break requirement also has a slightly negative effect on the customer surplus when the “self-interested” and “customer-first” strategies are used.

In summary, the break requirement most negatively affects the profits of the three stakeholders when the “self-interested” strategy is used, with the “customer-first” strategy having a less negative effect. This may be attributable to this requirement indirectly reducing the number of matched tasks that directly affect the platform revenue when the first strategy is used and that indirectly affect the customer surplus when the latter strategy is used. The break requirement had the least negative effect when the “hard-work-happy-life” strategy is used, while the “social-welfare” strategy has a more negative effect. This may be attributable to the break requirement

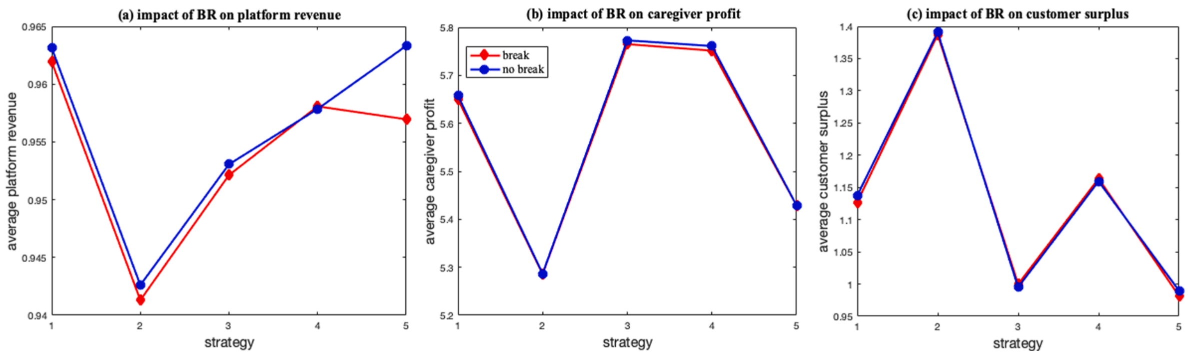

Fig. 6. Effect of the break requirement on the platform revenue, the caregiver profit, and the customer surplus.

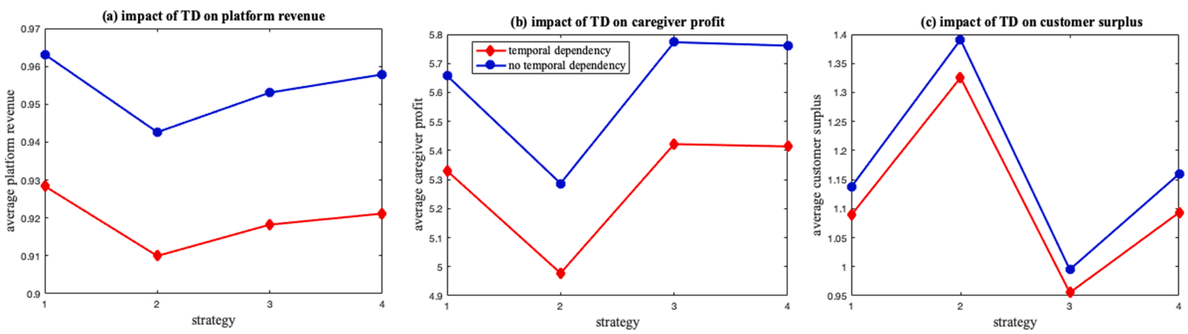

Fig. 7. Effect of temporal dependency on the platform revenue, caregiver profit, and customer surplus.

directly reducing the available caregiver service time slots but increasing the customer surplus.

(d) Temporal Dependency (TD)

Each x-axis in Fig. 7 uses the values 1, 2, 3, and 4 to represent the “self-interested”, the “customer-first”, the “hard-work-happy-life”, and the “social-welfare” strategies, respectively. The graphs demonstrate that temporal dependency reduces the platform revenue, caregiver profit, and customer surplus in the context of a service-sharing platform, regardless of the matching strategy that is used.

Fig. 7 indicates that temporal dependency reduces the service-sharing platform revenue to the greatest extent when the “social-welfare” strategy is used, while smaller reductions are obtained from the use of the “self-interested” and the “hard-work-happy-life” strategies, and the smallest reduction is obtained from the use of the “customer-first” strategy. Regarding the caregiver profit, temporal dependency among the tasks has the strongest negative effect when the “hard-work-happy-life” strategy is used, while successively less negative effects are obtained by use of the “social-welfare” strategy, the “self-interested” strategy or the “customer-first” strategy. Regarding the customer surplus, temporal dependency among the tasks has the strongest negative effect when the “social-welfare” strategy is used, while successively less negative effects are obtained by use of the “customer-first” strategy, the “self-interested” strategy or the “hard-work-happy-life” strategy.

Briefly, temporal dependency most negatively affects the profits of the three stakeholders when the “social-welfare” strategy is used, while successively less negative effects result from the use of the “hard-work-happy-life” strategy, the “self-interested” strategy or the “customer-first” strategies. This may be attributable to the “social-welfare” strategy reducing the number of matched tasks, and thus affecting the matching between tasks and caregivers. This would directly reduce the customer preference scores and the caregiver workload, while simultaneously maximizing the platform revenue, caregiver profit, and customer surplus.

As summarized by the aforementioned analysis, Table 6 indicates that a flexible service duration has the strongest positive effect on the performance when the “customer-first” strategy is used, but the weakest positive effect when the “hard-work-happy-life” strategy is used (where smaller values indicate better effects on performance). The break requirement has the weakest negative effect on profits when the “hard-work-happy-life” strategy is used, a more negative effect observed when the “social-welfare” strategy is used, and the strongest negative effect when the “self-interested” strategy is used. Temporal dependency has the weakest negative effect on performance when the “customer-first” strategy is used, and successively more negative effects when the “self-interested” strategy, the “hard-work-happy-life” strategy, or the “social-welfare” strategy are used. Therefore, the service platform can adopt a flexible service duration rule, because this has a positive effect regardless of the strategy. The service platform can allow caregivers to decide whether to take a break, as this requirement has a limited negative effect, and need to control the percentage of services with temporal dependency, which has an obvious negative effect.

5.3. Comparison with CPLEX

In this section, the performance of the B&P algorithm is compared with that of CPLEX, because the RMP included in the B&P algorithm is solved by CPLEX 12.6. All algorithms are coded in Java. The experiments were run on a computer equipped with an Intel Core i7-7700 3.6 GHz CPU, 12 GB of RAM, and the Windows operating system. A comparison of the results obtained with the CPLEX and B&P algorithms when using different matching strategies yielded similar outcomes. Therefore, this section focuses on a case in which the demand and supply are matched using the “social-welfare” strategy, with consideration of the key factors of flexible service durations, break requirements, and temporal dependencies. The only compared results are those from Instances 1–20 with 20% of the

Table 5
Time-window reduction based on precedence constraints.

Time windows of tasks i and j	Task i	Task j
Original	$[t_i^-, t_i^+]$	$[t_j^-, t_j^+]$
Reduced on $(i,j) \in \Delta$	$[t_i^-, \min(t_i^+, t_j^+ - \delta_{ij})]$	$[\max(t_j^-, t_i^- + \delta_{ij}), t_j^+]$
Reduced on$(j,i) \in \Delta$	$[\max(t_i^-, t_j^- + \delta_{ji}), t_i^+]$	$[t_j^-, \min(t_j^+, t_i^+ - \delta_{ji})]$
Left branch	$[\max(t_i^-, t_j^- + \delta_{ji}), t^s - 1]$	$[t_j^-, \min(t_j^+, t^s - 1 - \delta_{ji})]$
Right branch	$[t^s, \min(t_i^+, t_j^+ - \delta_{ij})]$	$[\max(t_j^-, t^s + \delta_{ij}), t_j^+]$

Table 6
Ranking of the effects of key factors on performance indicators.

Key factor Strategy	“self-interested”	“customer-first”	“hard-work-happy-life”	“social-welfare”
Service Duration (SD)	2	1	4	3
Break Requirement (BR)	4	3	1	2
Temporal Dependency (TD)	2	1	3	4

temporal dependency constraints and 10% of shared visits, for which CPLEX can find the best solutions within 1800 s.

Table 7 summarizes the results obtained using CPLEX and our B&P algorithm. It lists the computation times of the solved instances, the platform revenues, the caregiver profits, the customer surpluses, and the weighted sums of all profits with weight $w_1 = 1$ in Table 4,

Table 7
Results of Instances 1–20 using the "social-welfare" strategy.

instance	CPLEX					B&P					Gap
	RT(s)	**PR**	**CP**	**CS**	**TP**	**RT(s)**	**PR**	**CP**	**CS**	**TP**	
1–2-1	0.218	**1.000**	6.571	**0.818**	8.389	0.606	**1.000**	6.554	**0.818**	8.372	0.2%
2–2-1	0.094	**0.909**	3.948	0.818	5.675	0.652	**0.909**	3.745	**1.000**	5.654	0.4%
3–2-1	0.04	**0.818**	4.325	**0.636**	5.780	0.342	**0.818**	4.250	**0.636**	5.704	1.3%
4–2-1	0.089	**1.000**	5.668	**1.273**	7.940	0.821	**1.000**	5.663	**1.273**	7.936	0.06%
5–2-1	0.261	**0.818**	4.364	0.545	5.728	1.423	**0.818**	4.069	**0.818**	5.705	0.4%
6–2-1	0.248	**0.875**	6.542	**1.125**	8.542	1.120	**0.875**	6.339	**1.250**	8.464	0.9%
7–2-1	0.614	**0.875**	5.147	1.125	7.147	0.654	**0.875**	5.040	**1.188**	7.103	0.6%
8–2-1	34.124	**1.000**	5.767	1.375	8.142	**2.976**	**1.000**	5.590	**1.50**	8.090	0.6%
9–2-1	8.156	**1.000**	6.548	**1.563**	9.111	**0.4**	**1.000**	6.439	1.438	8.876	2.6%
10–2-1	0.557	**1.000**	4.283	**1.375**	6.658	23.003	0.938	4.177	**1.375**	6.490	2.5%
11–2-1	46.393	**0.909**	5.022	1.136	7.067	**28.454**	**0.909**	4.847	**1.227**	6.983	1.2%
12–2-1	1802.328	**1.000**	5.461	**1.318**	7.779	**19.487**	**1.000**	5.319	**1.318**	7.637	1.8%
13–2-1	1800.555	**1.000**	6.219	**1.318**	8.537	**20.866**	**1.000**	6.077	1.227	8.304	2.7%
14–2-1	100.278	**1.000**	6.416	**1.318**	8.734	**70.846**	0.938	6.223	1.273	8.496	2.7%
15–2-1	1800.512	**1.000**	5.758	**1.273**	8.031	**41.926**	0.955	5.517	**1.273**	7.744	**3.6%**
16–2-1	1800.534*	**1.000**	6.124	**0.955**	8.079	**120.374**	0.955	6.009	0.909	7.873	2.6%
17–2-1	1660.668	**0.909**	4.934	**1.227**	7.07	**1491.48**	0.864	4.831	1.182	6.877	2.7%
18–2-1	532.047	**0.955**	5.592	**1.091**	7.638	**51.633**	**0.955**	5.465	**1.091**	7.510	1.7%
19–2-1	136.313	**0.909**	6.045	1.273	8.227	**50.355**	**0.909**	5.858	**1.364**	8.131	1.2%
20–2-1	1801.245*	**0.909**	5.258	0.773	7.04	**3.021**	**0.909**	**5.303**	**1.000**	7.212	**−2.4%**

Note: RT means computing time of a solved instance, and a upper star means the instance is unsolved optimally within 1800 s, PR means the platform revenue, CP means the caregiver profit, CS means the customer surplus, and TP means the weighted sum of all profits with weight equaling 1.

and the gap between the total profits using CPLEX and our algorithm calculated by the equation ($100\% \times (TP_{CPLEX} - TP_{B\&P})/TP_{CPLEX}$). Here, the proposed B&P algorithm can achieve good solutions within 3% of the gap for 95% (19 out of 20) of instances and between 3 and 4% of gap for 5% (1 out of 20) of instances when compared to CPLEX. This gap may be attributable to the use of a solution pool that is initialized for the root node of the search tree in the proposed B&P algorithm, which is not ideal for optimal solutions. Specifically, the caregiver profit as calculated by CPLEX is greater than the profit calculated using our B&P algorithm, mainly because the latter uses limited choices for the flexible service duration of each task [e.g., $(0.8d_j^+, 0.9d_j^+, d_j^+)$] to reduce the exploration time in sub-problems, and a different range $[0.8d_j^+, d_j^+]$ for the optimizer. However, both algorithms achieve equally good platform revenues in 75% of instances. In contrast, the B&P algorithm achieves not worse customer surplus than the CPLEX in 75% of instances. In terms of computational time, the B&P algorithm identifies good solutions more quickly than the CPLEX when the size of the instances increases. This may be attributable to the search strategy of the B&P algorithm, wherein we select the node with the smallest lower bound to be processed next.

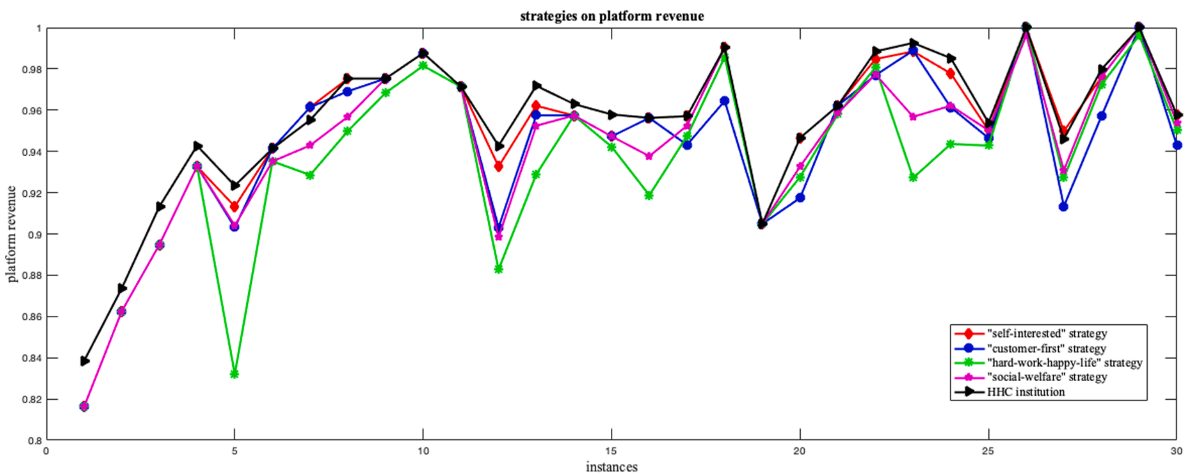

Fig. 8. Effect of the matching strategy on platform revenue.

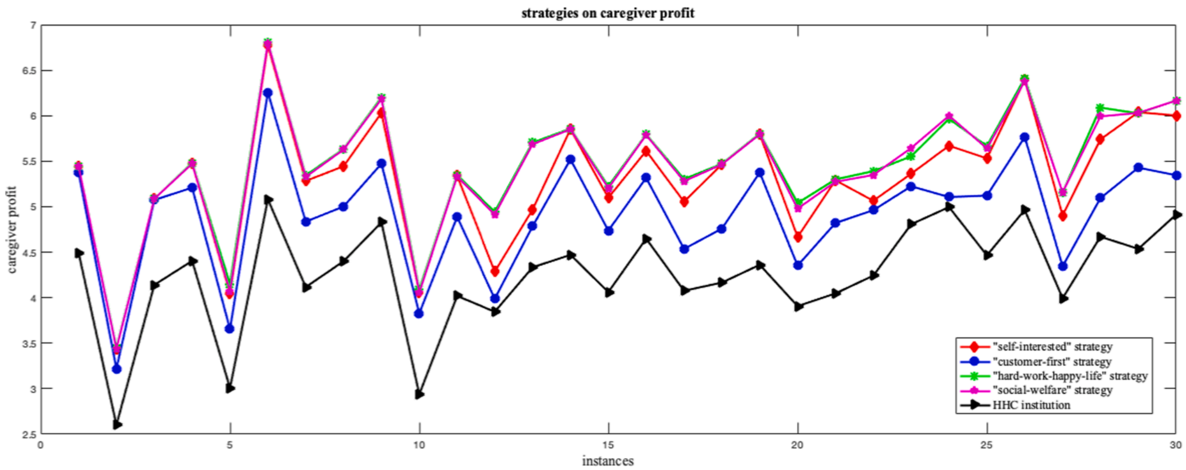

Fig. 9. Effect of the matching strategy on caregiver profit.

In summary, the results validate the effectiveness of the B&P algorithm, by showing that it achieves good solutions within acceptable computational times.

5.4. Comparisons among strategies

In this section, the platform revenue, caregiver profit, and customer surplus resulting from the application of the four different matching strategies are compared and discussed after accounting for all of the key factors in the models. Comparisons between traditional HHC institutions and service-sharing platforms are also conducted, to reveal the effect of the sharing economy. Each y-axis in the figures in this section represents the platform revenue, caregiver profit, or customer surplus, as calculated for each instance using Eqs. (27), (28), or (29), respectively.

As illustrated by Fig. 8, in most of the test instances, the service platform achieves the highest revenue when using the "self-interested" strategy, with less revenue obtained by use of the "social-welfare" strategy and the least revenue obtained by use of the "customer-first" or the "hard-work-happy-life" strategies. These latter two strategies may yield the lowest maximum platform revenues because both attempt to match as many tasks with long service durations but short travel times or high preference scores as possible. Traditional HHC institutions achieve the highest revenue relative to the service-sharing platforms when the "self-interested" strategy is used, as shown in Fig. 8.

As presented in Fig. 9, the "hard-work-happy-life" strategy generally enables the service-sharing platforms to achieve the highest caregiver profits, with slightly less profit obtained by use of the "social-welfare" strategy and the least profit obtained by use of the "self-interested" or the "customer-first" strategies. The "customer-first" strategy may yield the least profit for caregivers because the customer preference for a caregiver depends mainly on the latter's skills, experience level, and reputation, rather than the travel distance between the customer and the caregiver. The caregiver profit is also lower in the traditional HHC institutions than on the service-sharing platforms, regardless of the matching strategy, suggesting that a higher proportion of the workloads of caregivers from

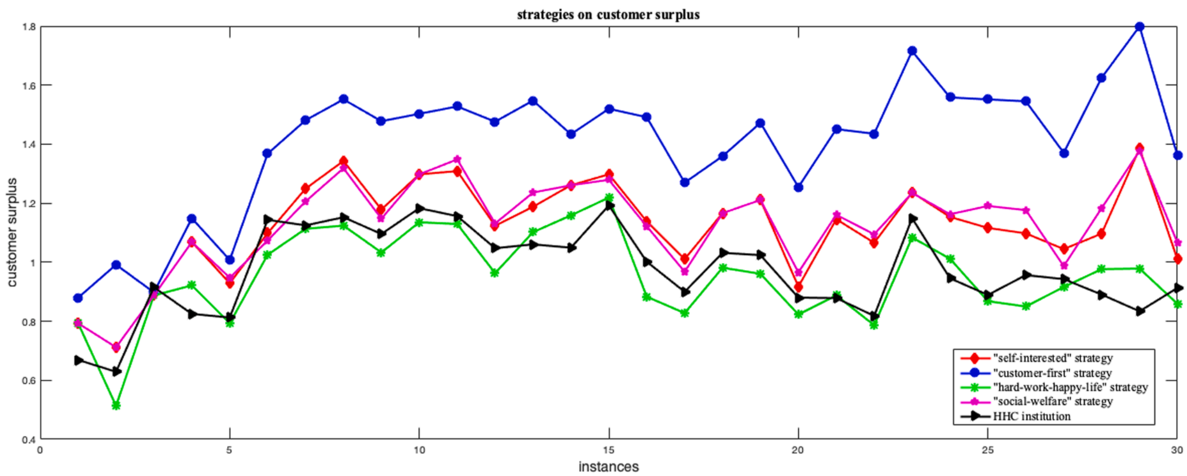

Fig. 10. Effect of the matching strategy on customer surplus.

Table 8
Average performances of different strategies.

Indicators		Platform revenue	Caregiver profit	Customer surplus
HHC institution		0.955	4.251	0.970
1. "self-interested"		**0.951**	5.307	1.118
2. "customer-first"		0.944	4.913	**1.402**
3. "hard-work-happy-life"		0.936	**5.462**	0.954
4. "social-welfare"	value	0.944	5.447	1.126
	1	$=\frac{0.944-0.951}{0.951}\times 100\% = -0.74\%$	$=\frac{5.447-5.307}{5.307}\times 100\% = 2.64\%$	$=\frac{1.126-1.118}{1.118}\times 100\% = 0.72\%$
	2	$=\frac{0.944-0.944}{0.944}\times 100\% = 0.00\%$	$=\frac{5.447-4.913}{4.913}\times 100\% = 10.87\%$	$=\frac{1.126-1.402}{1.402}\times 100\% = -19.69\%$
	3	$=\frac{0.944-0.936}{0.936}\times 100\% = 0.85\%$	$=\frac{5.447-5.462}{5.462}\times 100\% = -0.27\%$	$=\frac{1.126-0.954}{0.954}\times 100\% = 18.03\%$

the service-sharing platforms is directed towards serving customers and performing tasks. The traditional HHC institutions pay more attention to minimizing travel and overtime costs than to the utilization of the caregiver workload in customer service.

Fig. 10 demonstrates that the "customer-first" strategy yields the highest customer surplus among all tested instances. The "social-welfare" and "self-interested" strategies also yield higher customer surpluses than the "hard-work-happy-life" strategy. This outcome may be attributed to the focus of the "hard-work-happy-life" strategy on maximizing the service load while minimizing the travel load, rather than on maximizing the number of matched tasks that may contribute to an increase in the customer surplus. When compared to the traditional HHC institutions, the service-sharing platforms that apply appropriate matching strategies (except the "hard-work-happy-life" strategy) achieve higher customer surplus levels. In contrast, traditional HHC institutions achieve higher customer surplus levels than service-sharing platforms that use the "hard-work-happy-life" strategy in most instances (21/30), possibly because this strategy also performs worse than the "self-interested" strategy.

Table 8 summarizes the averages of performance indicators obtained for the traditional HHC institutions and the service-sharing platforms using different matching strategies. First, we compare the performances of the traditional HHC institutions and service-sharing platforms using the "self-interested" strategy, because both regard the revenue as the most important objective. Table 8 demonstrates that service-sharing platforms using the "self-interested" strategy and traditional HHC institutions earn equivalent revenues, although the former is also associated with greater caregiver profits and customer surpluses. Possibly, the platforms and institutions have different objectives. For example, for Level 2 objectives, HHC institutions aim to minimize travel and overtime costs, whereas service-sharing platforms aim to minimize the average caregiver profit and customer surplus directly.

As designed in Section 3.2.2, the "self-interested" strategy (ID = 1 in Table 8) first maximizes the platform revenue, followed by the caregiver profit and customer surplus at the same level of importance. The "customer-first" strategy (ID = 2 in Table 8) first maximizes the customer surplus, followed by the platform revenue and caregiver profit at the same level of importance. The "hard-work-happy-life" strategy (ID = 3 in Table 8) first maximizes the caregiver profit, followed by the platform revenue and customer surplus. The "social-welfare" strategy (ID = 4 in Table 8) maximizes and assigns the same importance level to all three indicators. The platform selects an appropriate matching strategy depending on the stage of development. For example, a service platform operating under a start-up strategy may use the "customer-first" strategy to attract customers, and later shift to the "hard-work-happy-life" strategy during the growth stage to retain caregivers. Finally, when the service platform reaches a stable stage, it may use the "self-interested" strategy to ensure a profit or the "social-welfare" strategy to benefit all stakeholders.

Although the "social-welfare" strategy is favorable for all stakeholders, there is a trade-off between the platform revenue, caregiver profit, and customer surplus. Therefore, we compare this strategy to the "self-interested", "customer-first", and "hard-work-happy-life" strategies to identify the gap between the best profit and a balanced profit for each stakeholder. First, we compare the "social-welfare" and "self-interested" strategies. When using the former, the platform revenue is 0.74% lower and the caregiver profit and customer surplus are 2.64% and 0.72% higher, respectively, than those obtained when using the latter strategy. Second, we compare the "social-welfare" and "customer-first" strategies. When using the former, the customer surplus is 19.69% lower and the caregiver profit is 10.87% higher than those obtained when using the latter strategy. Finally, we compare the "social-welfare" and the "hard-work-happy-life" strategies. When using the former, the caregiver profit is 0.27% lower and the customer surplus and platform revenue are 18.03% and 0.85% higher, respectively, than those obtained when using the latter. In conclusion, the "social-welfare" strategy must sacrifice a small amount of each stakeholder's profit to achieve a balanced maximum level of social welfare. In fact, it is necessary to sacrifice the customer surplus (although as high as 19.69%) in the supply side on the HHC service market so far. The government may provide funding to the stakeholders by cutting taxes or offering coupons. As service-sharing platforms that provide HHC services (e.g., many time banks) target socially and economically marginalized populations (e.g., the young, elderly, poor, or disabled), the maximization of social welfare helps to ensure the efficient long-term operation of these platforms. Therefore, the "social-welfare" strategy is beneficial for scheduled service-sharing platforms, caregivers, and customers in the HHC context. This strategy is also a goal of government funding for HHC services and sets the standards for service delivery.

6. Conclusions

This study aims to evaluate the matching of daily demands and supply in the context of HHC (HHCRSP) delivered via peer-to-peer service-sharing platforms. Four matching strategies are modeled and compared in terms of platform revenue, customer surplus, and caregiver profit. A B&P approach is designed to solve the optimal matching problem. A pulse algorithm is devised to include break rules, rollback with break rules, and dominance rules of partial paths, for pricing sub-problems that considers the features of break requirements and flexible service durations. Three branching strategies, namely branching on the time-window, on uncovered tasks, and on the assignment variables, are developed to ensure the temporal dependency constraints and solution integrity. Additionally, the effects of several key factors are examined, namely the arduousness level of the task, the flexible service duration of the task, the break requirement for the caregiver, and the temporal dependency among tasks.

Four multi-objective, mixed-integer linear programming models with four matching strategies ("self-interested", "customer-first", "hard-work-happy-life", and "social-welfare") are constructed for the HHCRSP of peer-to-peer service-sharing platforms, while considering several key rules, such as flexible service durations, break requirements, and temporal dependencies. The results obtained by the models in analyses of instances posted online indicate that flexible service duration increases the platform revenue, caregiver profit, and customer surplus to varying degrees when using different matching strategies. However, the break requirement and temporal dependency have various negative effects on the performance indicators, depending on the matching strategies. More specifically, the "customer-first" and "self-interested" strategies benefit more from flexible service duration, but are harmed to a greater extent by break requirement and to a lesser extent by temporal dependency, compared to the "social-welfare" and "hard-work-happy-life" strategies. The comparison between the service-sharing platforms and traditional HHC institutions confirms the positive effect of the sharing economy on profits of three stakeholders. One-to-one comparisons between the "social-welfare" strategy and the other strategies indicate that the former can achieve maximum social welfare by sacrificing a small amount of the profit of each stakeholder, and that these sacrifices can be replaced by government subsidies, such as tax cuts or coupons. Thus, in the context of a service-sharing platform, a "social-welfare" strategy is beneficial for all three stakeholders and the government.

However, this work has some limitations. A small number of instances with small size are used to validate the matching strategies and draw conclusions. The B&P algorithm is effective but cannot outperform CPLEX in terms of solution quality. A long time is required to achieve optimal matching solutions when large numbers of customers and caregivers are available. Therefore, future aims include the improvement of the B&P algorithms and the exploration of better methods that can effectively and efficiently solve the problem of matching daily demands with supply on a large scale and with reference to additional literature. Finally, the matching procedure does not consider pricing issues. In practice, however, the task price or caregiver's hourly rate on a service-sharing platform is dynamic and depends on the demand and supply. Therefore, another future aim is to expand the matching strategies to accommodate surge pricing.

CRediT authorship contribution statement

Meiyan Lin: Conceptualization, Investigation, Methodology, Validation, Formal analysis, Writing - original draft, Writing - review & editing. **Lijun Ma:** Conceptualization, Methodology, Validation, Writing - review & editing. **Chengshuo Ying:** Validation, Writing - review & editing.

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Appendix A. . Factors and models of the HHCRSP in literature

Article	Time-related factors					Visit-related factors				Model
	TT	SD	TW	OT	BK	UC	SK	PR	TD	OB
(Trautsamwieser and Hirsch, 2011)	×	×	√	√	√		√	√		√
(Rasmussen et al., 2012)	√	×	√			√		√	√	√
(Nickel et al., 2012)	×	×	√	√		×	√			√
(Bard et al., 2014)	√	×	√	√	√					√
(Trautsamwieser and Hirsch, 2014)	×	×	√		√	×	√			√
(Cappanera and Scutellà, 2015)	×	×		√			√			×
(Maya Duque et al., 2015)	×	×					×	+		+
(Braekers et al., 2016)	√	×	√	√			×	√		–
(Rest and Hirsch, 2016)	√	×	√	√	√		×			√
(Yalçındağ et al., 2016)	×	×					√			×
(Redjem and Marcon, 2016)	×	×	√						√	
(Liu et al., 2017)	×	×	√		√	×				√
(Grenouilleau et al., 2019)	√	×	√	√		×	√	√		√
(Cappanera et al., 2018)	×	×					√			×

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(*continued*)

Article	Time-related factors					Visit-related factors				Model
	TT	SD	TW	OT	BK	UC	SK	PR	TD	OB
(Yuan et al., 2018)	×	√	√			×				√
(Shi et al., 2018)	×	√	√							
(Lin et al., 2018)	×	×	√	√			×	×		√
(Mosquera et al., 2019)	√	√	√			√	×	+		+
(Gomes and Ramos, 2019)	×	×	√		√					+
(Moussavi et al., 2019)	×	×								
(Shi et al., 2019)	×	√	√				√			√
(Cinar et al., 2019)	×	×	√							√
(Frifita and Masmoudi, 2020)	√	×	√						√	×
This study	√	√	√	√	√	×	×	√	√	+ √

Note: For TW(time window), OT(overtime), BK(break), and TD (temporal dependency), √ means to be considered in study, while empty means not. For TT(travel time), × means travel time between two locations is the same for all caregivers/vehicles, √ means it is varied by caregivers, transportation mode, and departure time, and empty means it is not considered. For SD(service duration), × means service time is a constant, √ means it is stochastic or flexible. For UC (uncovered visit), × means uncovered visit with priority 1, √ means uncovered visit with different priorities, and empty means uncovered visit is not considered. For SK(skill requirement or qualification), × means each caregiver with a certain skill can handle the visit required that level of skill, √ means caregiver can do visit required less levels of skill (hierarchical), and empty means qualification is not considered. For PR(preference), × means caregiver preference is considered, √ means customer preference is considered, + means both caregiver and customer preference are considered, and empty means preference is not considered. For OB(objective), × refers to single-objective is formulated, √ refers to multi-objective in weight sum is formulated, + means multi-objective is deal with a lexicographical approach, - means multi-objective is deal with Pareto-based approach.

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