ARTICLE IN PRESS

Human Resource Management Review xxx (xxxx) xxx

Contents lists available at ScienceDirect

Human Resource Management Review

journal homepage: www.elsevier.com/locate/hrmr

Full Length Article

Two's company, platforms make a crowd: Talent identification in tripartite work arrangements in the gig economy

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ARTICLE INFO

Keywords:
Gig economy
Talent identification
Online labor platforms
Talent management
Non-standard work
Tripartite working relationships

ABSTRACT

The gig economy provides a novel setting that challenges many established ways of working. This paper unpacks the nature of talent identification in the gig economy through the role of three central actors; the online labor platform firm, the requester/customer and the gig worker. Talent identification in this context is especially novel as it emerges from tripartite relationships among independent economic actors, in contrast to traditional settings where talent identification is studied from a dyadic perspective (i.e., talented workers and the organization). We decipher the heterogeneity across online labor platforms and their gig workforces through the practice of talent identification. We provide an agenda to guide future research on the inclusive versus exclusive nature of talent identification in the gig economy as well as on online labor platforms as independent, yet powerful players who identify talents themselves alongside shaping talent identification processes between workers and hiring organizations. Accordingly, this paper extends the parameters of talent identification scholarship along with providing a different lens by which we examine work in the gig context.

1. Introduction

The growth of the gig economy along with the accompanying positive and critical discourse continue to gather pace across the world. This contemporary work setting represents an economic system whereby online labor platforms (OLPs)[1] such as Upwork, Fiverr and TopTal facilitate matches between freelance 'gig' workers and customers/organizations that request their services (Duggan, Sherman, Carbery, & McDonnell, 2020; Kuhn & Maleki, 2017; Meijerink & Keegan, 2019). These OLPs offer a type of on-demand, online pool of workers that enables requesters and individuals to be matched for the purpose of work needs and wants. On the face of it, these OLPs create a marketplace for freelance work and an online tool by which to connect such independent workers with organizations and individual consumers who have tasks to be performed. These OLPs enable the organization of work as a series of specific tasks or gigs that may incorporate a pool of people from across the world (Cascio & Boudreau, 2016).

Since gig work involves temporary work with no expectation of a longer-term or ongoing relationship, one may presume that gig workers fall outside the remit of talent management. We, like others (Corporaal & Lehdonvirta, 2017; Keegan & Meijerink, 2022b;

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[1] OLPs are the companies that develop/deploy software (e.g., algorithms, apps, online marketplace) for offering intermediation services.

https://doi.org/10.1016/j.hrmr.2024.101011
Received 21 April 2022; Received in revised form 19 December 2023; Accepted 14 January 2024

Kuhn, 2021; McKeown & Pichault, 2021; Meijerink, 2021), challenge this assumption. For example, Al Ariss, Cascio, and Paauwe (2014) noted that information technologies – as used by OLPs – allow organizations to source talent outside organizational boundaries in an on-demand fashion. In line with arguments by Kuhn (2021), OLPs indeed frame themselves as talent platforms (e.g., Toptal,[2] Upwork, Fiverr); they present themselves firmly as providing an online talent pool of gig workers with unique, specialist skills that confer value for those needing specific tasks or projects to be completed (Cascio & Boudreau, 2016). Other platforms (e.g., Uber, Deliveroo) are argued as commoditizing workers (Dunn, 2020; Wood, Graham, Lehdonvirta, & Hjorth, 2019) and therefore, may appear to have less resonance with respect to talent management. Accordingly, it remains a question in what ways OLPs are involved in talent management and whether this intimates a need to expand the boundaries of this scholarship (Cascio & Boudreau, 2016).

Talent identification refers to the process of determining which workers are of (most) value to an organization for differentially treating selected individuals (Björkman, Ehrnrooth, Mäkelä, Smale, & Sumelius, 2013; McDonnell & Wiblen, 2021). If one seeks to effectively manage talent, organizations must first identify the talent (Hartmann, Feisel, & Schober, 2010) which means talent identification centrally feeds into a wider set of talent management domains and practices, including talent development and retention (Meyers & van Woerkom, 2014). Accordingly, we propose that by uncovering the nature and practice of talent identification in the gig economy, this paper opens the avenue for future research on how OLPs expand our current understanding of the wider practice of talent management.

Consequently, the goal of this paper is to conceptually untangle talent identification in relation to the inherent complexity involved in the novel working arrangements that encompass the gig economy. This complexity is rooted in two types of heterogeneity; *within* an online marketplace where multiple actors are involved in talent identification; and *across* these platforms in terms of the diversity in how they work and decision-making on the inclusion or exclusion of (talented) gig workers. In line with this conceptualization, we make two primary contributions. First, we unpack how talent identification takes shape in the tripartite relationships between OLPs, workers and requesters (i.e., the within-market place perspective). Scholarship has primarily examined talent identification from a dyadic perspective (i.e., a talented individual and the organization). In this paper, we home in on the role of the OLP as a third and independent, yet powerful player, in talent identification processes. OLPs decide who gets access to their online marketplace, set norms on how market transactions should unfold, and deploy information technologies to enforce selected rules (Duggan et al., 2020; Meijerink, Keegan, & Bondarouk, 2021). Considering the role of OLPs – as technology-mediated organizations – is particularly salient given the increased interest in algorithms and artificial intelligence in the management of work (e.g. Basu, Majumdar, Mukherjee, Munjal, & Palaksha, 2023; Langer & König, 2023; Malik, Budhwar, & Kazmi, 2023; Meijerink & Bondarouk, 2023; Pan & Froese, 2023). We illustrate how OLPs are key talent identifiers and how they shape talent identification processes between workers and hiring organizations (i.e., also referred to as 'requesters') in four important ways by developing structures that determine (i) the way gig workers are included/excluded (from online marketplaces) and (ii) according to what criteria, (iii) the degree of autonomy that requesters have in identifying talent, and (iv) the level of transparency of talent identification processes in platform-enabled gig work (see Fig. 1).

Second, we decipher the diversity of these online labor or talent marketplaces in relation to talent identification (i.e., the between-market perspective). Extant literature has shown how gig work differs in terms of task characteristics like standardization, simplification, interdependencies and whether tasks are performed on-location or virtually (Duggan et al., 2020; Duggan, McDonnell, Sherman, & Carbery, 2022; Howcroft & Bergvall-Kåreborn, 2019; Nakatsu, Grossman, & Iacovou, 2014). We build on this literature by outlining under what conditions online labor platforms differ in how they shape talent identification processes, for instance, by identifying both inclusive (all of the workforce) and exclusive (some of the workforce) talent conceptualizations (Collings & Mellahi, 2009; McDonnell & Wiblen, 2021; Meyers & van Woerkom, 2014; Swailes, 2013) used by OLPs. Specifically, we draw on a series of gig work examples and organizations to illuminate how the four talent identification dimensions (i.e. type of inclusion/exclusion, criteria, requester autonomy and transparency) differ as a function of OLP, requester and gig worker characteristics (see Fig. 1).

Taken together, this paper offers a conceptual framework which is visualized in Fig. 1 and which elucidates how talent identification (and the absence thereof) differs across and within online marketplaces for freelance labor. In doing so, we set an agenda for future research into talent identification in the non-standard, tripartite work setting of the gig economy. We also point to the wider applicability of some of this argument, given the increasing and changing roles of innovative technology (such as algorithms and artificial intelligence) in talent decisions, to more traditional organizational environments (Claus, 2019; Gonzalez, Capman, Oswald, Theys, & Tomczak, 2019).

2. A conceptual framework of gig worker inclusion/exclusion

Talent identification typically involves judgment-oriented activities whereby designated intra-organizational actors (e.g., HR, line managers) determine which employees are of value or most value to the organization based on some combination of potential and performance. An individual's value is often assessed and denoted through a process of evaluation and scoring. In line with this, the talent management literature has advanced a dyadic perspective on talent identification in which organizations/employers – based on individual scores – confer talent status, create talent pools, and otherwise differentiate among individual workers (McDonnell & Wiblen, 2021).

Within traditional organizational settings, talent identification processes range from highly unstructured, informal, and gut-feel

[2] The name of the TopTal platform is strongly rooted in the idea of high talent potential and performance as suggests the platform offers TopTal (*ent*).

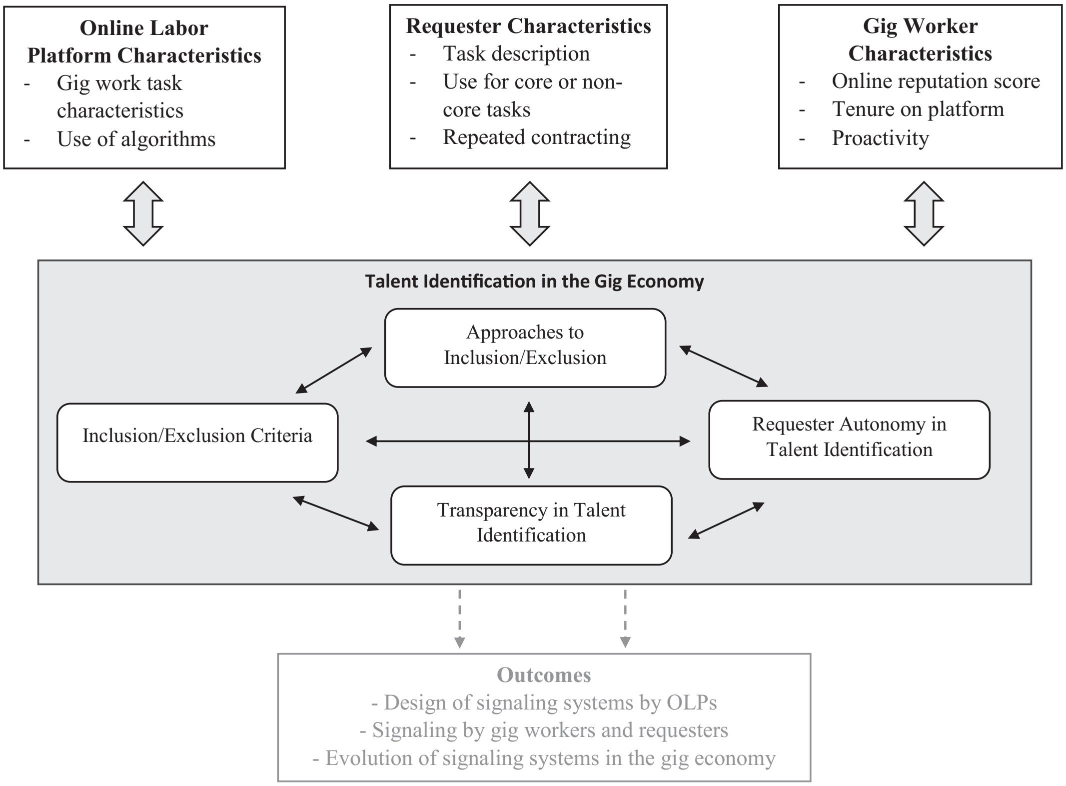

Fig. 1. Conceptual framework of talent identification in the gig economy: a tripartite perspective.

approaches to more systematic and evidence-based methods with various scoring systems (Jones, Whitaker, Seet, & Parkin, 2012; McDonnell & Wiblen, 2020). Even where objective data forms part of the identification process, subjective observation can often override the metrics (McDonnell & Wiblen, 2021; Wiblen, 2016; Wiblen & Marler, 2021) and unclear or inconsistently applied criteria for decisions are seemingly commonplace (Asplund, 2020; Jones et al., 2012; Jooss, McDonnell, & Burbach, 2021; Tyskbo, 2021). The results of the talent identification process are then used for managerial decision making about resource allocation, whereby specifically designated individuals (i.e., talents) get access to disproportionate levels of support and/or development. In other words, employees are segmented into different groupings based on the judged level of talent (Boudreau & Ramstad, 2005), allowing organizations to focus their development resources on the talent segments offering the promise of the greatest return on investment. This makes talent identification an essential precursor and driver of other talent management activities such as talent development and talent retention (Collings & Mellahi, 2009; Meyers, van Woerkom, Paauwe, & Dries, 2020).

2.1. Gig workers as key platform players

The rise of OLPs challenges the scholarship and practice of talent identification (and talent management more generally) because traditional thinking of talent identification assumes an ongoing dyadic relationship between an employee and employer. Talent identification involves employer-organizations gaining or extracting value from a specific worker over time. Organizations then invest in developing talented workers (Collings & Mellahi, 2009). In contrast, gig work occurs outside the confines of the employee-employer relationship, where OLPs work with a freelance workforce (Aguinis & Lawal, 2013; Stanford, 2017). As freelancers that look for paid work via an OLP, gig workers are neither employed by the OLP nor by the organization/individual that contracts with them (Duggan et al., 2020; Kuhn & Maleki, 2017; Meijerink & Keegan, 2019). Instead, gig work takes place in a tripartite working arrangement[3] that is orchestrated by OLPs that matchmake between freelance gig workers and requesters (i.e., organizations and/or consumers) that are in need of their services. As such, the type of gig work that OLPs intermediate for falls outside the confines of the standard, dyadic employment relationship (Meijerink & Keegan, 2019). It may therefore appear that gig workers do not meet the traditional definition of “talent” (i.e., employees who are of the highest levels of value to the organization based on some combination of potential and performance) for either the OLPs or the requesters given the lack of an ongoing employment relationship.

[3] Gig work also manifests in bilateral relationships between a freelancer and requester (e.g., a consumer that directly contracts with a freelance plumber). For the purpose of this paper, however, we examine what we refer to as ‘platform-enabled gig work’, that is, gig work that is inter-mediated by online labor platforms.

Indeed, seen from the perspective of the requesters or contracting organizations, gig work is a form of outsourcing or contractual work relationship (Meijerink & Keegan, 2019). That is, requesters use OLPs to gain access to a workforce of freelancers. Human capital theory has defined outsourcing and short-term contractual work arrangements as low in both uniqueness and strategic value (Lepak & Snell, 1999, 2002). These workers are not core to the organization, and therefore organizations should not invest in them. Accordingly, gig workers are unlikely to be viewed as talent by a requester given that key strategic positions are not traditionally put outside the boundaries of the firm (Collings & Mellahi, 2009). As a result, they would not be subject to talent identification processes or allocated talent status in the same ways as those in traditional organizational forms.

One nuance in the relevance and feasibility of talent identification practices in gig work is driven by the type of requester of the gig services, organizations/business or individual consumers/households. There may be reasons to believe that gig workers are subject to some degree of talent identification enacted by organizations. For instance, McKeown and Pichault (2021) show that independent professionals proactively signal their talents to potential client-businesses in an attempt to be selected and outcompete rival gig workers. Moreover, organizations do subject certain independent professionals (those with unique skills that are in high demand) to talent identification practices that assess these professionals' industry knowledge/experience and abilities to collaborate (Lepak & Snell, 2002). On the contrary, consumers/households are less likely to invest in talent identification practices, among others, because they are unlikely to have the competences and resources similar to business (e.g., an HR department). This is precisely why consumers turn to OLPs as these platforms provide tools such as online review systems which enable consumers to identify gig workers' talents (Lehdonvirta, Kässi, Hjorth, Barnard, & Graham, 2019). These review systems are fed with consumer-generated data which consumers produce once a gig-based assignment has been completed by the worker in the form of online ratings that gauge workers' performance. As such, although consumers may not set up talent identification practices themselves, they do actively take part in talent identification processes by administering online ratings and using online review systems that OLPs design and maintain.

OLPs do invest significantly in talent identification. Typically, a fee is charged by OLPs per match made between a worker and requester, meaning that gig workers are pivotal to the strategic and financial success of OLPs (Keegan & Meijerink, 2022b; Meijerink et al., 2021). It has been argued elsewhere that strategy should drive talent management (Becker, Huselid, & Beatty, 2009; McDonnell, 2011). In this context, it can be argued that human capital is being deployed in line with the OLPs' strategic intent which in turn realizes economic value (Bowman & Hird, 2014). This is precisely why Keegan and Meijerink (2022b) propose that gig workers – and their human capital – are strategically valuable to OLPs, despite not being in an employment relationship. It is in the interest of some OLPs to retain qualified, high-performing, high-potential (or some combination thereof) gig workers in their pool of contingent labor (Kuhn, 2021; Meijerink & Keegan, 2019), and control freelance service provision to satisfy and retain contracting organizations (Meijerink et al., 2021; Shapiro, 2018; Veen, Barratt, & Goods, 2019; Wood et al., 2019). Accordingly, OLPs may have an incentive to identify and treat a selected group of gig workers as 'talents' thereby engaging in talent identification processes. This implies an exclusive approach to talent identification is evident in some OLPs. At the same time, their business model often dictates that OLPs should be inclusive, an apparent contradiction which we review in the next section.

2.2. Talent identification by online labor platforms: not necessarily so inclusive

The extent to which talent identification is necessarily exclusive compared to inclusive has gained considerable scholarly attention (Bonneton, Festing, & Muratbekova-Touron, 2020; Meyers & van Woerkom, 2014; O'Connor & Crowley-Henry, 2019) with the dominant view being one that ascribes to some form of exclusivity (McDonnell, Collings, Mellahi, & Schuler, 2017; Swailes, 2013). The exclusive perspective refers to the idea that some people and/or positions make a more significant difference than others to current and future organizational performance, and therefore a limited number of people are considered as talent or high-potential/performer. The contrasting inclusive approach takes the perspective that every individual worker has talent and that this should be fostered and developed to increase each person's contribution to the organization.

On the face of it, OLPs typically appear as being open to all and, therefore, represent an inclusive online talent marketplace. This can be explained by considering a central tenet of the OLP business model. That is, OLPs generate revenue by charging a monetary fee per match made between a gig worker and a requester. It is, therefore, in the interest of an OLP to increase the number of transactions in its online marketplace (Meijerink et al., 2021). This, in turn, will drive the number of available gig workers (and requesters) willing to engage in transactions and create an incentive to place few or no restrictions for freelance workers to enter their online marketplace. For instance, Pelzer, Frenken, and Boon (2019) show that Uber lobbies against regulations that limit who can become a driver (e.g., taxi permit, diplomas, and car requirements) and start driving via the Uber platform. Moreover, research shows that OLPs' success depends on either growing the number *or* variety of platform users (Cennamo & Santalo, 2013), which requires an inclusive approach consisting of minimal entry criteria. Finally, the additional costs to OLPs for enabling workers to join their online marketplaces are minimal since few entry criteria are set and/or decisions are automated by means of algorithms (Duggan et al., 2020; Meijerink et al., 2021). Taken together, given their apparent inclusive nature, one may expect that OLPs are unlikely to practice talent identification with gig workers in a way that might limit the growth of their online marketplace.

We, however, argue that matters are more complicated and suggest that there are many cases in which online marketplaces appear to engage in talent identification by differentiating and segmenting their gig workforces. This suggests a more exclusive approach may also exist in some OLP contexts (Corporaal & Lehdonvirta, 2017; Kuhn, 2021; Meijerink, 2021). Research finds that differentiating and segmenting gig workers stems from the need to meet the interests of contracting organizations/requesters and ensure they continue to source freelance labor via the OLP (Corporaal & Lehdonvirta, 2017; Jarrahi & Sutherland, 2019; Kuhn, 2021; Meijerink, 2021). OLPs are dependent on a steady and growing number of requesters as much as they are dependent on a steady supply of workers (Meijerink & Keegan, 2019). After all, growing the demand and supply sides is what allows OLPs to increase revenue (Cennamo & Santalo, 2013;

Frenken, Vaskelainen, Fünfschilling, & Piscicelli, 2020; Meijerink et al., 2021). OLP's, therefore, require freelance "talent" to operationalize and realize strategic imperatives. While attracting sufficient labor supply requires an inclusive approach (i.e., the online marketplace is open to all), the attraction and retention of requesters may involve a more exclusive approach where high-performing gig workers are differentiated from others to ensure requester needs are met, and thus generate future business transactions. This may be more pronounced in some OLPs than others especially whereby some requesters are more important than others by way of the volume and value of transactions undertaken.

Taken together, OLPs have an incentive to control and coordinate the interactions between gig workers and requesters by means of talent identification processes. Accordingly, we envision that OLPs determine how inclusive or exclusive gig talent pools are, by what criteria (e.g., performance / potential) talent is defined and thus which workers are seen as talent or not, the autonomy granted to requesters to select (talented) workers themselves, and the level of transparency in talent identification processes for requesters and workers. This signifies how talent identification processes in OLP contexts differ from traditional contexts. In traditional contexts, talent identification takes shape in dyadic relationships between organizations (usually the employer) and (talented) employees. In such dyadic relationships, the organization is in the lead in designing talent identification processes as it decides on how talent is defined, which workers become 'talent' and whether to prioritize inclusive/exclusive talent pools. In contrast, in a platform-enabled gig work context, talent identification emerges from tripartite relationships between the OLP, gig worker and requesters. OLPs are in the driver's seat when it comes to designing talent identification processes for gig workers by designing online review systems (that include criteria by which the notion of talent is defined), algorithmically deciding on who gets access to (or is removed from) their online talent pools of gig workers, deciding what role requesters have in talent identification processes, and how much information is shared with workers and requesters on the design of talent identification by OLPs. Put differently, while requesters (i.e., employers) are relatively independent from third parties in traditional talent contexts, in platform-enabled gig work the role of requesters in talent identification is largely determined by the OLPs, even while the OLPs remain reliant on the requesters to provide much of the information needed for their own talent identification efforts. Given the prominent role that OLPs play in shaping talent identification processes, we outline how OLPs differentiate talents from non-talents to reinforce an exclusive approach to talent identification in tripartite relationships between OLPs, gig workers and requesters.

2.3. *Worker differentiation in online labor platform contexts*

OLPs may adopt several approaches in differentiating individuals into categories, and thus reinforcing exclusive talent identification to facilitate desired gig worker behavior and retain requester business. First, many platforms that appear inclusive at first eventually seek to exclude workers who fall below a certain performance threshold or standard. Uber is a well-known example as it algorithmically 'deactivates' the accounts of drivers whose average rating – provided by requesters/passengers – falls below a certain threshold, for example, 4.6 out of 5 (Lee, Kusbit, Metsky, & Dabbish, 2015; Rosenblat, 2018). Since Uber drivers are freelancers that cannot be 'fired', this essentially means that relatively poor performing workers are denied access to Uber's 'inclusive' online marketplace. This so-called de-activation practice that Uber operates can be considered a type of inclusive talent identification where poor-performers are segmented from high-performing workers. We term Uber as inclusive at the outset in that there are limited requirements to be met to enable access to work. OLPs such as TopTal, Upwork, and People Per Hour however, are stricter in admitting freelancers to their pool of available workers in that they undertake some initial screening to ensure gig workers in their pools have

Table 1
Examples of online labor platforms and talent identification practices.

Online Labor Platform	Well-structured tasks versus unstructured tasks	Independent versus interdependent tasks	Who selects workers? Requester vs. algorithm	Talent identification features
Fiverr	Varies – a feature of the individual task, not the platform	Interdependent	Requester	Fiverr Pro program to document potential and performance.
GigNow	Unstructured	Interdependent	Requester	Focused on longer-term contractor roles. Allows enterprise clients to create talent pools.
Upwork	Varies – a feature of the individual task, not the platform	Interdependent	Requester	Talent badge program (e.g., Rising Talent, Expert Vetted) to document potential and performance.
IntelyCare	Unstructured	Interdependent	Algorithm	Verifies required qualifications such as nursing license and COVID testing.
People Per Hour	Varies – a feature of the individual task, not the platform	Interdependent	Requester	Intensive selection of workers into the talent pool. CERT program to document potential and performance.
Toptal	Varies – feature of the individual task, not the platform	Interdependent	Requester	Intensive selection of workers into the talent pool.
Uber	Standardized	Independent	Algorithm	Minimal screening of talent before joining. Remove workers who fall below performance standards from the talent pool.
Deliveroo	Standardized	Independent	Algorithm	Minimal screening of talent before joining.

identifiably valued skills and/or experience (see talent identification features in Table 1).

Second, OLPs may engage in talent identification by differentiating high-performers (from regular performers) and offering this segment of workers more attractive gigs or additional work assignments. For example, Deliveroo offers high-performing workers priority access to financially lucrative work assignments to retain them and induce further high-level performance in the future (Meijerink et al., 2021; Veen et al., 2019). Moreover, OLPs offer selected benefits that are reserved for high performers. For instance, Upwork and Fiverr use talent pools whereby they identify highly skilled workers through programs such as Rising Talent and Expert Vetted on Upwork and Fiverr Pro, for which Fiverr states less than 1% of the applicants are accepted. While the Fiverr platform is open to all, workers can only become 'a Fiverr Pro' and join this exclusive marketplace when they prove to be 'the highest-caliber talent'. Fiverr Pro claims to hand vet (identify) these talents based on their professional background, education, and portfolio of previous work (performed via Fiverr). The benefit to gig workers in this talent pool is that they gain access to selected contracting companies that are less price-sensitive and have faster payment clearance. Along similar lines, Uber runs the Uber Pro program which involves identifying high-performing drivers (through requester/passenger evaluations) and rewarding them with benefits like free tuition in online classes, discounts on vehicle maintenance, and higher compensation rates (Kuhn, 2021).

Finally, next to identifying talents themselves, some OLPs such as Temper enable contracting organizations/requesters to establish their own 'favorite pools' (Meijerink & Arets, 2021). This essentially is a feature in an OLP's application where requesters can identify and label specific gig workers as preferred suppliers based on their past performance. These then are offered priority and/or exclusive access to work assignments by the requester. These requesters may decide to regularly re-contract with high-performing gig workers, thereby demonstrating exclusivity and segmentation in talent identification (Connelly & Gallagher, 2006; McKeown & Pichault, 2021). Therefore, in contrast with dominant thinking in talent management literature, talent identification of gig workers, who reside outside traditional organizational boundaries and employment relationships, does occur.

3. Explaining inclusion-exclusion in the gig economy

To better understand this apparent contradiction between inclusion and exclusion, we propose to break down talent identification in OLP contexts into four interrelated dimensions:

1) The way in which gig workers are included/excluded from online marketplaces. As outlined in the section "Worker Differentiation in Online Labor Platform Contexts," this concerns the inclusion and exclusion of workers by approaches such as (i) preventing selected groups of workers from entering the OLP's online marketplace (e.g. Upwork, TopTal), (ii) having an open/inclusive marketplace with limited boundaries to entry, yet with mechanisms in place to remove/exclude poor performing workers from their marketplace (e.g. Uber), (iii) an exclusive pool of 'talented' workers that represent a subsection of an OLP's online marketplace in which workers receive preferential treatment (e.g. Fiverr Pro) and (iv) OLPs enabling requesters to create their own exclusive pool of 'favorite' workers.
2) The criteria by which workers are included/expelled from an OLP's overall online marketplace as well as exclusive talent pools operated by the OLP and/or requesters. Similar to traditional contexts, we expect these criteria to be related to workers' past performance and/or future potential.
3) The degree of autonomy that requesters have in identifying talent. Although they may be offered the possibility to create exclusive pools of favorite workers, requesters may simulateneously experience restrictions in the freedom they have in selecting talented workers themselves. This depends, among other factors, on the design of OLP's algorithms for matching. While some OLPs match requesters to a single worker thereby leaving the requester the mere possibility to accept or reject the match (e.g. Uber that does not allow passengers to make a selection from a range of drivers), others present a larger pool of workers from which a requester can freely choose.
4) The degree to which OLPs are transparent about talent identification processes vis-à-vis workers and requesters. For workers, this involves transparency about their talent status, that is, whether or not they are included in a talent pool. For instance, in the case of Fiverr, workers are informed whether they belong to the exclusive Fiverr Pro talent pool (in fact, workers have to apply), while in other cases communication about talent status may be more ambiguous, for instance, when workers are not informed they are included a (requester's) favorite pool.

In what follows, we further detail these four dimensions by illustrating how various factors play a role in the way OLPs shape talent identification processes between workers and requesters. Specifically, we suggest considering variations *across* as well as *within* the online marketplaces that OLPs orchestrate. Our conceptual framework (see Fig. 1) centers on the characteristics of the three primary stakeholders: OLPs (i.e., the platform firms), requesters (i.e. contracting organizations and/or consumers), and gig workers (Duggan et al., 2020; Meijerink & Keegan, 2019) as relevant parameters that explain why OLPs make different decisions regarding the four talent identification dimensions outlined above (Meijerink & Keegan, 2019).

3.1. *Platform firm characteristics and talent identification*

There are characteristics of platform firms (i.e., OLPs that organize online marketplaces for freelance labor) that will affect how OLPs include/exclude workers and by what criteria, the degree of autonomy granted to requesters, and level of transparency in talent identification process. In this section, we address characteristics including the type of gig work, defined as the nature of the tasks facilitated by the OLP (e.g., degree of structure versus unstructured tasks, independence versus interdependence), and the platform's use of algorithms.

3.1.1. Types of gig work: the influence of underlying task characteristics

OLPs vary in the nature and variety of tasks offered (see Table 1). Some platforms intermediate for a narrow range of tasks, such as food delivery or ride sharing. Other platforms adopt a more heterogeneous model in which an almost unlimited variety of tasks are offered. Gig work tasks vary according to several important characteristics (Nakatsu et al., 2014). The first characteristic we consider is whether gig-based activities are *structured* or *unstructured*. In well-structured or standardized tasks, there is an established, known way to complete the task. As a result, the execution of structured tasks requires relatively low skill levels. In contrast, unstructured tasks rely more on the gig worker to identify the best solution to the task at hand (Nakatsu et al., 2014). These activities require higher levels of skills (e.g., programming via Upwork), may be more long-term in nature (e.g., a consultancy project via GigNow) and bear greater resemblance to job-based work (e.g., a short-term nursing assignment via IntelyCare). As noted in Table 1, when the type of work facilitated by the platform varies, the extent to which work is structured or unstructured will be more a feature of the individual task, not the platform itself.

A second characteristic is whether the tasks require workers to perform activities *independently* or *in close collaboration with the requesters in an interdependent way*. Independent tasks involve freelancers performing activities on their own and in segregation from the workforce of the organization they contract with (Kuhn & Maleki, 2017; Nakatsu et al., 2014). Conversely, interdependent gig work is characterized by the gig worker and requester providing mutual/reciprocal input to complete work activities. This involves organizations that use OLPs such as GigNow or TopTal (see Table 1) to contract with freelancers who collaborate with the workforce of the contracting organization to execute projects. Accordingly, interdependent tasks are more likely to involve activities that are core or strategic to a contracting organization (Cross & Swart, 2022). In fact, gig platforms are used for many types of jobs that are often performed by employees, such as journalism (through targeted platforms such as Contentedly) and nursing (through IntelyCare).

The third characteristic is *commitment*. The level of commitment required to complete a task will vary (Nakatsu et al., 2014). This can be represented by the time required to complete, and the resources the worker must bring to the task. Some tasks require short time periods to complete, such as transporting a meal or tagging a small set of photos. Others require substantially more time, such as writing a computer program or editing a book. Resource requirements can include investment in physical resources (a car or bicycle), software (for data analysis or visualization), certifications (a nursing license in a specific location), or acquisition of unique knowledge or skills to complete a task. Tasks spanning a longer time period and requiring new resources would represent the highest levels of task commitment. Furthermore, there can be differentiation within OLPs on the commitment required depending on institutional requirements. For example, Uber drivers in the Netherlands are required to obtain a taxi license while drivers in the United States are not (Pelzer et al., 2019). The time, effort, and money required to obtain this license represents a higher level of commitment for the Dutch Uber driver vis-à-vis the US driver.

A more inclusive approach to talent identification is likely to be practiced where tasks are structured, performed independently and require low levels of commitment, such as food delivery and ride sharing. These tasks often need to be performed 'on demand', meaning that the time between a requester posting a request and the actual performance of the 'gig' (e.g., delivering a meal) needs to be minimized. In these cases, there is neither much time for elaborate talent identification processes to take place, nor the need for a profound selection of a gig worker to complete the task at hand. Accordingly, requesters have very little autonomy in which worker is selected to perform the task. Instead, the OLP algorithmically matches requesters to workers, which only leaves requesters the option to decline a matched worker in case of a perceived misfit (and thus incur the risk of having to wait longer for the gig to be completed). Moreover, OLPs such as Uber and Deliveroo decide the price at which gig work is performed (Meijerink et al., 2021), thereby setting a value for the individual gig workers' talent. Given the relatively low-skilled work that characterizes highly-structured, independent gig work, we predict that little meaningful talent identification takes place at the point of entry when the worker is signing up for the platform.

In terms of OLPs' approaches to inclusion/exclusion, the inclusivity at the start subsequently moves towards a more exclusionary-based approach among OLPs specializing in structured tasks whereby workers fall below a performance threshold (e.g., Uber). OLPs also collect 'objective' data that signal workers' value to the platform, for instance, in terms of the number of gigs completed over time (Lehdonvirta et al., 2019). Low numbers of gigs or long periods of elapsed time between gigs may be used to indicate low performance or that one is insufficiently committed to completing the work. These workers may then be excluded from the platform, or at least excluded from access to newer or more lucrative tasks/gigs (Veen et al., 2019).

In contrast, for unstructured tasks that require high skill levels, OLPs are likely to take a more exclusive approach to talent identification from the beginning and restrict the gig workers who can join their talent pool. For example, TopTal actively screens workers interested in joining their online marketplace, assessing them on language skills, personality characteristics, and other job-related knowledge, skills, abilities, and other characteristics (KSAOs). They claim that only 3% of the applicants are accepted and allowed to join, clearly demonstrating an exclusive approach. On top of this, OLPs that facilitate matching for unstructured tasks may further reinforce worker exclusion by means of a two-stage process. For instance, as shown by Waldkirch, Bucher, Schou, and Grünwald (2021), Upwork gig workers must first be admitted to the OLP after which they may still be excluded when requesters do not hire them for selected gigs.

In addition, OLPs that facilitate matching for tasks that involve high interdependency may offer requesters higher levels of autonomy to exclude workers. Given the idiosyncratic nature of unstructured gigs that highly skilled gig workers perform interdependently with a requester's workforce, we predict that OLPs provide more leeway to requesters to identify and select talent gig workers themselves. Unlike the case with highly structured tasks, OLPs grant more autonomy to requesters on complex tasks that require high skill levels. Interdependent gig-based tasks are more likely to involve activities that are core or strategic to a contracting organization

(Cross & Swart, 2022), meaning there is a need for the requester to exercise control over who is hired. To facilitate contracting firms, OLPs offer the opportunity to requesters to search for gig workers in online talent pools by means of filtering systems. Gig workers are ranked on how well they meet requesters' preferences and requesters can themselves decide which gig worker they ultimately hire. OLPs offer the technological infrastructure that enables workers and requesters to negotiate the price for which the gig-based assignment will be performed. As such, although OLPs do play a role in determining the value of a talented gig worker, it is predominantly the requester and gig worker who decide on the talents' worth.

3.1.2. Platform use of algorithms

Algorithms enable OLPs to evaluate gig worker potential and performance at scale through automating decision-making regarding access or exclusion to the platform (Duggan et al., 2020; Meijerink et al., 2021; Veen et al., 2019). Some OLPs use algorithms to fully automate decisions about whether individuals will be permitted to join the platform and thus, whether they can offer their freelance services to requesters. Applicants judged to have insufficient talent are excluded from the entire platform (Waldkirch et al., 2021). Other platforms use algorithms to determine membership in an exclusive pool of workers within the platform. For example, Upwork uses algorithms to evaluate worker profiles for indicators of potential even when they are new to the platform and have no performance record. New workers considered to have high potential (on Upwork they are called Rising Talent) receive resources through better exposure to requesters and receive a badge on their profile that makes it easy to identify them. Alternatively, such talent pool decisions may be made by human decision makers who review gig worker offers to determine who should be placed in the Fiverr Pro or Upwork Expert Vetted pools indicating a higher level of quality or value to potential requesters. Thus, the role of the algorithm is not uniform.

Algorithms are also used to match workers to tasks, either directly assigning tasks to qualified gig workers or guiding the decision-making processes of requesters (see Table 1). In the more automated case, the algorithms match workers and requesters with little or no human intervention. This occurs when individual requesters are not permitted to choose from a range of workers and instead are matched with an individual worker who the algorithm deems most suitable in terms of past performance and/or availability (Rosenblat, 2018). Accordingly, workers and requesters have little autonomy in deciding which other platform users to transact with. As noted earlier, this model appears most often with platforms such as Uber and Deliveroo that offer highly structured tasks where unique skills are not generally needed to perform the work (Duggan et al., 2020; Kuhn & Maleki, 2017; Meijerink et al., 2021). This makes OLPs a powerful player in talent identification as they may algorithmically decide to exclude individual workers from accessing (lucrative) work assignments by simply not matching them to selected requesters. Seen through a transparency lens, we view these as micro instances of talent identification which may not be noticeable to workers and also leave them in the blind as algorithmic decision making by OLPs may be highly opaque (Lamers, Meijerink, Jansen, & Boon, 2022; Lee et al., 2015; Rosenblat, 2018).

OLPs also use algorithms to support requester decision-making about which gig workers to engage. Algorithms may rank gig workers based on their listed skills and past performance on the platform and in doing so, provide requesters with a short list of "best match" workers from which they can choose to contract. Platforms may also highlight gig workers who have been identified as high potential based on external skills and experience, such as with the People per Hour CERT program or Upwork Rising Talent and Expert Vetted programs. These workers are then included in algorithmic recommendations despite a lack of platform-specific performance data. As noted earlier, platforms typically provide higher decision-making autonomy in the case of platforms specializing in interdependent and unstructured tasks (e.g., Upwork, GigNow), in which algorithms provide input rather than make the worker selection decision based on clearly optimizable criteria (Kuhn & Maleki, 2017; Waldkirch et al., 2021). Although requesters of interdependent/unstructured tasks can make their own decision about which worker will be the best match for their task, the OLP, through algorithms, nevertheless influences this decision-making process by determining the criteria against which matches are made and which workers are recommended to requesters. For instance, Williams, McDonald, and Mayes (2021) show that the position of platform workers' profiles as presented to requesters involved a hidden process that prioritized workers with high client ratings and good reviews. Algorithms, therefore, play a powerful role in excluding gig workers (on a micro, day-to-day level) and preventing them from accessing work in online marketplaces that initially may seem open and inclusive.

3.2. Requesters' characteristics and talent identification

We next examine the ways in which requesters (contracting organizations in particular) use OLPs and the impact on talent identification processes. From a requesters' perspective, identification of talent in the gig labor market is often viewed differently than with employees, as they "hire people on a permanent basis for what they can potentially do; they hire a contractor for what they can do" (McKeown & Pichault, 2021, p. 10, quote from an interviewee). However, based on how requesters are using the OLPs for different types of tasks, how well they define tasks performed by a gig worker, and if they use the OLP for repeated contracting and temp-to-hire, requesters may try to use more exclusive talent identification practices and consider worker potential in addition to demonstrated performance for identifying talent. This section does not address the platforms that automate task assignment through algorithms, as requesters have limited autonomy and are (mostly) excluded from involvement in talent identification on those platforms as just outlined.

3.2.1. Accuracy of task descriptions

The way requesters describe the 'tasks' they post on OLPs will impact the level of exclusivity in the talent identification process. Because requesters are often outside of the HR function (e.g., procurement managers), they may have less of an understanding of how to write a clear task description highlighting the required knowledge, skills, and abilities (Bals, Schulze, Kelly, & Stek, 2019). If requesters are hiring a freelancer to perform work that they themselves do not know how to perform, they may be able to describe the desired outcome but not milestones or the skills necessary to complete the task effectively (Lustig, Rintel, Scult, & Suri, 2020). Requesters may also fail to identify and describe the important task characteristics discussed above (structure, independence, commitment). When tasks are less well defined, requesters are likely to have more inclusive talent identification practices because they do not have a clear idea of what they are looking for. This will increase the transaction costs to the requester and decrease the quality of the talent pool considered, as many more unqualified workers are likely to be available when tasks are poorly defined. To make up for this, some OLPs intervene in talent identification processes, for instance, by supporting requesters in drafting their task descriptions and work assignments before sharing these with gig workers (Meijerink & Arets, 2021).

Another potential concern with task description is the extent to which desired behaviors are fully defined as a relevant criterion for talent identification and inclusion/exclusion. This may create challenges for the gig worker who is unaware of extra-role behavioral expectations. Individual performance, even for contingent workers, consists of both in-role and extra-role behaviors (Fisher & Connelly, 2017). Requesters may implicitly expect certain extra-role behaviors from gig workers, such as willingness to adapt to project changes or help others on the project team. Unstructured tasks are most likely to lead to an opportunity for performing extra-role behaviors, although we do observe the performance of extra-role behaviors even in very structured tasks like ride sharing (e.g., Uber drivers providing a free bottle of water to riders; Rosenblat, 2018). Participation in high commitment tasks, particularly those lasting a longer period of time, may result in workers having increased attachment to a requester, leading to displays of extra-role behaviors as a relevant indicator of past performance and thus a criterion to be included in a requester's talent pool of favorite workers.

3.2.2. *Use for core or non-core tasks*

The strategic HRM literature has historically suggested that work that is strategic or core to an organization should be performed by a standard, internal employee rather than an external or contingent worker (Cappelli & Neumark, 2004; Keegan & Meijerink, 2022b; Lepak & Snell, 1999). We see evidence of this mindset changing and the gig economy may test such long established beliefs. Gig workers are becoming more strategic talent for requesters (Kuhn, 2021). Specifically, they are used for core tasks that are more straightforward and which require skills that are widely available in the labor market so that internal (and so-called 'knowledge-based') employees are freed up for strategic tasks that are less straightforward and require firm-specific skills (Kuhn, Meijerink, & Keegan, 2021; Lepak & Snell, 1999; Lustig et al., 2020). Here, an example is piecework core tasks in journalism which are increasingly performed by freelance journalists (McKeown & Pichault, 2021). Several authors have argued why hiring gig workers may seem counter-intuitive initially, but be strategically relevant when adopting a more long-term perspective (Snell & Morris, 2021; Snell, Swart, Morris, & Boon, 2022). In industries that see rapid technological and market changes, organizations need to continuously adapt, renew their strategies and reconfigure their workforce composition. Human capital that is core today may be peripheral tomorrow. Snell et al. (2022) argue that firms refrain from internalizing all core human capital to cope with the high pace of change, preserve some degree of freedom, and keep employment options open, especially when the demand for core human capital is transitory in nature or non-firm specific. When involving gig workers for such core (yet transitionary or straightforward) tasks, we expect that contracting firms/requesters are likely to use a more exclusive model of talent identification, and are granted higher levels of autonomy by OLPs, to ensure the quality of the work matches the importance of the work. One exception is if a competition model is used, in which case the requester might engage with multiple workers, ultimately using the output of a freelancer who, for example, writes the best story or produces the highest quality code (Lustig et al., 2020; Nakatsu et al., 2014; Williams et al., 2021).

3.2.3. *Repeated contracting*

Talent identification processes will differ depending on the intended frequency of the gig engagement(s). Requesters offering a one-time task will be less invested in the decision and therefore may consider a more inclusive pool of workers for the task. In these cases, requesters may be more price sensitive rather than attending to specific indicators of talent. Requesters who are seeking a freelancer they could use repeatedly for recurring tasks or projects (i.e., Kuhn, 2021) are likely to take a more exclusive approach and evaluate talent more thoroughly. In these cases, they may also want to evaluate potential of the freelancers to perform a wider range of tasks and be more likely to rely on formal talent cues such as inclusion in the OLP's specialized talent pool rather than just the performance ratings. One concern with performance ratings on most OLPs is that they are aggregated at the worker level, not by type of task or skill, thereby affecting the talent identification processes of requesters as distinct criteria for determining past performance are not clearly discernable. Many workers on platforms that facilitate unstructured work such as Fiverr or Upwork offer a portfolio of skills. For example, a worker may offer both translation and digital whiteboarding services. With a single aggregated performance rating across tasks, requesters are unable to distinguish between performance on these different types of tasks, making it difficult for a requester to accurately assess the worker's potential to perform well on a new task. While formal indicators of potential are unlikely to offer more detailed information about a worker's skills, they may be interpreted as evidence that gig workers have higher levels of skills and characteristics that are not task specific, such as commitment and motivation (McDonnell, Carbery, Burgess, & Sherman, 2021) or conscientiousness and time management.

Taken to a greater extreme, the desire to engage in repeated contracting with gig workers may lead some requesters to create a unique pool of pre-approved freelancers. As discussed earlier, some OLPs (e.g. Temper) offer organizational clients the possibility to develop pools of favorite workers (or preferred suppliers) with unique talents (Meijerink & Arets, 2021). Moreover, organizations may also establish freelance platforms to create an external talent pool that augments their internal talent pool (Kuhn et al., 2021). Such an external pool is arguably akin to a group of high-potential employees within a traditional organization because requesters consider these workers as their 'go-to talent' from which non-talents are excluded. The desire to re-engage with these workers is based on how the worker performed during previous interactions and the perceived value of the workers' skills, capabilities, and task execution. It would ease the process of individual requesters making selections for individual tasks, reducing the transaction costs typically involved in engaging new gig workers (Lustig et al., 2020). Requesters would clearly have an incentive to be exclusive as they identify workers for this pool, and presumably would apply higher potential and performance standards for selecting workers for a pool than for a single task. There is already variation among traditional organizations regarding the transparency of talent identification, specifically if employees are informed about being identified and included in the talent pool (Björkman et al., 2013; McDonnell et al., 2017). This is an open and unanswered question in the gig work context. Workers can see when they are part of a talent pool on the OLP but may not be informed about membership in a requesting organization's internal talent pool. From a transparency perspective, informing gig workers they have been identified as members of a talent pool could increase worker attachment to the requester organization and result in higher quality work outcomes, including more extra-role behaviors (De Boeck, Meyers, & Dries, 2018). On the contrary, it may also raise expectations about an ongoing and more relational work relationship which is typically at odds with the idea of this working arrangement.

3.3. Gig workers' characteristics and talent identification

Finally, we discuss the ways in which gig workers' characteristics shape talent identification processes. Although OLPs and requesters play a dominant role in differentiating online workforces based on gig worker characteristics, workers also can play an active role in talent pool identification processes (Meyers, 2020). OLPs' and requesters' talent decision making in areas such as inclusion/exclusion (criteria), autonomy and transparency in talent identification is contingent on selected worker attributes such as their online reputation scores which can be actively influenced, managed and, at times, manipulated by workers (Bucher, Schou, & Waldkirch, 2021; Waldkirch et al., 2021). As discussed next, both worker characteristics as well as behaviors play a key role in the identification of gig work talent and its underlying dimensions.

3.3.1. Online reputation scores

A key feature of platform-intermediated gig work is the use of online reputation scores that gauge a worker's potential and/or performance (Kuhn, 2021; Meijerink, 2021) as relevant indicators of talent. In line with the work of Lehdonvirta et al. (2019), we distinguish three types of reputation scores that signal worker potential and performance. First, gig workers may signal their potential by means of *unverified signals*; that is, self-reported evidence of quality such as educational qualifications, a list of skills gained, or a portfolio of gigs performed outside the OLP's online marketplace. OLPs allow gig workers to share relevant information via their user profiles. Second, *platform-verified signals* amount to feedback ratings given by requesters. This involves OLPs creating tools that afford requesters to offer ex-post evaluations of gig worker performance by means of five-star rating schemes or Thumbs-Up/Thumbs-Down buttons. Although reflecting past performance, platform-verified signals are used by requesters to assess a worker's potential for making hiring decisions (Pavlou & Gefen, 2004). Finally, OLPs afford gig workers to signal their potential and performance by means of *platform-generated signals*. These amount to data collected, stored and aggregated by the OLPs in terms of the number of gigs/projects completed by a gig worker (Lehdonvirta et al., 2019).

These three types of reputation scores enable gig workers to be identified as high-potential and/or high-performing workers thus inferring that some individuals on the platform are of greater value or more talented than their peers. Unverified signals, albeit not necessarily being a reliable source to requesters, nevertheless play a role in requesters' decisions. This most likely holds for gig workers with unique skills who strategically offer freelance services via an OLP to sell their skills to the highest bidder for maximizing earnings (McKeown & Pichault, 2021).

Platform-verified signals – online customer reviews in particular – play a key role in talent identification decision processes in both desirable and undesirable ways from the worker perspective. On the upside, gaining high reputation scores enables workers to gain exclusive or better access to lucrative assignments and rewards. For example, Uber drivers with high average customer ratings fall under the exclusive Uber Pro program that provides benefits like discounts on vehicle maintenance and higher compensation rates (Kuhn, 2021). On the contrary, when a driver's average rating falls below 4.6 (on a scale from 1 to 5), they run the risk of being denied access to, and thus excluded from, Uber's online marketplace (Rosenblat, 2018).

Finally, platform-generated signals (e.g., the number of completed work assignments) best enable gig workers to signal their potential to future clients. In support of this, research by Lehdonvirta et al. (2019) shows that platform-generated signals, in comparison to unverified and platform-verified signals, are most strongly and positively related to the hourly pay rate charged by workers (as a proxy of their potential to clients). In addition, on platforms such as TaskRabbit and Wonolo workers can earn a preferred-worker status by completing a minimum number of assignments via the platform over a specified time period (as well as earning positive customer reviews) (Kuhn & Maleki, 2017). Nevertheless, platform-generated signals have fewer desirable consequences for workers' performance and talent pool inclusion. That is, on platforms such as Upwork, workers must strike a balance between avoiding signing up for too many gigs (for building platform-generated signals) versus accepting too little work. This is because signing up for too many assignments while simultaneously accepting too few job offers could result in exclusion from the platform (Bucher et al., 2021; Jarrahi & Sutherland, 2019; Waldkirch et al., 2021). Moreover, in an attempt to increase the number of gigs performed, workers may have to accept work assignments coming from clients that are prone to leaving poor online reviews (Bucher et al., 2021). This means that platform-verified and platform-generated signals can be in tension, particularly for newcomers in the online marketplace, which ultimately can have negative consequences for an individual worker's ability to gain talent status and access more exclusive benefits.

3.3.2. Tenure in the online marketplace

The tenure of a gig worker, defined as how long gig workers have been registered on and performed assignments via an OLP, has implications for talent identification and inclusion/exclusion. That is, workers with a high tenure have had more time to complete work assignments and garner customer reviews for building a favorable online reputation that offers access to exclusive benefits. On the contrary, so-called 'newbies' (workers who recently joined an OLP) need to build a favorable reputation, which in some cases may require them to undervalue their work to acquire work assignments (Bucher et al., 2021; Lehdonvirta et al., 2019). Put differently, to showcase their potential (as a relevant criterion used in talent identification) by means of their online reputation, newbies first need to undervalue their potential by charging lower hourly rates to clients. Although clients may view newbies as having limited potential, OLPs may adopt a different perspective and view newcomers as having potential.

Specifically, the potential for OLPs amounts to the possibility to capture (future) economic value from newbie gig workers (Keegan & Meijerink, 2022a). One of the strategies of OLPs for capturing economic value from gig workers is by creating so-called lock-in effects (Rosenblat, 2018). Lock-in effects occur in OLPs when gig workers incur costs when leaving the OLPs' online marketplace. If this were to be the case, gig workers become increasingly dependent on the OLP to acquire work and generate income (Kuhn & Maleki, 2017). This occurs, for instance, when gig workers cannot take their online reputation to other platforms. In this respect, newcomer gig workers who are yet to build their online reputation have the potential to become dependent on the platform. To increase this dependency, platforms facilitate newbies to make significant investments in expensive equipment. As an example, Uber often connects its drivers to subprime lenders that offer poor credit (Kuhn & Maleki, 2017). In addition, it is said to offer a high number of assignments to newcomer drivers to increase their dependency on the OLP. After a few months of operations – and once the Uber driver became 'sufficiently' dependent on the platform – Uber limits the number of jobs assigned to the selected driver and instead, starts realizing the potential to capture economic value from the 'newbie' worker by algorithmically lowering the fee for the driver's services (Rosenblat, 2018). As these examples show, worker potential in the gig economy not only relates to their future work performance (in terms of offer value to clients), but also the potential to capture substantial monetary value from gig workers labor efforts (Keegan & Meijerink, 2022a). Put differently, while being very open and inclusive to 'newbies' at first, OLPs may become more exclusionary once these workers lose their 'newbie' status.

3.3.3. Proactivity

Like regular employees who are proactive players in talent management processes (Meyers, 2020), we expect that gig workers proactively seek to signal their potential and performance to clients (and the OLP). Some OLPs support gig workers with advice on how to maximize their opportunities to be selected for tasks (Fisher & Cassady, 2019). Given the role those online reputations systems play in talent identification processes, gig workers are actively engaged in building a favorable online reputation. For example, research shows that gig workers actively request positive reviews or attempt to renegotiate a lower review (Bucher et al., 2021; Rosenblat, Levy, Barocas, & Hwang, 2017). In fact, gig workers ask requesters not to leave a rating after an unsuccessful encounter, often in return for doing extra unpaid work (Bucher et al., 2021). Moreover, in low-volume platforms (and where unstructured work is taking place), workers might find it difficult to build a base of performance reviews that would convince a prospective requester of adequate potential. For example, if a worker has performed three long-term gigs during a year, then having only three reviews on their profile may not be very convincing as a demonstration of past performance, even if all those ratings are high. If a platform algorithm considers the number of successful gigs as a factor in which workers are highlighted or recommended to requesters, this could further reduce the opportunity for selection. Jarrahi and Sutherland (2019) elucidate how gig workers overcame this challenge by asking clients to break down a long-term assignment into smaller gigs to increase the number of reviews and provide a stronger signal of potential to prospective requesters.

Along similar lines, workers may disaggregate tasks as a method for being matched to more tasks by subcontracting elements to other gig workers (Wood et al., 2019). The worker then takes on aspects of project management in addition to performing the stated work. For example, a worker might offer a broad package of services related to editing books but then outsource aspects of that (e.g., formatting of references) to another freelancer. Alternatively, a worker might offer web design services but outsource the search engine optimization tasks to another freelancer. In some cases, OLPs provide the technological infrastructure to subcontract work to other gig workers and install rating schemes on how well workers subcontract work to others (Meijerink & Arets, 2021), thereby facilitating workers to build a favorable online reputation. Finally, gig workers offer support to one another to avoid receiving poor customer reviews. Next to sharing tips and tricks on how to satisfy customer needs, this also involves warning others for clients that are known for leaving poor ratings via platforms such as Reddit (Waldkirch et al., 2021).

4. Avenues for future research on gig talent identification

This paper considers the enactment of talent identification within the gig economy; an idea that at first glance appears in conflict with the prevailing and largely accepted assumptions about which kind of organizations undertake talent identification and to whom is incorporated. Given the independent contractor status and lack of any explicit expectation of ongoing commitment between the OLP and gig worker, it may appear that talent management, and more specifically here, talent identification, is inconsequential. We however take an alternative position and argue that the existing boundaries of talent management research need to be extended to incorporate gig work and all its constituent forms. As a first step, we conceptually untangle the nature of talent identification in the gig economy, with a particular focus on whether talent identification is inclusive or exclusive in nature.

Our paper charts the diversity that exists across platforms, requesters and gig workers according to several characteristics including the level of interdependence involved in the tasks/gigs, the extent to which the jobs are structured or unstructured, the nature of the human capital required by requesters, and the proactivity, tenure and online reputation of individual workers. These characteristics impact the nature and outcomes of talent identification. For example, where requested tasks are highly structured and the supply of workers is abundant, it would seem sufficient to have a large enough pool of competent workers who will work for low wages, be available as needed, and can be easily replaced. In such contexts, talent identification will be mostly inclusionary in nature and have limited emphasis other than the achievement of appropriate performance levels which will impact access to new gigs. Differentiation between gig workers is minimal other than where preferential access to gigs may be offered to those with the highest performance levels (i.e., scores from requesters), and there are low barriers to individuals wishing to join the OLP. In contrast, OLPs that are based around more unstructured, interdependent tasks which are core to the strategic goals of the contracting organization will involve a greater focus on talent identification and take a more exclusionary approach because there is a requirement for a talent pool that consists of high-level skillsets.

Accordingly, we decipher how talent identification takes shape in tripartite relationships between OLPs, workers and requesters. First, we unpack how OLPs themselves are key talent identifiers that differentiate workers on their potential and/or performance in terms of tenure, online reputation or qualifications. While OLPs may seem to be inclusive at first, their use of segmentation implies a more exclusive approach to talent identification, for instance, when workers are denied access to their online marketplaces (e.g., Uber's deactivation policies), placed in a top talent pool (e.g., Upwork's Rising Talent or Vetted Talent program), or are ineligible to perform selected lucrative work assignments. Second, OLPs are powerful players that shape talent identification processes between individual gig workers and requesters by algorithmically recommending workers to requesters, determining criteria for identifying high potential/performing workers, and/or enabling requesters to create designated online pools of ‘favorite’ workers with which requesters repeatedly contract. Requesters, therefore, can create their own talent pools and conduct talent identification parallel to the OLP's talent evaluation processes.

The diversity of OLPs, their reliance on algorithmic technologies as sources of power, and their involvement in these tripartite talent identification processes opens up new questions and avenues for future research. We see particular use in applying signaling theory[4] (Bergh, Connelly, Ketchen Jr, & Shannon, 2014; Connelly, Certo, Ireland, & Reutzel, 2011) to better understand some of these questions. Signaling theory revolves around the idea that the signaler or agent (i.e., the worker) has qualities such as high potential/performance that are important to the receiver or principal (i.e., the OLP and/or requester). The principal will want to contract the best person for the task but typically the quality of that person will be unknown until such a time as they witness their performance and skills, knowledge, capabilities. Consequently, a risk is placed on the principal that a less productive agent may be hired given the limited knowledge. Signaling theory is concerned with reducing the information asymmetry that exists between parties (Spence, 2002). The receiver cannot directly observe the information they need rather can only estimate them on the basis of the signals sent by the signaler. Therefore, the signaler can reduce the information asymmetry by signaling their skills and qualities to the principal. Signaling theorists predict that such signals are honest when they are costly (i.e. sending the signal requires an investment of resources, the cost of which only the most qualified individuals can bear) and/or hard to fake as they are not easily manipulable by the signaler (Bangerter, Roulin, & König, 2012; Connelly et al., 2011). Both types of honest signals need to be associated with high cheating costs. Signaling theory predicts if these criteria are met, that signaling systems remain more or less stable over time with signalers and receivers relying on the same signals to arrive at cooperative relationships. Bangerter et al. (2012) argue, however, that organizations cannot always rely on honest signals and/or keep up cheating costs due to societal and technological changes (e.g., increased accessibility to higher education, information about selection techniques that are available online), which may lead signalers to adapt by sending dishonest signals. In such cases signaling systems escalate, leading organizations to search for and establish more sophisticated selection systems (Bangerter et al., 2012). Aligned with these signaling principles, we consider avenues for future research on talent identification and the ramifications for signaling processes and systems in the gig economy. We commence with considering further research around the OLP which has a particularly powerful role in shaping and mediating the information exchange between the signaler (worker) and receiver (requester).

4.1. Future research into OLP involvement in talent identification

OLPs are powerful players that shape talent identification processes in the gig economy. Accordingly, OLPs shape signaling systems by designing the online technologies (e.g., review systems, online performance ratings) which determine what signals workers can send, and by establishing the relevant cheating costs (e.g., deactivation of a worker's account). The notion that OLPs shape talent identification processes between workers and requesters affords a range of research questions. For instance, what incentives do OLPs have to ensure stability in the signaling systems that they create, for instance, to afford balancing supply and demand for labor in their online marketplaces and/or ensure workers-requesters can be efficiently matched? Also, do OLP-managed signaling systems tend to stabilize when OLPs are inclusive in nature (and exclude poor performers at best) and create marketplaces for non-core, routine tasks (e.g. because there is little incentive for workers to cheat and limited need for requesters to gauge many worker qualities)? On the contrary, under what conditions do gig economy signaling systems escalate, for instance, when OLPs operate exclusive marketplaces for non-routine core tasks that require unique skills? If this were to happen, how would OLPs balance gig workers' and requesters' potential conflicting interests?

The above also allows us to identify several areas and questions that we feel are especially important for research. How do choices about inclusive/exclusive talent management by these different actors affect the quality of the talent pool? Do exclusive approaches indeed lead to smaller pools with higher skill levels? Does this create more value for OLPs than having a larger pool with the potential

[4] We thank the anonymous reviewer for the suggestion to adopt a signaling theory as an analytical lens.

for more transactions to be conducted? What is the relationship between approaches to talent identification (e.g., the extent to which differentiation and segmentation occur) and the use of algorithms?

Finally, traditional organizations – especially those that adopt an inclusive approach to talent identification- are increasingly considering embedding diversity and inclusion in their hiring practices and wider talent management activities. To what extent are such considerations incorporated in the design of OLP algorithms, and what is the impact on diversity and inclusion for gig workers? For example, what impact may the talent philosophies of software designers have on how the algorithm is designed and used? One stated goal of using algorithms and big data is to produce fairer, more objective decisions and outcomes, but there is also a real danger of in-built bias being more problematic due to algorithms (Fisher & Howardson, 2022). Consequently, gaining a better understanding of the positive, negative, and unintended effects of using algorithms for talent identification purposes is welcomed.

4.2. Future research into requesters' involvement in talent identification

The role of requesters in talent identification is noteworthy with respect to how explicit and substantial an influence such actors have on gig workers. Gig workers' continued access to work tasks and rewards received are heavily influenced through the performance evaluation by requesters that is central to the operation of many OLPs (Lehdonvirta et al., 2019). We have a considerable body of knowledge to build up in this regard given the novelty of this actor's role in talent identification decisions and outcomes. In line with signaling theory, key questions readily emerge that we believe are worth pursuing regarding the signals that requesters rely on to include/exclude workers. How do requesters judge and evaluate the value and talent of gig workers when selecting them on OLPs? To what extent do requesters pay attention to information about performance compared to potential? How much weight do they place on the signals generated by automated algorithmic recommendations compared to their own evaluations of the available data or signals that gig workers send themselves? How do requesters perceive the honesty of platform-verified and platform-generated signals? Other questions relate to the critical process of how requesters evaluate gig worker performance. For example, do requesters understand the influence that their evaluation has on the gig worker? To what extent do requesters consider in-role vs. extra-role behaviors in assessing gig worker performance? Do gig workers need to go 'above and beyond' (e.g., Uber drivers providing bottled water for the riders) to obtain the highest ratings? To what extent do requesters then expect this type of performance, even when they do not include it in their task definition? Fundamentally, we need to better understand these key inputs to the talent identification processes.

Also, the characteristics of gig-based tasks and the corresponding inclusive/exclusive nature of an OLP's talent pool have implications for the talent identification activities of requesters. Next to receiving signals from gig workers, requesters also need to send signals to gig workers to reduce information asymmetry and attract talented gig workers. Key questions that emerge here are: to which extent do requesters signal an exclusive approach to talent identification when they look for scarce talent that is capable of performing non-standard tasks of high strategic value? Do requesters make their talent identification processes less exclusive in an attempt to attract workers? Under what conditions may competition among requesters result in escalation in gig-based signaling systems? For instance, if requesters feel they cannot distinguish themselves from rival requesters through signaling channels offered by the OLP, do they look for other means outside the OLP's online marketplace (e.g., the requesters' corporate website, installing temp-to-hire schemes, repeated contracting) to attract gig workers? How do OLPs respond to this, provided that they want requesters and workers to transact in their online marketplace?

4.3. Future research into workers' involvement in talent identification

Finally, we turn to the gig workers, who are not a new actor in relation to talent identification given that the individual employee is a central part in traditional organizational settings. What is novel to consider however is how gig workers who lack formal employment status are impacted by talent identification processes employed by OLPs and requesters. We envision a dynamic context in this regard where individual processes and actions may change over time as a gig worker pursues tasks on any given platform. For example, how can gig workers who are new to a platform deal with the 'newbie effect' when they lack performance ratings and therefore do not have the information needed to signal their talent to requesters? In such cases, newbies may have to undervalue their potential by charging lower hourly rates to clients. There may be ways to make up for this, which might lead them to incur cheating costs. For instance, do newbies fake the signals they send by dividing long-term work assignments into multiple smaller gigs to increase their reputation score? Under what conditions does this create escalation in signaling systems? Do OLPs accept such acts and if not, what sanctions do they apply? Are workers willing to incur the cheating costs that come along with such sanctions? In fact, workers risk incurring cheating costs from both OLPs and requesters, and these costs may be negatively related. As discussed before, on platforms such as Upwork, workers need to strike a balance between signing up for too many gigs (for building platform-generated signals) versus accepting too little work. Signing up for and performing many gigs signals their potential to requesters but may simultaneously be classified by the OLP as undesirable behavior and a signal of poor work quality. So far, we lack an understanding how workers balance their signal acts vis-à-vis the OLP and requesters and if needed, which signal receiver (e.g., OLP) they prioritize at the expense of sending weak signals to the other receiver (e.g., the requester).

Given the evidence of OLPs engaging in processes and decisions of identifying and differentiating gig talent, it would be useful to understand to what extent more experienced gig workers seek to 'rise to the top' and pursue talent status within their respective OLPs. Extant ideals in the talent management literature assume that some individuals want to be considered valuable and gain talent status while others do not (Meyers, 2020). How do these ideals of career progression play out in the gig economy where there is no ongoing employment relationship? Also, to what extent do gig workers strategically consider how they may become overly dependent on one OLP due to reputation-based locked-in effects, and how do they seek to avoid or overcome this? Duggan, Sherman, Carbery, and

McDonnell (2021) identify how algorithmic systems create unmovable boundaries that constrain the individual worker's capacity to develop transferable competencies. Is there any mechanism that enables gig workers to transfer their reputation/track record? There are potential concerns around bias being built into and remaining omnipresent in algorithms that drive OLPs. To what extent do these algorithms discriminate (e.g., by age, sex, ethnicity, national origin) against workers? Does this result in an escalation in signaling systems when workers feel they are being discriminated against, requiring them to adapt their signaling techniques to look more attractive to requesters? It is likely that if such issues persist, then how do they get recognized and addressed given the nature of these organizations and the difficulty that national labor and employment legislation and regulations appear to have with these novel working arrangements?

Finally, talent management scholarship has considered the role of transparency and procedural fairness of identification decisions on talents and non-talents (De Boeck et al., 2018; Gelens, Dries, Hofmans, & Pepermans, 2013). In the context of gig work it would be interesting to understand how gig workers perceive the level of fairness and justice given the centrality of algorithmic decision making. Issues of ethics and opaque algorithms (Lamers et al., 2022; Langer & König, 2023; Rodgers, Murray, Stefanidis, Degbey, & Tarba, 2023; Varma, Dawkins, & Chaudhuri, 2023) may be particularly important for OLP's given that OLP's business models, competitive position, and revenue are founded on algorithms. How can the tension between the need and desire for workers to know and better understand how they are evaluated by algorithms be married with the OLPs desire to keep the operationalization of the algorithm confidential? Does this lead to worker-driven escalation in signaling systems and/or OLP-driven attempts to mitigate such escalation? Which elements of talent management lead to greater worker satisfaction with platforms, and how does that relate to their connection with and commitment to the platforms? To what extent could there be a role for some sort of algorithmic auditing in improving this for workers? Should OLPs improve the algorithmic literacy of workers? Should OLPs be assisting gig workers more in dealing with the tensions around platform-verified and generated signals which have a key impact on the workers' ability to gain a more exclusive status?

4.4. Methodological considerations for future studies

We now briefly consider the challenges and opportunities around research design and methodologies. While good research access is often challenging in traditional organizational settings, this context may bring more significant difficulties. For example, gaining access to workers in traditional organizations would typically be undertaken by gaining permission from senior organizational stakeholders who would facilitate the research. However, as gig workers are not treated as employees, such an approach is likely to be unfruitful as OLPs may be less open to critical, academic scrutiny. Given the nature of gig work and how algorithms function, there should be a considerable opportunity to draw on big data to perform highly sophisticated statistical analyses. However, gaining access to such data represents a roadblock.

Besides the use of large sets of quantitative data, there is much scope to look at more interpretivist, qualitative-type methodological approaches. Positively, there is evidence of less common methodological approaches in the field of HRM research such as auto/ethnography, direct observation, participative, and mixed methods (Gegenhuber, Ellmer, & Schüßler, 2021; Meijerink et al., 2021). Garnering a foundational perspective of how different actors engage in the gig economy and undertake and experience talent identification is valuable because the interactions are complex and dynamic. Observing humans in their natural environment and examining how and why requesters and gig workers participate in such work will permit insights into the actions encompassing this context. Ethnographic methods are especially important given that garnering an informed understanding of how different actors make decisions and judge value is at the heart of increasing our knowledge of the practice of talent identification (Goodman, 2021; Wiblen, 2021).

The gig economy represents a highly dynamic context both from an institutional and regulatory perspective and also in the way that algorithms are automated self-learning decision-makers. Over time, market pressures and power plays by OLPs may lead to escalation in signaling systems in the gig economy. As a result, longitudinal research designs will have an especially marked and positive impact on advancing understanding and theorization of talent identification in gig work and how this evolves. As our discussion shows, there is potential for shifting understandings of who and what is valuable within the gig economy across OLPs and over time. Examining changes over various periods can foster a better-informed understanding of the evolution of value-based judgment frameworks and how these change as requesters and gig workers increase the number of interactions (the number or complexity of the tasks) and increase levels of socialization. Expectations and understanding of how the gig worker performs their 'talent' will change because talent and work are both dynamic phenomena.

4.5. Limitations and implications for future research

In this conceptual paper, we focused on the inclusivity versus exclusivity of talent identification in the gig economy. Many other salient issues in talent identification processes warrant further research and which we were unable to incorporate here. First, we see merit in future studies that examine talent definitions in talent identification processes. Specifically, we see the need to examine how potential versus performance definitions of talent take shape in the gig economy. Currently gig workers typically signal their potential by means of online ratings they have accumulated. These online ratings gauge workers' past performance. This raises the question of in what cases gig workers' future potential and (past) performance are conflated, particularly when requesters only have performance ratings available to identify a gig workers' talent.

Second, we see potential in the study of liability[5] in talent identification processes. There have been cases where OLPs are held liable for damage done to requesters, workers and other third parties. For instance, multiple court cases around the world have addressed the question of whether Uber should be held accountable for its drivers injuring passengers or pedestrians. We ask the question of whether OLPs can be held liable for identifying bad talents resulting in other negative business outcomes. After all, the OLPs' core business is to match (talented) gig workers and requesters. Whether this is the case likely depends on the level of autonomy granted to requesters, with OLPs potentially avoiding liability issues by giving ample leeway to requesters to identify and select talents themselves. Finally, it would be useful to examine how talent identification by OLPs relates to other talent management activities. As noted earlier, talent identification is the precursor of talent management activities such as talent development and retention. We encourage future studies to examine the implications of exclusive talent identification processes by OLPs, what preferential treatment is offered to talented gig workers, and what role requesters may play in the development and retention of high-potential or high-performing gig workers.

5. Conclusion

The world of work continues to evolve with the changing nature of employment relationships which are heavily related to increased digitalization, automation and calls for the disaggregation of work into tasks. As talent is a socially constructed concept (McDonnell & Wiblen, 2021; Wiblen, 2016), stakeholders adopt different perspectives as to what to be talented means. However, the talk about talent invariably leads one to think of employees who have relatively secure employment and are core to an organization (Lepak & Snell, 1999, 2002). We, however, question the aptness of this perspective in light of the rise of OLPs. In this paper we have argued that while gig work occurs outside an organization's formal boundaries, talent identification as one of the cornerstones of talent management remains relevant (Corporaal & Lehdonvirta, 2017; Kuhn, 2021; McKeown & Pichault, 2021; Meijerink, 2021). Specifically, we offer an analysis and conceptual framework for talent identification in OLPs whereby differentiation and segmentation of workers, central elements in talent management (McDonnell et al., 2017), are evident. As such, we argue that there is a need to extend the boundaries of talent management scholarship to include the gig economy whereby 'renting' rather than 'building' talent is the central tenet. While the concept of renting talent is not new, the tripartite relationships between OLPs, requesters and workers, as well as the role of OLPs as powerful, third-party players in talent identification is different and raises many important research questions. We hope that our conceptual model and the research questions put forward in this paper spark new lines of research on the idiosyncrasies of talent identification in the gig economy.

CRediT authorship contribution statement

Jeroen Meijerink: Conceptualization, Writing – original draft. **Sandra Fisher:** Conceptualization, Writing – original draft. **Anthony McDonnell:** Conceptualization, Writing – original draft. **Sharna Wiblen:** Conceptualization, Writing – original draft.

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[5] We thank the anonymous reviewer for this suggestion.

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