# TALENT MANAGEMENT IN THE GIG ECONOMY: A MULTILEVEL FRAMEWORK HIGHLIGHTING HOW CUSTOMERS AND ONLINE REVIEWS ARE KEY FOR TALENT IDENTIFICATION

*Jeroen Meijerink*

*University of Twente*

## INTRODUCTION: HRM PRACTICES IN THE GIG ECONOMY

Online labor platforms such as Uber, Deliveroo and Amazon Mechanical Turk delegate a variety of human resource management (HRM) activities to consumers by means of digital technologies (Cassady, Fisher, & Olsen, 2018; Duggan, Sherman, Carbery, & McDonnell, 2019; Ellmer & Reichel, 2018; Kuhn & Maleki, 2017; Meijerink & Keegan, 2019). Operating in the so-called gig economy, online labor platforms do not employ workers. Instead, they matchmake between gig workers (i.e. independent contractors/freelancers) and consumers who request an on-demand service (e.g. a taxi ride, delivery of a meal or programming software codes) (Aloisi, 2016; Stanford, 2017; Wood, Graham, Lehdonvirta, & Hjorth, 2019). This way of working creates tensions as online labor platforms seek to control gig workers by means of HRM activities, while simultaneously disavowing they are employers (Friedman, 2014; Kuhn & Maleki, 2017; Meijerink & Keegan, 2019). To resolve these tensions, online labor platforms require consumers to enact HRM responsibilities on their behalf to ensure gig worker efforts are controlled (Meijerink, Keegan, & Bondarouk, 2019).

HRM practices within the gig economy afford customers a significant role in deciding which online gig workers are “valuable”. Academics and practitioners alike debate the salience attributed to "customers" and the associated customer enacted HRM responsibility. Operating within HRM practices resides *performance appraisal* (Kuhn & Maleki, 2017; Lehdonvirta, Kässi, Hjorth, Barnard, & Graham, 2018; Rosenblat, Levy, Barocas, & Hwang, 2017). In the gig economy, consumers appraise the performance of "gig workers" – i.e. individual freelancers who offer their services to clients through an online labor platform – by leaving online reviews, through five-star rating schemes or leaving Thumbs-Up/Thumbs-down, after a transaction is completed. While very few would argue that online reviews are synonymous with "talent identification", evaluating an individual's "performance" in a binary "thumbs up/thumbs down" and posting comments from pervious customers can influence future customers perceptions of that individual in ways that previous performance review "scores" shape future expectations. As such, through leaving and inquiring online reviews, consumers play a key role in deciding upon a gig worker's value and thus, who is seen as a talent.

Delegating performance appraisal responsibilities to consumers can have serious consequences for gig workers and their ability to be deemed valuable within their specific online platform. Online reviewing by consumers is shown to impact gig workers' access to the online labor platform (Lee, Kusbit, Metsky, & Dabbish, 2015; Rosenblat et al., 2017), influences the fees which gig workers can charge for their freelance services (Lehdonvirta et al., 2018), and/or creates anxiety among gig workers (Rosenblat, 2018). Given the influential role of online appraisals on financial outcomes, talent identification and careers, it is important and opportune to explore why consumers (do not) leave reviews. The goal of this chapter is to outline a conceptual framework on the drivers that explain why consumers engage in online appraisal in the gig economy. In developing this model, I depart from the notion that online labor platforms are nested arrangements of workers, consumers and platform firms (Jacobides, Cennamo, & Gawer, 2018; Meijerink &

Keegan, 2019). Accordingly, this chapter draws on multilevel theory (Klein & Kozlowski, 2000; Renkema, Meijerink, & Bondarouk, 2017) to (1) identify the levels at which online appraisal/reviewing by consumers and its antecedents manifest, and (2) propose a set of future research questions on why consumers (do not) leave reviews on online labor platforms. Ultimately, adopting multilevel theory enhances our understanding why customers leave online reviews on online labor platforms and thus how talent identification in the gig economy takes place.

The chapter is organized as follows. I start off with discussing the gig economy, online labor platforms and the role of consumers in identifying the value/talent of gig workers. This is followed by a discussion why customer reviews play an important role in talent identification in the gig economy and on online labor platforms. I conclude with outlining a multilevel framework on why customers do (not) leave online reviews, and discuss implications of this framework for academics and practitioners.

## TALENT MANAGEMENT IN THE GIG ECONOMY AND ONLINE PLATFORMS

Although an agreed-upon definition of the gig economy is lacking, it is generally referred to as an economic system in which freelance 'gig workers' and customers engage in transactions which are intermediated by online labor platforms (Duggan et al., 2019; Meijerink & Keegan, 2019; Wood et al., 2019). Platform-enabled gig work is the key economic exchange which takes place in the gig economy, and be defined as the performance of fixed-term activities through an online platform by individuals (i.e. gig workers) for an individual consumer or organization, without being actually employed (Aloisi, 2016; Daskalova, 2018; Kuhn & Maleki, 2017; Meijerink & Keegan, 2019; Stanford, 2017). Instead, gig workers are freelancers who obtain work assignments (i.e. 'gigs') through intermediary platforms firms such as Deliveroo, Uber or Amazon Mechanical Turk. These intermediary platform firms develop and maintain online labor platforms for matchmaking between gig workers and those who request their services in industries such as transportation (e.g. Uber), cleaning (e.g. Helpling), household do-it-yourself (e.g. TaskRabbit) and programming (e.g. Clickworker). As noted by Duggan et al. (2019), the platform-enabled gig work taking place in these industries can be classified into three groups: *capital platform work* where individuals use a platform to lease assets (e.g. Airbnb), *crowdwork* where workers remotely complete online tasks which are allocated to them through an online platform (e.g. Clickworker) and *app-work* which involves platform-intermediated tasks taking place locally (e.g. Uber).

Technology plays an important role in the operation of online labor platforms and thus, in the rise of the gig economy. Most notably, intermediary platform firms rely on the internet and related technologies for match-making between supply and demand for labor. To do so, intermediary platform develop algorithms that assign gig workers to requesters, while web / smartphone interfaces (e.g. mobile 'apps') allow customers to recruit and select gig workers (Duggan et al., 2019; Ellmer & Reichel, 2018; Kuhn & Maleki, 2017). Beyond these mere operational activities, intermediary platform firms also rely on technology to implement a range of HRM activities. These include the use of algorithms to determine gig worker *compensation* (e.g. surge pricing by Uber where rates automatically increase when demand surges), *dismissal* with gig workers being (temporarily and) automatically denied access to the online platform in case their performance falls below a certain threshold, or *workforce planning* where algorithms predict the number of gig workers needed during selected time slots (Duggan et al., 2019; Meijerink et al., 2019; Rosenblat, 2018; Wood et al., 2019).

Seen from a talent management perspective, the rise of the gig economy not only implies an increase in use of technology for talent management purposes (such as talent attraction, selection and retention), it also suggests an inclusive approach towards talent management (Meyers & van Woerkom, 2014). In essence, by enacting their intermediary role, platform firms establish talent pools (Collings & Mellahi, 2009) which gig workers – as freelancers – are free to join and from which customers can recruit a worker. It is in the interest of both platform firms and customers to be inclusive in providing gig workers access to the virtual talent pool of platform firms, as this creates network effects. Here, network effects emerge when an increase in the number of users of an online labor platform (i.e. both gig workers and customers) leads to a direct increase in value for all users (Gawer & Cusumano, 2002; Jacobides et al., 2018; Parker & Van Alstyne, 2005). For customers, an inclusive approach towards talent management in the gig economy is beneficial as it allows them to more easily recruit gig workers that match their unique needs and wishes. Moreover, being inclusive is beneficial for intermediary platform firms as it enables them to capture value from network effects. Namely, network effects imply more exchanges between gig workers and requesters from which the platform firm can capture a fee and which ultimately enables growth and, in some cases, market dominance (Gawer & Cusumano, 2002). Given the desire for intermediary platform firms to create network effects, it should not come as a surprise that they open their doors for new gig workers, without much selection taking place (Meijerink et al., 2019; Rosenblat, 2018). As an example, Uber claims to foster maximum inclusivity and seeks to lower the (legal) barriers for gig workers to enter its online platform. Although an inclusive approach to talent management may seem apparent at a first glance, a more closer look into the use and workings of online appraisal systems on online labor platforms shows that the gig economy is not necessarily that inclusive altogether.

## WHY STUDYING APPRAISAL ON ONLINE LABOR PLATFORMS IS IMPORTANT

At first sight, performance appraisal by consumers in the gig economy may appear to be a straight-forward HRM activity. Upon the completion of a transaction via an online labor platform, consumers are presented an online rating scale with the question to evaluate the gig worker that served them. Through a single tap on a smartphone, the appraisal of a gig worker can take literally just a second. While customers may think that the process is quick and easy, the evaluation inputted and processed by the embedded algorithms influences work allocation/job security and fosters an exclusive approach to talent management

Research shows that consumers do not always leave an online review. As an example, more than a third of the transactions taking place via the Airbnb platform are left unevaluated (Fradkin, Grewal, & Holtz, 2018). In other online platforms, such as eBay, these statistics are similar and show that only 67% of platform-mediated transactions are evaluated (Dellarocas & Wood, 2008). The reasons for this need to be understood, because the availability of consumer reviews, and lack thereof, can have consequences for gig workers as well as consumers. First, research has shown that gig workers are 'deactivated' (i.e. dismissed in traditional HRM terms), meaning they lose access to the online platform and thus generate no income, when consumer evaluations fall below a certain threshold. For instance, the accounts of Uber drivers are deactivated when their average evaluation falls below a 4.6 on a scale from 1 to 5 (Rosenblat et al., 2017). Seen from a talent management perspective, gig workers are excluded from a platform firm's talent pool in case their average customers evaluations fall behind. This becomes problematic when dissatisfied consumers leave reviews more often than satisfied consumers, in particular when a gig worker recently joint the online labor platform (Teubner & Glaser, 2018).

Secondly, the online appraisal by consumers introduces power asymmetries between gig workers and consumers (Newlands, Lutz, & Fieseler, 2018; Rosenblat & Stark, 2016). For instance, the risk of deactivation forces gig workers to spend money and other resources on offering additional services (e.g. Uber drivers offering free drinks to passengers) hoping this induces consumers to leave a (positive) review. This obviously is out of line with the idea that online rating schemes are designed to reduce moral hazard. That is, gig workers and their consumers wish to transact without knowing whether each party to the transaction can be trusted. Online reviews play a key role here in establishing trust among ‘strangers’ that want to engage in transactions (Pavlou & Gefen, 2004). Besides facilitating trust building, rating schemes also make gig workers unnecessarily dependent on the evaluation of consumers (Rosenblat & Stark, 2016). Customer reviews further increase levels of power asymmetries between workers and consumers when online labor platforms require gig workers to evaluate customers. Namely, platform firms use gig worker-generated reviews for expelling consumers when consumers violate the rules and regulations set by the platform firm. Gig workers however say they are anxious to discipline consumers that misbehave and refrain from leaving a negative review because they are afraid that consumers take revenge on them by leaving a negative review (Rosenblat, 2018). Such negative reviews may include customers reporting how dissatisfied they were with a gig worker’s performance, recommendations to future customers to not hire the selected gig worker or simply, leaving a one star rating / a Thumbs Down score.

Finally, online appraisal by consumers may introduce all sorts of (new) biases related to the identification and (e)valuation of talents. A well-documented bias relates to so-called ‘reputation inflation’ which occurs when available customer reviews are always positive, regardless of the actual performance of a gig worker (Dellarocas & Wood, 2008; Horton & Golden, 2015). Reputation inflation is thus a result of satisfied consumers leaving (positive) online reviews more often than dissatisfied consumers, which inflates the performance appraisal scores of gig workers. Available evidence suggests that reputation inflation is omni-present in the gig economy, by highlighting that customer reviews on online (labor) platforms are heavily skewed towards positive ratings (Dellarocas & Wood, 2008; Fradkin et al., 2018; Horton & Golden, 2015; Teubner & Glaser, 2018; Zervas, Proserpio, & Byers, 2015). Research has shown that the online reputation of gig workers is positively related with the hourly rate that gig workers charge to consumers (Lehdonvirta et al., 2018). Taken together, this suggests that reputation inflation has undesirable consequences for consumers as they end up paying higher fees to gig workers which are not justified on the basis of the actual levels of gig worker performance. Seen from a talent management perspective, this implies that gig workers are overvalued meaning that the majority of gig workers are wrongfully classified as ‘talented’.

In conclusion, online reviewing by consumers of online labor platforms has major implications for both gig workers, consumers and the process of talent identification. Therefore, an important question is: why do consumer (not) leave an online review after being served by a gig worker? Besides the technical design of online appraisal systems, many antecedents of online reviewing by consumers can be considered, such as customer satisfaction (Horton & Golden, 2015; Meijerink & Schoenmakers, 2019), incentive schemes implemented by the platform (Fradkin et al., 2018; Teubner & Glaser, 2018), online reputation of the gig worker (Lee & Lee, 2012), consumer personality traits (Mowen, Park, & Zablah, 2007), gig worker behavior (Rosenblat, 2018), etc. The sheer number of antecedents that are at play and that explain why consumers leave online reviews, requires a unifying framework that pulls together these antecedents into meaningful clusters. As such, the purpose of this chapter is not to provide an exhaustive list of antecedents, but instead offers a framework that highlights the vast array of factors which influences talent management in the gig economy. This is important for academic research as the framework can be used in future studies for creating a complete overview and classification of antecedents of online appraisal by consumers in the gig economy. The framework is also useful for practitioners that wish to engage with gig workers, as it offers insights into how customers can be induced to leave online reviews and which factors can be considered to improve the workings of online review systems in the gig economy. The following section presents this framework.

## TOWARDS A MULTILEVEL FRAMEWORK OF ONLINE CONSUMER APPRAISAL

### Introducing multilevel theory: why online customer reviews are multilevel in nature

The framework is presented here draws on multilevel theory. Multilevel theory departs from the notion that social systems of individuals, groups and institutions are nested arrangements. In HRM research, multilevel theory is often applied to understand that HRM activities reside on and relate to outcomes on multiple levels of analysis, such as the organization-, team- and individual employee-level (Renkema et al., 2017). Multilevel theory presents different principles on how, where, when and why multilevel relationships occur, and thus constitute the fundamental theoretical buildings blocks that allow to conceptualize multilevel research models (Klein & Kozlowski, 2000). Adopting multilevel theory for understanding  why do consumer (not) leave online reviews is important because online appraisal by customers manifests on different levels of analysis, namely: the transactional level, consumer level and platform level (see Figure 1). The lowest level at which customer appraisal can be observed, is the transaction level where consumers evaluate the transaction with a gig worker. At this level, variance in online appraisal thus manifests in terms of whether a consumer did or did not leave an online review after engaging with a  gig worker. All reviews of these transactions by an individual consumer, aggregate to the second level on which online appraisal manifests, that is, the consumer level. Essentially, on the consumer level, variance occurs in terms of the percentage of transactions which an individual consumer did evaluate during a selected time frame. This is what Dellarocas and Narayan (2006) refer to as *review propensity* which is defined as the ratio between the total number of transactions reviewed by an individual consumer during a given time period over the total number of transactions the consumer has engaged in during the same period.

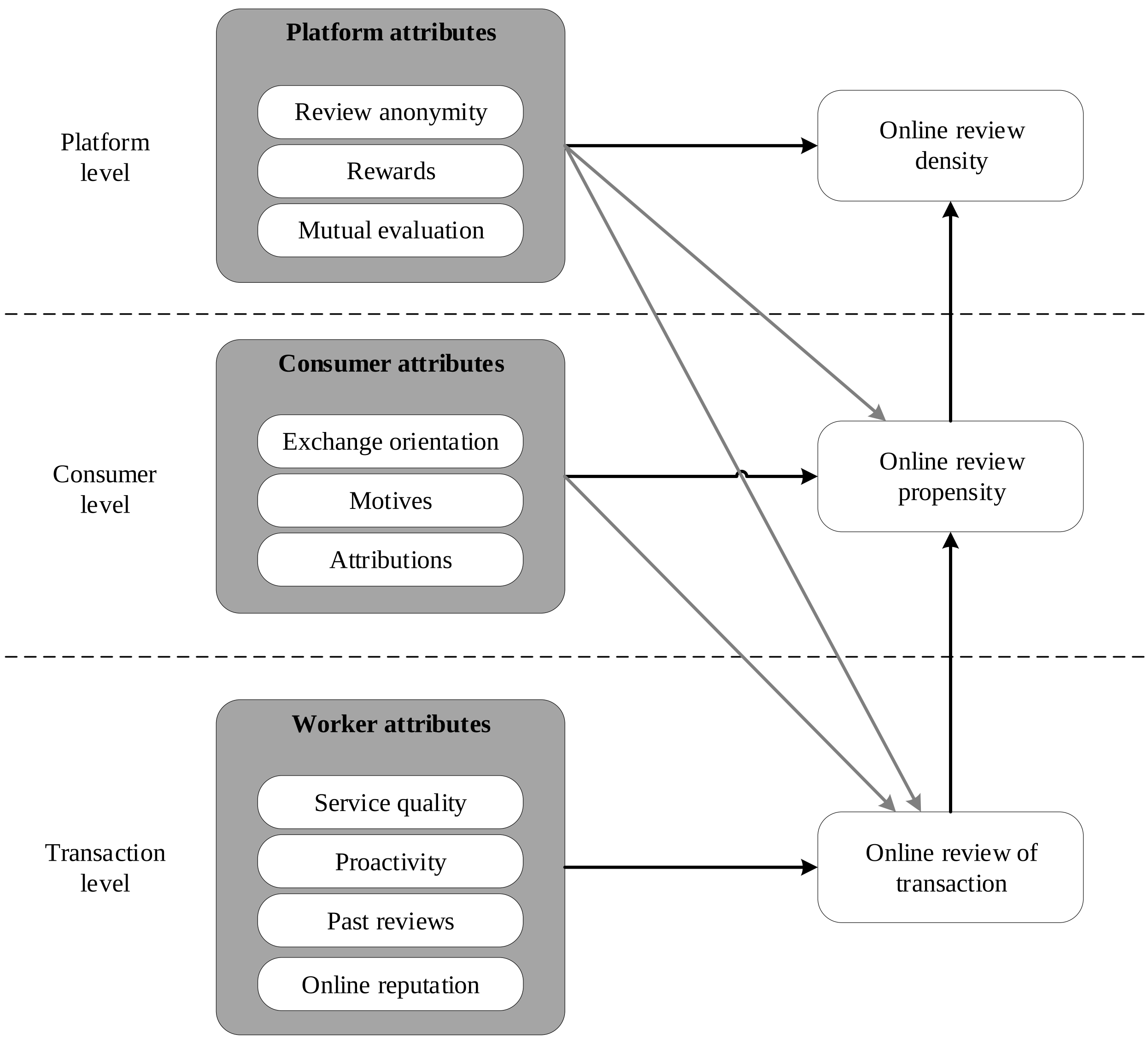


**Figure 1:** Multilevel framework of online appraisal by consumers of online labor platforms

Finally, variance in online appraisal manifests on the platform level in terms of the aggregate of the review propensity of all consumers active on a selected online labor platform. On this level, online appraisal by consumers can be conceptualized as *review density,* that is, the total number of transactions reviewed by all consumers of an online platform during a given time period over the total number of transactions that took place on the online platform during the same period (Dellarocas & Narayan, 2006).

**Clustering the antecedents of online appraisal on three levels of analysis**

To better understand why customers leave online reviews and thus, how talent identification and evaluation takes place within the gig economy, I propose to consider various factors at three levels of analysis: the transaction-level (one which relevant worker attributes resides), the customer-level and the platform level (see Figure 1). As noted by Meijerink and Keegan (2019), the implementation of HRM activities in the gig economy is contingent on the attributes and actions of the platform firm, consumers and workers. In line with this, I propose that online appraisal by consumers (as a form of HRM implementation) is contingent on the attributes and actions of the very same three actors. The three actors form a hierarchical / multilevel structure with workers being ‘nested in’ consumers (as an individual consumer is/can be served by multiple workers) and consumers being nested in online labor platforms (i.e. an individual platform allows a pool of consumers to engage in transactions with workers). These three levels equate the levels on which the online appraisal concepts manifest, making the worker, consumer and platform levels useful categories for clustering the antecedents that explain why customers do (not) leave reviews on online labor platforms. Below, each level/cluster is discussed in terms of how the attributes and actions of the platform, customer and worker play a role in explaining online appraisal by consumers of online labor platforms.

***Transaction-level antecedents.*** An important antecedent to online appraisal is the level of (perceived) performance or service quality provided by a gig worker (Dellarocas & Wood, 2008; Meijerink & Schoenmakers, 2019). The primary goal of online appraisal by consumers is to assess the performance of gig workers. Intuitively, one might expect consumers to leave an online review when a gig worker offers an excellent or extremely poor service. Research however shows that this is not necessarily the case in online (labor) platform settings. For instance, Dellarocas and Wood (2008) found that consumers are more likely to leave an online review when satisfied than when dissatisfied with a service. In line with this, Meijerink and Schoenmakers (2019) report a positive relationship between consumer perceptions of service quality and online reviewing on Airbnb, which implies that satisfied consumers are more likely to leave an online review than dissatisfied consumers.

Second, gig workers may be proactive in eliciting online reviews by consumers. Researchers for instance showed that Uber drivers seek to maintain their online reputation by asking passengers to leave a (positive) review (Kuhn & Maleki, 2017; Rosenblat, 2018). The effect of such initiatives may however be mixed as some consumers might find this disturbing and therefore do not leave an online review (or post a negative review), while others see it as a call to actually leave a review (particularly when they are satisfied with the gig worker's performance).

Third, online platforms such as Airbnb, Werkspot and HiHiGuide show the volume (i.e. number) of reviews a gig worker has received in the past. Research has shown that online review volume impacts consumer behavior. For instance, Kostyra, Reiner, Natter, and Klapper (2016) show products are more likely to be bought when their average rating improves. However, this effect weakens as review volume for a selected product increases (Kostyra et al., 2016). In line with this, it can be expected that the volume of reviews of a gig worker is negatively related with the number of reviews s/he receives in the future. Here, consumers might perceive the marginal effect (in terms of changing a gig worker's online reputation), of leaving a review for a gig worker that has previously gained a substantial amount of reviews, to be low. In such cases, a consumer might be less likely to leave an online review.

Finally, the given average rating (on a scale from 1 to 5) of a gig worker, which represents average customer satisfaction and reflects a workers' online reputation, likely impacts online reviewing by consumers. Consumers may be less likely to leave a review when their experience with a gig worker does not match the average rating of a gig worker, as this creates cognitive dissonance. Cognitive dissonance refers to mental discomfort experienced by a person whose beliefs clash with new evidence presented to that person (Festinger, 1957). In the gig economy, consumers' beliefs about a gig worker are shaped by the online reviews as consumers strongly rely on available reviews to make purchase-related decisions (Ert, Fleischer, & Magen, 2016; Ter Huurne, Ronteltap, Corten, & Buskens, 2017). If these beliefs do not match the actual performance of a gig worker, a consumer might be less likely to leave a review as this makes cognitive dissonance more salient. Previous customer reviews (indirectly) establish performance expectations, creating a situations whereby reputational value precedes performance of the service/ task.

***Consumer-level antecedents.*** A variety of consumer attributes may explain the likelihood of online appraisal by consumers on online labor platforms. An important attribute may be a consumer's exchange orientation. According to Buunk and Van Yperen (1991) exchange orientation refers to "the personality disposition of individuals who are strongly oriented to direct reciprocation, who expect immediate and comparable rewards when they have provided rewards to others, and who feel uncomfortable when they receive favors they cannot immediately reciprocate" (p. 802). In comparison e-commerce platforms where products are transacted, the role of exchange orientation is likely to be important in the gig economy context, because platform-mediated labor involves humans offering a service on a recurrent basis (e.g. meal deliverers servicing restaurants, or housekeeping professionals cleaning a property on a weekly basis). This creates social exchange processes, where consumers and gig workers may reciprocate each other's efforts. As an example, Wood et al. (2019) show that consumers, when granting orders, reciprocate gig workers' past performance by favoring high-performing workers. These reciprocal acts may also drive online reviewing, where consumers reciprocate high-level gig worker performance by leaving a (positive) online review. Such reciprocal acts are more likely to occur among consumers who score high on exchange orientation. Moreover, a consumer with a high exchange orientation may more likely engage in online reviewing to reciprocate the online reviews of his/her peers which the focal consumer relied on to make purchase related decisions (Ert et al., 2016; Ter Huurne et al., 2017).

The motives of consumers to rely on online (labor) platforms likely play a role in explaining online reviewing. Research shows that these motives relate to issues such as convenience, utility, transaction costs, meeting new people (Hamari, Sjöklint, & Ukkonen, 2016; Möhlmann, 2015). Depending on these motives, consumers may have different expectations of gig workers and thus differ in the degree to which they experience high-quality service provision. These service quality perceptions in turn explain whether consumers leave a review (Dellarocas & Wood, 2008; Meijerink & Schoenmakers, 2019). In line with this, research has shown that consumers' abilities relate positively with their perceptions of service quality of technologymediated services (Van Beuningen, De Ruyter, Wetzels, & Streukens, 2009). This implies that consumers with high-level abilities and long-term experience in making use of an online platform and/or gig work, experience higher levels of service quality and therefore, are more likely to leave (positive) reviews. In support of this, Horton and Golden (2015) show that over time, online reviews on online labor platforms such as oDesk and Elance tend to become more positive.

Finally, online reviewing may be dependent on consumers' attributions about why online labor platforms request online reviews. Online platforms rely on online reviews to create trust, deactivate gig workers, improve service provision and/or match workers and consumers on the basis of their online reputation (Kuhn & Maleki, 2017; Lee et al., 2015; Rosenblat, 2018). In line with the work of Nishii, Lepak, and Schneider (2008), I propose that consumers – as important HRM players in the gig economy – may develop at least two types of attributions why platforms rely on online reviews: commitment-focused attributions (e.g. to create trust, improve service provision) and control-focused attributions (to exploit gig workers, capture disproportionate value from consumers/workers). Provided that individuals respond more positively to commitment-focused attributions than control-focused attributions (Nishii et al., 2008; Van De Voorde & Beijer, 2015), I expect that that consumers are more likely to leave online reviews when they develop commitment-focused attributions.

***Platform-level antecedents.*** Various design features and attributes of the online platform (firm) play a role in explaining online reviewing by consumers. First, the privacy and anonymity of online reviews influences the motivation of consumers to leave (negative) online reviews (Bridges & Vásquez, 2018; Horton & Golden, 2015). Platforms such as Uber and Deliveroo, which algorithmically dispatch orders, keep the reviews of individual consumers private by aggregating consumer reviews to an average rating per gig worker. Other platforms which offer consumers the freedom to select a gig worker, like Airbnb, Werkspot and HiHiGuide, make (written) reviews publicly available. The field experiment by Horton and Golden (2015) shows that consumers who had a negative experience with a gig worker are more likely to leave a (negative) review when their review is kept private by the platform firm, compared to when reviews are shared in public.

Second, platform firms offer rewards to induce consumers to leave an online review. These rewards can be both monetary in nature (e.g. coupons, discounts) as well non-monetary (e.g. assign a ‘superior’ status to consumers that leave frequently leave reviews) (Fradkin et al., 2018; Teubner & Glaser, 2018). Research shows that such rewards influence the likelihood of consumers leaving an online review. For instance, Fradkin et al. (2018) conducted a field experiment which showed that consumers of Airbnb who were offered a $25 Airbnb coupon in exchange for a review left online reviews more often than those who were not offered this coupon. Moreover, offering a coupon increases the likelihood that dissatisfied consumers actually leave a (negative) review, which implies that online reputation inflation can be partially offset through offering monetary rewards in exchange for a review (Fradkin et al., 2018).

Finally, platform firms differ in whether they let consumers and workers mutually evaluate one another. For instance, whereas Uber drivers get to evaluate passengers, in many meal delivery platforms such as Deliveroo and Uber Eats, gig workers are evaluated by consumers, but not vice versa. Mutual performance appraisal may lead gig workers to strategically induce a reciprocal response from a consumer. This may happen for instance, when a gig worker leaves a positive review of a consumer hoping the consumer will reciprocate the act by also leaving a (positive) review (Fradkin et al., 2018; Rosenblat & Stark, 2016).

## WHERE TO NEXT FOR ACADEMICS?

Viewing online appraisal by consumers as a multilevel phenomenon and clustering its antecedents on different levels of analysis, opens the road for new research initiatives on performance appraisal on online labor platforms. Here, multilevel theory is very useful as it offers multilevel principles that can be applied to derive questions for future research. These principles revolve around the WHAT, HOW, WHEN, WHERE AND WHY of multilevel relationships (Klein & Kozlowski, 2000; Renkema et al., 2017). Below, I discuss these principles and how they can be translated into novel research questions/avenues on online reviewing by consumers of online labor platforms.

**The WHAT of online appraisal by consumers**

The WHAT principle concerns the level at which the phenomenon of interests is manifested (Klein & Kozlowski, 2000; Renkema et al., 2017). In the case of online appraisal, consumer reviews manifest at the level of transaction/worker, consumer and online platform (see Figure 1). Klein and Kozlowski (2000) recommend researchers to start their multilevel analysis with defining and justifying the level at which the variable of interest resides. Accordingly, it is important for future research to uncover at which level the majority of variance in online reviews resides. In my view, the majority of variance in online reviews by consumers resides on the worker/transaction level, since consumers of online labor platforms are matchmade with different workers. Moreover, the primary purpose of online labor platforms is to spark repeated transactions (Friedman, 2014; Kuhn & Maleki, 2017; Stanford, 2017). It are the transactions and the workers offering freelance services which are evaluated. This implies that the majority of variance in online reviewing resides on the transaction/worker level. In line with this, it is important that future academic studies seek to answer research questions such as: how is the variance in online reviews by customers distributed across the transaction-, consumer-, and platform-level? To what extent does the majority in this variance reside on the transaction-level? Is the percentage of variance in online reviews the lowest on the platform-level? Are different online platforms similar in the percentage of transactions which ultimately get evaluated?

**The HOW of online appraisal by consumers**

The HOW principle describes how two or more levels are linked, that is, through top-down and/or bottom-up processes (Klein & Kozlowski, 2000; Renkema et al., 2017). Top-down processes describe the influence of higher-level contextual factors on lower-level phenomena. In the case of online reviewing, top-down effects occur when platform and/or consumer attributes influence whether a gig worker or a transaction is evaluated by a consumer. Bottom-up effects manifest through so-called emergence processes through which lower level phenomena aggregate to higher-levels of analysis. Bottom-up emergence occurs through either composition (i.e. individual level phenomena remaining the same as they aggregate to a higher level) or compilation (i.e. individual level phenomena sharing a common domain, but remaining distinctively different across levels) (Ployhart & Moliterno, 2011; Renkema et al., 2017). In line with this, future research could examine whether online reviews emerge from the transaction level to the consumer level and onwards to the platform level through a process of composition or compilation. As such, relevant questions are whether an individual consumer leaves both positive and negative reviews (i.e. compilation) versus only negative or positive reviews (i.e. composition), as well as whether online reviews on the platform level have a tendency to become homogenous and positive (i.e. composition) versus being a mix between negative and positive reviews (i.e. compilation).

In explaining how online reviews emerge to higher level of analysis, research may draw on the notion of emergence *structure* which describe the higher-level contextual factors that shape the process of emergence (Klein & Kozlowski, 2000). In the case of online review, emergence structure reflects the attributes of the online platform (firm). In line with this, future research could examine whether online reviews emerge to the platform-level through compilation or composition, and on which platform-level characteristics this is dependent. For instance, Horton and Golden (2015) show that online reviews on the platform level tend to become more positive and homogenous over time (i.e. composition-based emergence). They attribute this to the fact that online reviewing is not anonymous, which demotivates dissatisfied consumers to leave a review. Building on their results, researchers could ask the question whether online reviews emerge through a process of compilation (i.e. being more heterogenous on the platform-level) when online labor platforms decide to solicit anonymous reviews.

**The WHERE of online appraisal by consumers**

The WHERE principle describes where multilevel relationships originate and culminate (Klein & Kozlowski, 2000; Renkema et al., 2017). This principle can be studied using the concept of *bond strength* which refers to the extent to which variables at one level of analysis affect outcomes on another level. The notion of bond strength predicts that relationships between levels of analysis are stronger when these levels are more proximate (Klein & Kozlowski, 2000). Bond strength can therefore be considered to predict how strongly variables on different levels of analysis are related. In line with the notion of bond strength, platform-level attributes (e.g. incentives for inducing reviews or technical design of the review application) are more strongly linked with online reviewing on the consumer level (i.e. review propensity) than with reviewing on the transaction level as the latter level is more distal to the platform level. On this basis, researchers could ask the following research questions: are customer attributes more strongly linked to online reviewing on the worker/transaction level in comparison to platform-level attributes? Is the link between platform-level attributes and online reviewing on the transaction-level weaker than the link between customer-level attributes and online reviewing on the transaction-level? To what extent do attributes on the platform- and consumer-level explain variance in online customer reviews on the transaction-level?

**The WHEN of online appraisal by consumers**

The WHEN principle centers on the role of time in multilevel relationships. According to Klein and Kozlowski (2000), time can be seen as a *boundary condition* that specifies the direction of multilevel relationships. For instance, changes in the technical design of review systems (i.e. a platform-level phenomenon) may have a rapid top-down effect on the online appraisal of transactions. The time needed for the changes in transaction-level reviews to emerge and alter the review density on the platform-level may take place later in time. For instance, the results of Horton and Golden (2015) show that at least four years passed before customer reviews on the oDesk and Elance platforms become more or less consistent across transactions (i.e. for composition emergence to occur). In line with this, future studies could theorize and empirically explore whether top-down effects manifest predominantly right after the platform or a change in its review system 'went live', with bottom-up effects occurring in later stages. Moreover, it is important for researchers to answer questions questions such as: how much time (e.g. weeks, months, years) does it take for changes in the technical design of review systems (i.e. a platform-level phenomenon) to result in changes in the online appraisal of transactions? How much time does it take before changes in transaction-level reviews emerge to changes in review propensity or review density?

Furthermore, researchers could examine *time-scale variation across levels*, which reflects the time needed before an event occurs on other levels of analysis (Klein & Kozlowski, 2000). Given the sheer number of transactions taking place on online labor platforms, it will likely take a time before changes in reviews on the transaction-level emerge to (and thus cause) changes in the aggregate reviews on the platform level (i.e. review density). In line with this, future research could examine how long it takes before changes in online reviews on lower levels of analyze result into changes in reviews on higher levels of analysis, and whether this is contingent on emerge structure (i.e. the attributes of the online platform (firm)).

**The WHY of online appraisal by consumers**

The WHY principle stresses the need for researchers to provide theoretical explanations for the multilevel relationship under study (Klein & Kozlowski, 2000; Renkema et al., 2017). Since most online review systems are easy to use, it is likely that consumer abilities explain only but a small portion of variance in online reviewing by consumers. Instead, examining consumers' willingness to leave only reviews is more promising, making motivation-based theories suitable for explaining the multilevel effects in online reviewing by consumers of online labor platforms.

Here, self-determination theory may explain how worker, consumer and platform attributes relate with online reviewing. Self-determination theory proposes four types of extrinsic motivation which differ in their relative autonomy and thus degree to which they motivate action (Deci & Ryan, 2000). The least autonomous type of extrinsic motivation is *external regulation* which drives behavior through external demand and possible reward. In online labor platform contexts, external regulation thus explains how rewarding consumers (e.g. through coupons) influences online reviewing. *Introjected regulation* is slightly more autonomous in nature and reflects the idea that individuals are motivated to showcase their ability to maintain self-worth. Online labor platforms that make online reviews publicly available provide consumers the opportunity to showcase their capability to e.g. acquire online services, appraise gig worker performance or sanction poor performance. This implies that platform-level attributes such as the technical design of an online reviewing system relate to online reviewing through the mediating role of introjected regulation. The remaining motivational states of *regulated identification* (e.g. valuing a goal or regulation) and *integrated regulation* (internalized norms and values) are autonomous in nature and come from within the individual (Deci & Ryan, 2000). These are therefore more likely to explain how consumer-level attributes (e.g. personality traits, exchange orientation) relate to online reviewing. In line with this, future academic studies may address important research questions like: to which extent do the four types of extrinsic motivation differ in their validity to explain how customer- and platform-attributes relate to online review outcomes on lower levels of analysis? Is customer motivation a better predictor of online customer reviews than customer ability?

While self-determination theory can explain top-down processes in multilevel online reviewing, attraction-selection-attrition (ASA) theory may explain bottom-up effects (Schneider, 1987). The ASA theory predicts that individuals in organizations become more homogenous in their perceptions and behaviors as individuals with similar backgrounds, expectations, orientations and characteristics feel attracted to an organization and are selected by organization members who are similar to them, while those who are different from group members will leave. The same may occur with the consumers (and workers) of online labor platforms: some consumers feel more attracted to a platform and select workers who are similar to them. Consumers and workers who do not fit this may leave the platform. Over time, this creates a homogenous set of workers and consumers who understand each other's interests and needs, which results in (perceived) high-quality service provision. Ultimately, this may drive compositional emergence where only positive reviews emerge on the platform level. In support of this claim, Teubner and Glaser (2018) show that over time, review scores on Airbnb become more homogenous (and positive) and attribute this to the attrition of poor service providers and those with limited reviews being selected out of the market. Accordingly, future research would benefit from answering research questions such as: to which extent do online customer reviews on the platform-level become more homogenous over time? Which platform attributes best explain why these homogenization processes occur?

## WHERE TO NEXT FOR PRACTITIONERS?

The multilevel framework of online appraisal by consumers has implications for gig workers, consumers and platform firms. First, for gig workers, it helps to show that their (perceived) value and whether they are classified as talented, is dependent on a range of variables. The multilevel framework can assist them in bringing back the plethora of variables into three meaningful categories, that is: worker, consumer and platform attributions. On the basis of this, gig workers can develop pro-active strategies that are instrumental to solicit (positive) customer reviews. Besides seeking to offer high-quality services, such strategies may include asking for a review from customers whose attributes reduce the likelihood of leaving reviews (e.g. consumers with a low exchange orientation) or explaining why the platform firm solicits online reviews for shaping consumers' attributions. Moreover, the multilevel framework may offer (potential) gig workers a tool to decide which online platform(s) they want to join. In so doing, they could consider the technical features of the online platform firms' review system that benefit gig workers (e.g. non-anonymous reviews by customers).

Second, the multilevel framework is helpful to make consumers aware of their role in talent identification and evaluation in the gig economy. More specifically, it spells out which consumer attributions induce or refrain consumers from leaving reviews on an online labor platform. It might be helpful for consumers to be aware of these attributions, to avoid e.g. reputation inflation. For instance, a consumer who scores low on exchange orientation may be less likely to leave a review after s/he experienced poor service quality levels. Being aware of this might help to ensures that gig workers are evaluated appropriately. Moreover, the role of past reviews and a gig worker's online reputation likely affect the likelihood that a transaction is reviewed by a consumer. It is good for consumers to realize that their review can have a substantial marginal effect, in particular when their experience differs from those reported by others consumers. Ultimately, it is important that consumers leave reviews that reflect the service quality provided by a gig worker to ensure that online reviews reliably reflect the value of a gig worker.

Finally, the multilevel framework has implications for online platform firms and those who design online customer review technologies. Specifically, some of the features designed into online review systems may refrain customers from leaving online reviews. For instance, by making reviews non-anonymous, consumers may feel less likely to share their negative experiences. At the same time, having non-anonymous reviews may help to create the trust needed for future customers to hire a gig worker (Pavlou & Gefen, 2004). As such, online labor platforms likely have to make a trade-off between making reviews public to stimulate ongoing exchanges on the platform versus making reviews anonymous to ensure customers feel comfortable to leave negative reviews. Furthermore, online platforms have to consider the number of reviews that add to the online reputation of a gig worker for motivating consumers to leave an online review. For instance, if online reputations are based on the latest 500 reviews received by a worker, consumers might feel that the marginal effect of their review is low. As such, online platforms may want to limited the number of reviews included in an average review score as much as possible, yet without making a gig worker's online reputation heavily dependent on a few reviews. Finally, online platforms may want to be clear in their communication to consumers on the purpose of online reviews. Here, consumer might be less likely to leave online reviews when believe that online reviews are used to exploit gig workers or sanction workers without human intervention. Instead, online platforms may want to stress that online reviews are used to improve customer experiences and to improve gig worker performance – and, importantly, live up to these promises – to induce online customer reviews.

## CONCLUSION

By drawing on multilevel theory, this chapter presents a conceptual, multilevel framework on the drivers that explain why consumers engage in online appraisal in the gig economy. Online appraisal is proposed to manifest on three levels: the worker/transaction level, the consumer level and the platform level. In line with this, the drivers of online appraisal by consumers in the gig economy can be grouped into three clusters (or levels of analysis): platform attributes (e.g. rewards and technical design of the online review system), consumer attributes (e.g. personality traits and orientations) and interaction level (e.g. performance/behavior and online reputation of a worker). Although online reviewing on online platforms is studied extensively, this chapter is the first to cluster relevant antecedents into meaningful clusters. Moreover, by adopting a multilevel theoretical perspective, this chapter opens the road for answering important and novel research questions on the what, how, where, when and why of multilevel effects of platform, consumer and worker attributes on online reviewing.

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