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Technology-Mediated Control Legitimacy in the Gig Economy: Conceptualization and Nomological Network

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Abstract: The rise of the gig economy has become a global phenomenon that encompasses various industries. Instead of hiring full-time employees, gig economy companies 'outsource' work via online platforms to freelance workers who are paid for completing a given task ('gig'). While gig workers are often portrayed as independent contractors, gig firms leverage advanced digital technologies and smart algorithms to exercise control over their freelance workforce, referred to as technology-mediated control (TMC). This independence-control paradox raises interesting questions in terms of how gig workers perceive the legitimacy of such controls. Against this backdrop, this chapter builds on extant research to propose a three-dimensional conceptualization of TMC legitimacy attuned to the unique features of the gig economy: autonomy, fairness, and privacy. On this conceptual basis, the chapter sets forth to start exploring the nomological network of gig workers' perceptions of TMC legitimacy and outlines a set of key antecedents, consequences, and contextual boundary conditions, thereby offering directions for future research in the area.

Keywords: Gig economy, Online platforms, Technology-mediated control, Perceptions of control legitimacy, Conceptualization, Nomological network.

1   Introduction

In the current digital age, a growing number of workers are no longer employed in traditional, full-time 'jobs'; rather, they work as independent contractors who are paid for completing a particular task, or 'gig' (Friedman 2014). Here, it should be noted that the dramatic decline in full-time employment—which has been considered the norm for decades—and the associated

rise of the so-called gig economy are not unique to individual countries, but describe a global phenomenon. For example, according to a recent survey, up to 162 million individuals in Europe and the United States engage in some kind of independent work, reflecting 20-30% of the working-age population in those countries (McKinsey Global Institute 2016).

Generally, gig work can be characterized by high work autonomy, payment by task, and a short-term nature of work arrangements (McKinsey Global Institute 2016). While gig work largely shares these characteristics with other forms of temporary work (e.g., De Stefano 2016), what is new is the extent to which gig work is disconnected from the notion of traditional organizations and is managed through online platforms and algorithms (Cherry & Aloisi 2017; Friedman 2014). One prominent example of a gig economy company is the ride-hailing firm Uber, which offers platform-based transportation services by connecting drivers of privately-owned cars with people seeking a ride.[1] Uber drivers—referred to as "partners" by the company—work as independent contractors who are free to set their own schedule and make money on their terms (Rosenblat 2018). However, despite drivers' freelance status, Uber uses advanced digital technologies and smart algorithms to exercise (tight) control over its workforce, referred to as technology-mediated control (TMC) (Cram & Wiener 2019; cf. Constantiou et al. 2017). Specifically, to ensure high service reliability and quality, Uber uses a mobile app that collects detailed data on driver behaviors and leverages algorithmic management capabilities to steer their actions, for instance by enforcing "blind passenger acceptance" (Rosenblat & Stark 2016, p. 3762).

The paradox between independent work and tight control raises interesting questions regarding gig workers' perceptions of TMC legitimacy. For example, in traditional, human-to-human control relationships, the controller's ability to influence controllee behavior is typically derived from legitimate sources of social power (French & Raven 1959), such as the controller's formal position in the organizational hierarchy, formal job descriptions, or legal contracts (Wiener et al. 2016). However, neither of these legitimate power sources arguably applies to the control relationship between Uber and its drivers, nor to controller-controllee relationships observed in other gig-economy contexts (e.g., Airbnb vs. hosts). Against this backdrop, we take into account the unique characteristics of gig work and draw on the organizational control and information systems (IS) security and privacy literatures to propose a multidimensional conceptualization of TMC legitimacy. On this basis, we then set forth to

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[1] Throughout the chapter, we use Uber as a running example for illustration purposes.

explore the concept's nomological network by outlining and discussing a set of antecedents, consequences, and boundary conditions, which can serve as a basis for future research.

2   Conceptual Foundations

In this section, we introduce key concepts that form a foundation for our work. In particular, we first describe the characteristics that distinguish different types of gig economy platforms. Next, we introduce the concept of technology-mediated control (TMC) and discuss two basic types of how organizations utilize TMC in day-to-day operations.

2.1 Gig Economy Platforms

The term 'gig economy' stems from the music industry and originally referred to musicians playing a 'gig' in the sense of a one-time performance at a specific location and time. In the current digital age, gig work describes a form of non-standard employment and spans a wide spectrum of work tasks and industries (Friedman 2014). A central characteristic of gig work is that it is supported by, and managed through, online platforms (e.g., Cherry & Aloisi 2017). According to De Groen et al. (2016), gig economy platforms can be differentiated along two dimensions. First, corresponding platforms differ in terms of worker skills required, ranging from low/medium-skilled work (e.g., Uber) to high-skilled work (e.g., Upwork). Second, they differ in terms of services offered, ranging from virtual services that can be provided from everywhere in the world (e.g., Amazon Mechanical Turk) to physical services to be performed at a specific location (e.g., Uber). Further, Constantiou et al. (2017) highlight that gig/sharing economy platforms differ in terms of the level of control exerted by the platform owner (loose vs. tight) and the degree of rivalry among platform participants (low vs. high). Based on these two dimensions, they distinguish among four platform types: *chaperones*, *franchisers*, *gardeners*, and *principals* (see Figure 1 below).

In Constantiou et al.'s (2017) typology, *gardeners* and *franchisers* represent the two extreme cases. Featuring low rivalry and loose control, *gardeners*—such as the peer-to-peer accommodation sharing platform Couchsurfing—focus on supporting the development and maintenance of an online community. In particular, *gardeners* offer an infrastructure for a community to use, while setting only minimum standards for platform participation and fostering low or no rivalry among participants on the supply side (Constantiou et al. 2017). On the other hand, *franchiser* platforms—such as the one operated by the ride-hailing firm Uber—feature high rivalry and tight control. Specifically, in contrast to *gardeners* and *principals* (e.g., Handy), Uber's online platform promotes intense rivalry among drivers who

are in direct competition for passengers, while fares are set by Uber based on current market demand and supply. Also, in contrast to *chaperones* (e.g., Airbnb) and *gardeners*, Uber exerts tight control over platform participants in that drivers are required to adhere to strict rules and standard procedures when using the platform to deliver ride-hailing services (e.g., Lee et al. 2015; Möhlmann & Zalmanson 2017; Rosenblat & Stark 2016). These rules and procedures are enforced via Uber's driver app, which is also used to influence when, where, and how long drivers work (Scheiber 2017). The control approach used by Uber thus represents a prime example of technology-mediated control, as discussed in the following section.
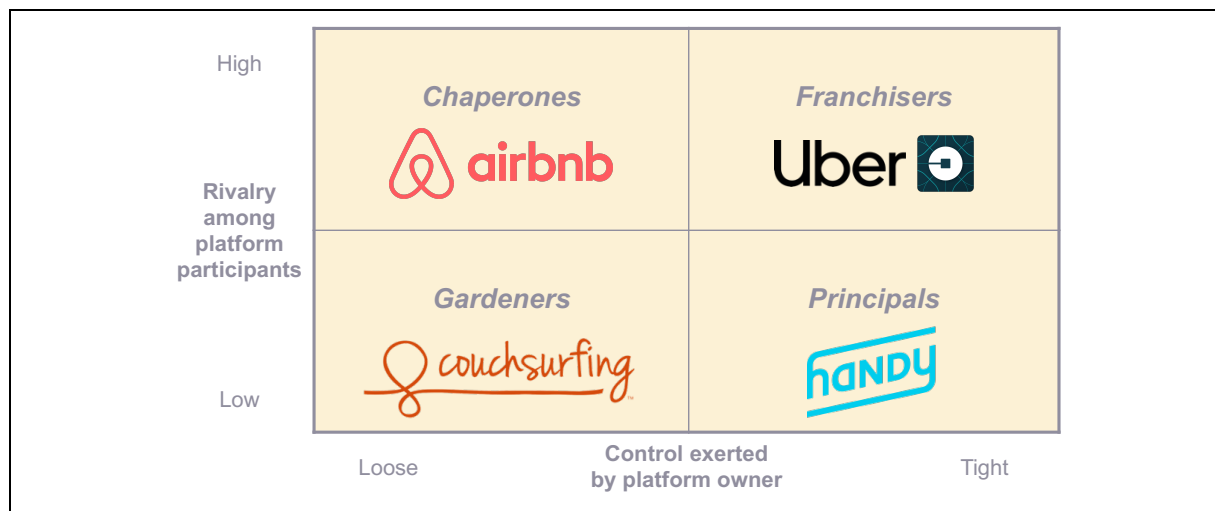

Figure 1. Typology of gig economy platforms (based on Constantiou et al. 2017, p. 232)

2.2 Technology-Mediated Control (TMC)

TMC is broadly defined as the managerial use of advanced digital technologies (e.g., Internet of Things [IoT] sensors, mobile apps, wearable devices) and smart algorithms as a means to influence workers to behave in a way that is consistent with organizational expectations (Cram & Wiener 2019; Wiener & Cram 2017). This view of TMC is largely consistent with past conceptualizations of algorithmic management, which has been characterized by constant tracking of worker behaviors, continuous evaluation of worker performance, and automatic implementation of decisions (Lee et al. 2015; Möhlmann & Zalmanson 2017).[2]

According to Cram and Wiener (2019), two basic types of TMC can be distinguished (see Figure 2). In the first type, digital technology is used to *support* managerial control processes by acting as a monitoring tool that provides (human) managers with useful insights

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[2] Whereas algorithmic management specifically considers how the behavior of remote workers is influenced by software algorithms, exclusive of any human intervention (Lee et al. 2015; Möhlmann & Zalmanson 2017), we follow Cram and Wiener's (2019) conceptualization of TMC, which recognizes the potential for technology to *support* the control activities of human managers, as well as the potential to *automatically* act in place of human managers.

into subordinate behaviors. For example, the global logistics firm United Parcel Service (UPS) equips its trucks with sensors that collect detailed data about driver behaviors. UPS managers (controllers) then use this data to ensure that drivers (controllees) behave in a manner that is consistent with pre-specified guidelines and rules. Where workers are not adequately complying with the policies, the manager can act to correct the behavior. In the second type of TMC, technology is used to *automate* managerial control processes by acting as a proxy for human controllers. This TMC type is commonly used in the gig economy. For example, as noted above, the ride-hailing firm Uber uses intelligent algorithms in combination with a mobile app to guide, monitor, evaluate, and reward or sanction driver behaviors without any substantive human intervention, thereby minimizing the need for costly and time-consuming interactions between Uber managers and drivers (Rosenblat & Stark 2016).
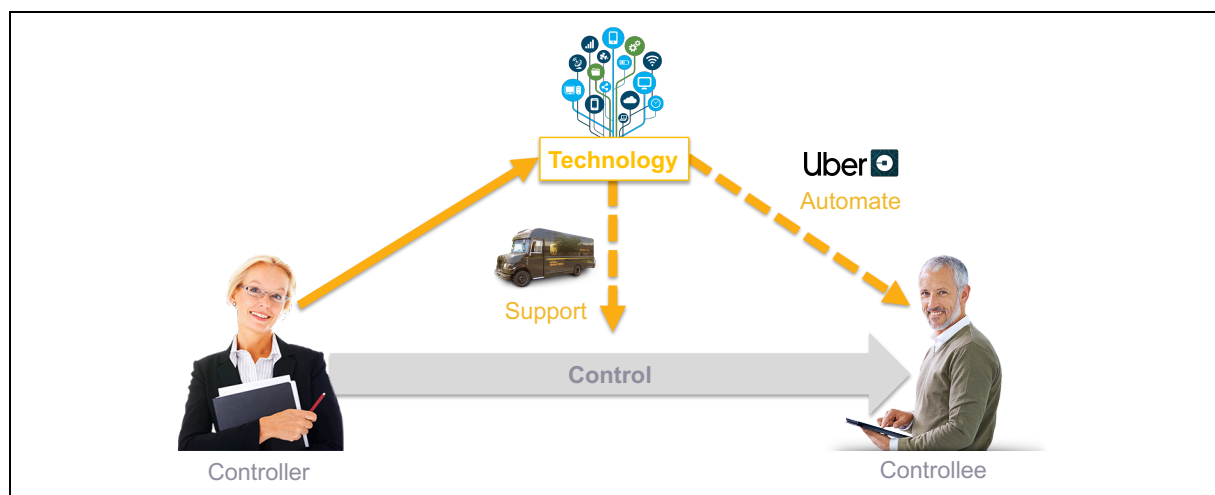

Figure 2. Basic TMC types: Support vs. Automate (Cram & Wiener 2019)

The use of automated TMC approaches shows several unique characteristics that set them apart from automated controls embedded in traditional software systems (e.g., SAP ERP). For example, while enterprise systems are usually limited to the collection of cross-sectional, behavioral data (e.g., who entered what data), the use of TMC relies on ubiquitous technologies, including smartphones and mobile sensors, which are able to capture the minutiae of worker behaviors (Marabelli et al. 2017). Further, system-embedded controls tend to enforce static rules, such as forcing software users to provide certain information before they can move on to the next process step. In contrast, TMC employs dynamic controls and rules that take into account relevant context factors, while still being applied without human involvement. For instance, Uber employs complex algorithms to determine and inform drivers about so-called "surge pricing zones" that require more drivers at a particular point in time due to a temporary spike in customer demand (Rosenblat & Stark 2016). Or, when trying to log off, Uber drivers may receive alerts informing them about being close to achieving the

next earning target (Scheiber 2017). Given these characteristics, the organizational use of TMC has the potential to put workers at a considerable disadvantage by creating a number of information and power asymmetries in favor of the platform operators (cf. Rosenblat & Stark 2016). Arguably, this is in sharp contrast to gig economy companies, such as Uber, promising workers a partnership-like relationship and flexible employment (ibid), which in turn raises questions about gig workers' perceptions of TMC legitimacy.

3   Conceptualizing Control Legitimacy in the Gig Economy

Drawing on pioneering work from the sociology and organizational literatures as well as more contemporary perspectives in the related research from IS, this section first reviews different perspectives on legitimacy. Focusing on the specific context of the gig economy, it then introduces the concept of TMC legitimacy and conceptualizes this concept in terms of three focal dimensions.

3.1 Perspectives on Legitimacy

Legitimacy is widely acknowledged to be a socially constructed phenomenon (Brenner & Ambos 2013) that "represents a reaction of observers to the organization as they see it; thus, legitimacy is possessed objectively, yet created subjectively" (Suchman 1995, p. 574). For example, Suchman (1995) defines legitimacy as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed systems of norms, values, beliefs, and definitions" (p. 574).

Past legitimacy research has adopted a diversity of approaches and perspectives when studying the phenomenon (Deephouse & Suchman 2008). In one approach, legitimacy is considered from the perspective of managers, focusing on the actions they can deploy to enhance legitimacy as means to achieve organizational goals. This compares to a higher-level institutional perspective of legitimacy that is oriented around the societal view of structures and belief systems that lead to cultural pressures within organizations (Suchman 1995). Furthermore, extant research indicates that an organization (as a whole) can be collectively viewed as legitimate by workers (Brenner & Ambos 2013; Dowling & Pfeffer 1975), but that this outcome is, in part, a consequence of individual-level perceptions of lower-level structures, such as top management teams or technology innovations (Deephouse & Suchman

2008). These microfoundations[3] point to the multi-level nature of legitimacy, which past commentators have recognized as forming at an individual level (e.g., an employee perceives a technology innovation as legitimate) and then over time aggregating together to form higher-level macro-judgements on legitimacy (e.g., employees view the overall organization as legitimate) (Deephouse & Suchman 2008; Suddaby et al. 2017). Under this approach, legitimacy can be considered as either a *property* (i.e., a stable, measurable degree of fit between an organization and its environment), a *process* (i.e., an actively changing product of ongoing social interactions), or a *perception* (i.e., an individual-level judgement on whether an organizational action is appropriate) (Suddaby et al. 2017).

In considering how IS scholars have approached legitimacy in the past, it becomes apparent that corresponding studies—including Avgerou (2000), Kohli and Kettinger (2004), and Mehrizi et al. (2019)—primarily incorporate legitimacy fundamentals as a perspective for evaluating employee perceptions related to new technologies. However, one emerging area of study within the organizational literature that has not yet been widely applied to IS research is the study of *control* legitimacy (Cram & Wiener 2018; cf. Bijlsma-Frankema & Costa 2010), which adopts a narrower view of legitimacy by focusing specifically on the collection of controls enacted by managers as the driver of employee perceptions. The value in studying control legitimacy stems from the resulting implications, which include the potential for increased employee trust (Sitkin & George 2005), compliance (Bijlsma-Frankema & Costa 2010), job satisfaction (Niehoff & Moorman 1993), and organizational success (Meyer & Rowan 1977). The study at hand seeks to build on this emerging perspective by focusing on the concept of TMC legitimacy in the specific context of the gig economy.

3.2 TMC Legitimacy Concept and Dimensions

Within the gig economy context of this research, we adopt a managerial perspective on legitimacy and define TMC legitimacy, in a broad sense, as an individual gig worker's general *perception* that the TMC approach used by a given gig company is appropriate to guide day-to-day worker behavior. The concept of TMC legitimacy thus suggests that gig workers do not blindly follow the enacted controls, but instead make judgements on the controls used by the platform operator (cf. Brenner & Ambos 2013; Schnedler & Vadovic 2011; Yang 2015).

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[3] In the context of legitimacy, microfoundations represent the perceptions, attitudes, and judgements of individuals. By clarifying the microfoundational legitimacy perceptions of individuals, we can better understand a key antecedent to the collective, macro-level view of organizational legitimacy (Barney & Felin 2013; Suddaby et al. 2017).

Prior studies have identified several dimensions, or sources, that contribute to the formation of an individual's perception of (control) legitimacy. For example, focusing on traditional control relationships between managers and employees, Bijlsma-Frankema and Costa (2010) identify four sources of control legitimacy perceptions (autonomy, competence development, group identification, justice/fairness). They argue that an employee's perception of the legitimacy of a given control, or set of controls, is a direct consequence of a combined interpretation to what extent that control positively contributes to these four sources. However, Bijlsma-Frankema and Costa (2010), as well as other studies (e.g., Suchman 1995), also recognize that the conceptualization of legitimacy is dependent on the type of legitimacy being examined (e.g., control vs. institutional) and the work context.

Against this backdrop, and considering the individual-level focus that commonly defines gig economy work (in comparison to the increasingly team-oriented focus that exists in organizational processes, such as systems development projects), we determined that group identification is of only limited importance in this work context, where arguably all of the work is completed in isolation from co-workers (Anthes 2017). In addition, we reason that because the TMC approaches used on gig economy platforms are often very prescriptive and explicit, there is relatively little opportunity for extensive competence development in gig work. For example, an Uber driver is instructed what kind of car is required, where to pick up passengers, and what route to take. On the other hand, keeping in mind our study's focus on gig workers' individual perceptions of TMC legitimacy, we were able to derive a set of three legitimacy dimensions that clearly apply within a gig economy context. Although we acknowledge that other dimensions might contribute to TMC legitimacy perceptions as well, we believe that the three dimensions noted below—autonomy, fairness, and privacy—are the most prominent and relevant in this context (see also Table 1 for an overview and brief description of each dimension). This viewpoint is consistent with Bijlsma-Frankema and Costa (2010), who argue that only a few sources of legitimacy tend to be the most prominent within a particular context.

First, autonomy contributes to perceptions of control legitimacy when controls are viewed as empowering workers and allowing them to act freely and independently (Bijlsma-Frankema & Costa 2010). Grounded in self-determination theory and empowerment theory, autonomy provides employees with a sense of freedom and competence (Niehoff & Moorman 1993). Relatedly, Suddaby and Greenwood (2005) recognize the importance of autonomy for employees by providing them with a sense of identity. In doing so, where (gig) workers view controls as allowing them to act with autonomy, it contributes to their overall perception of

control legitimacy and can lead to improved work quality and continuance intentions (cf. Goldbach et al. 2018). Although flexible work hours are often cited by gig economy workers as an enticing characteristic of the overall job (Kessler 2016; Rosenblat & Stark 2016), TMC is generally oriented towards reducing the opportunity for workers to act independently of the platform-based app (Möhlmann & Zalmanson 2017). For example, the day-to-day activities of workers are typically monitored closely by the app and automated guidance is provided where non-compliance with accepted practices is noted (Addady 2016, Griffin 2016).

Second, fairness is commonly identified as a key contributor to perceptions of control legitimacy (e.g., Bijlsma-Frankema & Costa 2010; Brockner et al. 2001; Long et al. 2011; Ouchi 1980; Sitkin & George 2005). In this context, managers implementing controls that employees judge to be fair, rational, and reasonable, will contribute to establishing a routine of organizational interactions and allow employees to make sense of the organizational structures around them. Where employees believe they are being treated equitably on a day-to-day basis, they attribute legitimacy to the control (Ouchi 1980). This view is grounded in the workplace justice and employee citizenship behavior literature (Bijlsma-Frankema & Costa 2010; Long et al. 2011). Within gig economy work, a foundational assumption surrounding fairness perceptions is that platforms often claim to be in a partnership-like relationship with its workers (Rosenblat & Stark 2016). As such, workers often have expectations that the controls enacted by the platform app will treat them in an equitable way. Where platforms do not provide sufficient transparency into their business practices or how the underlying algorithms operate, workers may perceive controls as unfair. At Uber, for example, drivers commonly view the ratings system and fare calculations as being obscure and unreasonable (Chan & Humphreys 2018; Möhlmann & Zalmanson 2017).

Third, privacy refers to an individual's ability to decide who gets access to personal information and what is done with that information (Smith et al. 1996; Stone et al. 1983). With very few exceptions, such as Alge et al. (2006) and Posey et al. (2011), privacy has not been considered as a key contributor to control legitimacy perceptions. However, due to the unique context of the gig economy, the heavy reliance on monitoring worker behavior (Addady 2016; Goldstein 2014; Woyke 2018) has introduced a growing collection of granular and real-time worker data, including location, response time (e.g., how long it takes a worker to respond to a request), and mobile device usage (e.g., texting while driving). Past research finds that workers perceive their privacy expectations to be met when they conclude that controls are in place to ensure that: (a) the personal information being collected relates to an existing relationship; (b) workers have the ability to decide how the information is used; (c)

the information is relevant to a transaction; and (d) the information will translate into reliable judgements (Culnan & Armstrong 1999). Where organizations have fulfilled these information management expectations, workers will increasingly view the controls as legitimate (Alge et al. 2006; Posey et al. 2011). However, where an organization provides insufficient notice (e.g., lack of clarity on why personal information is being collected or what it will be used for), consent (e.g., worker is unable to opt out), or is seen to use the data in an inappropriate way (e.g., intrusive data collection, not used for a relevant business decision), individuals are increasingly likely to perceive the company's activities as invasive and illegitimate (Bies 1993; Culnan & Armstrong 1999; Malhotra et al. 2004; Marx & Sherizen 1987). We consider the privacy dimension to be distinct from the fairness dimension on the basis that it is oriented specifically around the controls associated with the appropriate use and safeguarding of personal data. This compares to the fairness dimension, which is concerned with more broad-based judgements on the overall equitability and reasonability of controls.

Table 1. TMC legitimacy dimensions

Dimension	Brief description	Illustrative example	Relevant literature base
Autonomy	Controls are perceived to empower workers, allowing them to act freely and independently.	An Uber driver values the flexibility of working when and where she or he chooses.	Organizational control
Fairness	Controls are perceived as fair, just, and reasonable.	An Uber driver perceives the passenger ratings to be an effective, fair, and reasonable feedback mechanism.	Organizational control IS security and privacy
Privacy	Controls are perceived as appropriately respecting personal worker information during its collection, use, and storage.	An Uber driver feels that the location and app-usage information collected by the company is relevant to her/his daily work and will contribute to better customer service.	IS security and privacy

4 Exploring the Nomological Network of TMC Legitimacy

Based on the three-dimensional conceptualization of TMC legitimacy introduced above, this section presents an initial exploration of the concept's nomological network.[4] In particular, again using the gig economy firm Uber as an illustrative example, we first explore the role of different (formal and informal) control modes as key antecedents of TMC legitimacy. Next, we shed light on key behavioral consequences related to the dichotomies between continuance

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[4] In line with the definition provided above (see section 3.2), we acknowledge that when referring to TMC legitimacy, it implies the perception of TMC legitimacy by an individual gig worker.

and turnover intentions, as well as between control compliance and violation. Lastly, we look into contextual boundary conditions that are likely to influence workers' perceptions of TMC modes and legitimacy, as well as their downstream effects.

4.1 Antecedents of TMC Legitimacy

Formal TMC modes: To exercise control over their freelance workforce, gig companies use TMC approaches that typically rely on a combination of all three basic modes of formal control: input control, behavior control, and output control (e.g., Jaworski 1988; Wiener et al. 2016). For example, before accepting a new driver, Uber requests formal documentation from each applicant (e.g., proof of residency and vehicle insurance), checks the candidate and her/his car against a list of formal requirements, and conducts background checks (***input control***) (Lee et al. 2015; see also Uber 2019a). Here, it should be noted that, more recently, Uber started running background checks each year in an effort to "ensure drivers continue to meet [its] standards on an ongoing basis, long after they take their first trip" (Khosrowshahi 2018). Relatedly, Uber invested in new technology that "can identify new criminal offenses via public records or pending DUI [driving under the influence] charges as they happen" (O'Brien 2018). In relation to ***output control***, Uber drivers are rated by passengers on a five-point scale after each and every trip. These ratings arguably constitute the "most significant performance metric" (Rosenblat & Stark 2016, p. 3772), not least because drivers are required to maintain a minimum rating of around 4.6 in order to remain active (ibid). This suggests that Uber's driver rating feeds back into input control. In terms of ***behavior control***, Uber sends regular feedback messages to each driver, including reports on driver-specific issues (e.g., concerns about driving safety and professionalism) along with suggestions on how a driver can improve their customer ratings. For example, drivers may receive a message such as the following: "*Riders give the best ratings to drivers who [go] above and beyond to make the experience special, such as opening doors for riders when possible*" (Rosenblat & Stark 2016, p. 3776).

Taking into account the unique characteristics of algorithmic management, we argue that gig workers' perceptions of the three formal TMC modes (refer to Table 2 for brief definitions and illustrative examples) can be expected to vary considerably for at least two reasons. First, due to individual preferences, personality traits and other context factors, gig workers are likely to perceive the very same control mechanism (e.g., the Uber driver rating) very differently (e.g., as loose vs. tight control). Second and relatedly, since automated TMC approaches mimic the behavior of a human controller, the perceived control degree will also

vary for objective reasons. For example, high-performing Uber drivers will arguably receive, and thus most likely perceive, less behavior control than low-performing drivers.

Table 2. Perceptions of formal TMC modes

Antecedent	Brief definition	Illustrative example
Perceived input control	The degree to which a gig worker perceives that a given online platform operator uses gatekeeping and screening procedures to allow her/him to work, or to continue working, on the platform (adapted from Croitor & Benlian 2019; Tiwana 2015).	Through the driver app, Uber requests formal documentation from each potential driver (e.g., proof of residency and vehicle insurance); also, the company uses advanced technology to continuously monitor each driver's criminal record.
Perceived behavior control	The degree to which a gig worker perceives that the platform operator oversees and guides her/his work behaviors (cf. Goldbach et al. 2018).	Through the driver app, Uber offers suggestions to drivers on behaviors that have been found to increase customer satisfaction (e.g., opening doors, playing jazz music, etc.).
Perceived output control	The degree to which a gig worker perceives that the platform operator monitors and provides feedback on her/his work performance (cf. Goldbach et al. 2018).	Through the driver app, Uber provides drivers with performance metrics, including average customer ratings as well as ride acceptance and completion rates.

Further, we argue that the control logic that underlies input control is fundamentally different from the logic that underlies behavior and output control. In particular, while the former is used to determine *who* is allowed to participate, the latter explicates *what* participants should do and *how* they should behave. This key difference in underlying control logic can be expected to have a notable effect on how drivers perceive the control modes, as well as their legitimacy. For example, given its coercive design (cf. Adler & Borys 1996), input control is likely to be perceived as a 'constant threat' by Uber drivers. In contrast, providing drivers with clear and direct feedback on their performance along with suggestions on how to improve it, behavior and output controls may be perceived as empowering, or enabling (ibid), thereby contributing to driver perceptions of autonomy. In addition, while earlier studies highlight that algorithmic management in general is characterized by low transparency (Möhlmann & Zalmanson 2017), we argue that the level of transparency can differ noticeably across formal TMC modes, leading to distinct effects on gig workers' perceptions of TMC legitimacy. For example, driver ratings and other output controls (e.g., acceptance rates) are communicated clearly and are thus well known among Uber drivers. In this regard, it has been argued that automated controls that adhere to a generally accepted set of rules increase transparency, leading to perceptions of fairness among controllees (Hansen & Flyverbom 2015; Möhlmann & Zalmanson 2017). For example, when Uber drivers receive a ride request through the app, they are well aware that they have around 15 seconds to accept

or reject it (Rosenblat & Stark 2016; see also Uber 2019b). Also, while the Uber driver app collects detailed data on driver behaviors for control purposes (Cram & Wiener 2019), Uber openly shares information on what and how data are collected on its website (e.g., Beinstein & Sumers 2016). In contrast, Uber drivers tend to perceive some of the enacted input controls, and in particular the required background checks, to be an invasion of their privacy. Among other things, this is because it is not entirely clear to drivers how Uber conducts these background checks, and especially what data are collected and analyzed (O'Brien & Yurieff 2017).

However, at this point, we would like to acknowledge that, especially in the specific case of Uber, one could also argue that the behavior and output controls enacted through the driver app follow a coercive logic as well, along with high control frequency and intensity (cf. Cram & Wiener 2018; Gregory et al. 2013). For example, feedback reports delivered via the driver app may be perceived as overly tight, as they are sent out at least weekly and include very detailed directions on how an Uber driver should behave on the job (behavior control), thereby restricting a driver's perceived autonomy. The latter is in keeping with earlier research, which finds that tight behavior control is associated with controllee perceptions of low autonomy (Cram & Wiener 2018). In addition, while the basic (behavioral) rules associated with enacted behavior and output controls are clearly communicated to drivers, Uber does not disclose the 'rules' that underlie those controls (e.g., who receives what suggestions). Also, the underlying rules are adaptive in nature and thus frequently change (Rosenblat & Stark 2016). In such situations, as noted by Möhlmann and Zalmanson (2017), control transparency in algorithmic management is generally low, prompting Uber drivers to question the fairness of the enacted controls. Moreover, some behavior controls (e.g., 15-second time limit to accept or reject a ride request) put considerable pressure on drivers, while leveraging information asymmetries in favor of the platform owner (Rosenblat & Stark 2016). For example, when Uber drivers receive a ride request through the app, they are not shown relevant information (e.g., trip destination, fare estimate) until they accept the request, even though this information is already known by the company (ibid). Finally, not only input control (see above) but also behavior and output controls may be perceived as an invasion to driver privacy. In this regard, related research finds that the use of behavior controls—which is closely linked to, and often based on, worker monitoring/surveillance—is particularly prone to triggering privacy concerns (e.g., Moussa 2015). Arguably, this general observation translates to the specific control context of Uber, where the driver app is used to collect detailed data on driver behaviors for control purposes (Cram & Wiener 2019). For example,

the company uses "harsh braking and acceleration as indicators of unsafe driving behavior" (Beinstein & Sumers 2016; see also Scheiber 2017).

Informal TMC modes: In addition to gig workers' perceptions of the three formal TMC modes discussed above, prior studies on gig economy platforms indicate that TMC legitimacy dimensions, such as autonomy, are influenced by a worker's perceived degree of **self-control** (e.g., Goldbach et al. 2018; Lehdonvirta 2018). Generally speaking, self-control is an informal control mode that relies on a worker's intrinsic motivation and individual standards (e.g., Jaworski 1988). More specifically, in self-control, gig workers (controllees) set their own goals, define the actions required to achieve these goals, and self-monitor their behavior (e.g., Kirsch 1996; Wiener et al. 2016). While Uber's business model builds on the promise of flexible employment, its tight TMC approach arguably leaves little room for perceived self-control (cf. Constantiou et al. 2017; Rosenblat & Stark 2016). Still, prior research indicates that gig economy companies use their TMC approach to promote and facilitate the exercise of self-control by providing workers with information and tools (e.g., earning tracker) for self-organization and self-regulation (Goldbach et al. 2018; Lehdonvirta 2018). For example, analyzing the TMC approach used on Google's mobile software platform, Goldbach et al. (2018) find that Android app developers' perceptions of self-control are positively and significantly related to their perceived autonomy.

A second informal control mode is **clan control**, which operates when goal-direct behavior in a peer group is guided by shared norms and values, along with a common vision (Kirsch et al. 2010; Wiener et al. 2016). When compared to three formal TMC modes and self-control, clan control appears to be less pertinent on many gig economy platforms because workers, such as Uber drivers, tend to work in isolation from one another (i.e., not as part of a team or peer group). However, we recognize that several gig economy platforms do employ a model that draws on ad-hoc group work to perform tasks, referred to as crowdsourcing, which in some scenarios makes clan control increasingly relevant. Specifically, while crowdsourcing platforms such as Amazon Mechanical Turk or 99Designs focus on micro-tasks (i.e., small-scale, simple activities) that are completed independently by individual workers and then consolidated together, other platforms—such as 10EQS and OnFrontiers—pursue the crowd-based completion of macro-tasks, which represent more complex activities and often, though not always, include worker collaboration (e.g., Robert 2019; Schmitz & Lykourentzou 2018). For those platforms that engage in collaborative macro-tasks, clan control has the potential to play an important role for workers, as there may be a need to interact and establish social

norms and values.[5] Here, platform features such as FAQ lists, work-progress trackers, and peer ratings (including 'voting a member out' functionality) can promote the exercise of (social) clan control by enabling peers to guide, monitor, and sanction others' behavior (Gallivan 2001). However, the question of how the enactment of clan controls relates to gig workers' perception of TMC legitimacy appears to be anything but clear-cut. One possibly important clue to solving this 'puzzle' relates to Gallivan's (2001) distinction between core and peripheral workers (observed in the context of open source software projects), which may also apply to group work on crowdsourcing platforms. In particular, a small core group of gig workers may play a decisive role in shaping and enacting team-based clan controls (and thus perceive these controls to be legitimate), whereas workers not being part of this core group may only 'react' to those controls and thus perceive them to be illegitimate. The latter can be explained by what Lowry and Moody (2015) term reactance theory, which defines reactance as "a negative emotional response caused by threats to or losses of behavioral freedom (often resulting from a persuasion [or control] attempt by another party)" (p. 439). Here, Lowry and Moody emphasize that a person's expectation of behavioral freedom (e.g., an expectation of not being controlled by her or his peers) is a key condition for the occurrence of reactance.

4.2 Consequences of TMC Legitimacy

Continuance vs. turnover intentions: Gig economy companies rely on workers' willingness to be part of, and keep contributing to, a specific ecosystem (Boudreau 2012; Ceccagnoli et al. 2012). In this context, Goldbach et al. (2018) define gig workers' continuance intentions as their behavioral intention to remain part of a platform ecosystem and offer their services on that platform. Here, the importance that gig economy workers place on securing flexible work arrangements is consistent with the historical preferences of independent contractors (Hall & Krueger 2015). As a result, the flexibility, or autonomy, that gig workers have in setting their own schedules represents an important recruitment and retention mechanism for companies such as Uber (Lee et al. 2015; Möhlmann & Zalmanson 2017; Rosenblat & Stark 2016). For example, in a 2015 survey commissioned by Uber, 85% of respondents agreed that flexibility was a major motivator for driving for the company, while 42% of women and 29% of men stated that a flexible schedule was mandatory for them, due to family, education, or health factors (Hall & Krueger 2015).

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[5] Robert (2019) finds that the vast majority of past crowdsourcing research focuses on the performance of micro-tasks and includes no discussion of informal controls.

As well, existing literature establishes a range of benefits that result from worker perceptions of fairness. From a continuance perspective, workers who believe they will be treated fairly are able to more clearly anticipate the long-term benefits of remaining with an organization (Cropanzano et al. 2007). This is supported by organizational research, which finds a positive relationship between fairness/justice and organizational commitment (Folger & Konovsky 1989) and a negative relationship between fairness and turnover intentions (Alexander & Ruderman 1987; Chalykoff & Kochan 1989). In a similar vein, prior research finds that organizational processes—which includes managerial control processes—that are perceived by workers as fair contribute to the building of trust and commitment, and eventually lead to voluntary cooperation (Cropanzano et al. 2007).

Further, with regard to privacy, gig workers are often well aware of firms' surveillance capabilities but still seem to perceive them differently. For example, some drivers value Uber monitoring their behavior as it can act as a means to adjudicate disputes with riders, as noted in an interview conducted by Rosenblat & Stark (2016), where a driver highlighted that Uber can "actually log the exact route that you took" (p. 3765). However, generally, in cases where workers perceive their privacy has been infringed upon by an organization, existing research suggests that lower levels of organizational commitment and increased turnover will result (Smith & Tabak 2009; Tabak & Smith 2005). For example, prior studies find that constant tracking and close monitoring can lead to feelings of anxiety and tension (e.g., Lee et al. 2015; Möhlmann & Zalmanson 2017), or may be perceived by workers as an indication of a lack of trust (Smith & Tabak 2009). In this regard, Pfaffenberger (1992) notes that "the surveillance systems used to track the performance of airline telephone reservation clerks […] were constructed with the designers' conscious assumption that the clerks have little loyalty to the firm, are poorly educated, will try to avoid giving good service, and will quit in a few months anyway; the surveillance tries to transform them into tractable, cooperative cogs in a smooth-running machine" (p. 283).

Control compliance vs. violation: In general, controls that are viewed as legitimate by gig workers are expected to be increasingly accepted and followed by workers, while controls that are viewed as illegitimate will be at increased risk for non-compliance (Bijlsma-Frankema & Costa 2010). For example, studying IS security policies and conceptualizing legitimacy in terms of perceived fairness (i.e., the extent to which such policies are perceived to be appropriate and just), Son (2011) finds that perceived legitimacy has a significant and positive relationship with policy compliance. In other words, workers that are treated more justly are more likely to comply with corporate policies and less likely to engage in counter-

productive work behavior (Cohen-Charash & Spector 2001). Therefore, "if the process is perceived as just, employees show greater loyalty and more willingness to behave in an organization's best interests. They are also less likely to betray the institution and its leaders" (Cropanzano et al. 2007, p. 38). Relatedly, past research finds that where controllees perceive their need for autonomy to be met, they are more willing to pursue managerial goals (Bijlsma-Frankema & Costa 2010; Williams & Deci 1996). For example, in the case of Uber, these goals revolve around providing fast and professional services to riders.

On the other hand, the use of workarounds is of particular concern for organizations, as it represents a form of control violation and leads to managers being increasingly unaware of how work is actually being undertaken by workers (Woltjer 2017). Laumer et al. (2017) define workaround use as a worker's "conscious adaptations of work activities that are not expected or specified to be changed in this manner" (p. 335). Here, previous research shows that, where organizational and personal interests are aligned, inappropriate workarounds are less likely to be undertaken (Alter 2014). However, even if interests are aligned, gig workers can still be expected to engage in workarounds if their perceptions of the autonomy they are granted differ from what they had been promised. To that end, Ferneley et al. (2004) argue that "often employees will resist and, if possible, ignore a system which does not allow them the level of discretion and autonomy they see as part of their profession" (p. 1005). Similarly, Pollock (2005) argues that workarounds are employed as "resistance on behalf of users and the means by which they attempt to wrest control back from a technology or an institution" (p. 497). For instance, Rosenblat and Stark (2016) note that some drivers "perceive that Uber favors the passenger in adjudications, and even report having to gather their own data to prevent wages from being retracted" and that, in response, drivers may "resist Uber's power of interpretation by tracking their trips with manual or electronic logs and dash-cams" (p. 3765). Other evidence suggests that some drivers attempt to manipulate their interactions with the app (e.g., turning it off after a long ride, so as not to get too far away from home) when they perceive its guidance to be unfair or inconvenient (Lee et al. 2015).

Other consequences: Going beyond the TMC legitimacy consequences discussed above, past research supports the general assertion that workers who perceive organizational activities as being legitimate will not only behave differently but also perform differently than those who perceive a low level of legitimacy. In particular, perceptions of high legitimacy have been found to be associated with improved job satisfaction (Long et al. 2011) and commitment to team goals (Niehoff & Moorman 1993), while low legitimacy perceptions have been linked to reduced effort (ibid) and decreased work performance. For instance,

existing research suggests that, where workers perceive their privacy has been infringed upon by an organization, not only increased turnover (see above) but also decreased performance will result (Smith & Tabak 2009; Tabak & Smith 2005).

4.3 Contextual Boundary Conditions

When exploring a concept's nomological network, it also becomes important to highlight relevant boundary conditions, and in particular to discuss the contextual conditions under which the proposed relationships are most likely to hold (cf. Rivard 2014; Whetten 2002). In this regard, a variety of contextual factors can be expected to influence gig workers' TMC legitimacy perceptions, or to moderate, the relationships between TMC modes and legitimacy, on one hand, and TMC legitimacy and the consequences outlined above, on the other hand. In the following, we focus our discussion on three broad sets of context factors that seem to be particularly relevant in the specific context of the gig economy, namely: worker attitudes and types, as well as platform features.

Gig worker attitudes: A prime example of an attitudinal context factor that is likely to moderate the link between (formal) TMC modes and legitimacy is a gig worker's ***attitude toward gamification***. In the literature, gamification has often been defined as "a process of enhancing services with (motivational) affordances in order to invoke gameful experiences and further behavioral outcomes" (Hamari et al. 2014, p. 2; see also Hamari 2013). For example, some of the gamification elements embedded in the Uber driver app are quite literal: Like video game players, Uber drivers can earn badges for achievements, such as "neat and tidy", "excellent service", and "great amenities" (Uber 2019c). Although the integration of gamification elements into online platforms, and TMC approaches in particular, is a fairly common strategy among gig economy companies (e.g., Scheiber 2017), individual workers' attitude toward such a gamification strategy can be expected to vary considerably (cf. Broer 2017; Tomaselli et al. 2015); that is, while some gig workers may feel negatively about game-like platform features and game-based competition, others seem to enjoy these features. For example, in an interview with the *New York Times*, an Uber driver expressed his pride in the badges he had earned and highlighted the important feedback role that they fulfill: "*It tells me where I'm at.*" (Scheiber 2017).

Gig worker types: The extent to which a gig worker perceives a given TMC approach to be legitimate might differ between ***full-time and part-time workers***. In particular, while the former make a living from their gig work, and are thus highly dependent on this work, the latter often 'just' use the income from their gig work to supplement the income from a regular

job. A similar pattern may apply to ***high- and low-income workers***. For example, Rosenblat and Stark (2016, p. 3763) point out that the "rhetoric of risk and reward has been retooled to suit a contingent of lower-income workers who are recruited to perform service labor under working conditions controlled by the design and affordances of Uber's platform." In essence, this suggests that low-income drivers are more likely to perceive Uber's TMC approach to be legitimate. On a related note, TMC legitimacy perceptions may vary between workers being active on a single gig platform (e.g., Uber) and workers being active on multiple platforms simultaneously (e.g., Uber and Lyft), also referred to as ***single- vs. multi-homing***. In this regard, Möhlmann and Zalmanson (2017) find that many ride-hailing drivers work for more than one company and switch between platforms to regain control: "This switching behavior provides drivers with leverage against the platform by lowering the risks associated with a ban from existing platforms and allowing them to threaten to or actually abandon the Uber platform" (p. 12).

Another gig worker-related context factor that can be expected to moderate the TMC legitimacy relationships discussed in sections 4.1 and 4.2 is the level of ***worker experience***. For example, an Uber driver with several years of experience and thousands of completed rides is likely to interact with the app, and view the controls embedded in this app, differently than a driver with only a few weeks of work experience. Experience-induced differences in TMC legitimacy perceptions seem to be of particular relevance in a gig economy setting due to the relatively high turnover rates (Rosenblat 2018). Relatedly, extensive experience as a gig economy worker allows for an increased opportunity to learn the 'tricks' of how best to utilize the platform, as well as when and how to use workarounds to circumvent or trick the control algorithms. Also, experienced Uber drivers will be savvier in understanding the specific implications of control violations, such as failure to meet the minimum acceptance rates.

Gig platform features: Extant research highlights that gig economy platforms differ sharply in terms of the 'actual' ***degree of control*** exerted by the platform owner (Constantiou et al. 2017). This, in turn, implies that TMC legitimacy perceptions are likely to differ across platforms as well. For example, being characterized by tight control and high rivalry among participants, *franchiser* platforms such as Uber appear to be particularly prone to TMC legitimacy concerns, especially when compared to *gardener* platforms (loose control and low rivalry) (ibid). Similar differences in legitimacy perceptions might be found between gig economy platforms that focus on the mediation of ***high-skilled work*** (e.g., Upwork) and platforms focusing on the mediation of ***low-skilled work*** (e.g., Uber) (De Groen et al. 2016),

with low-skilled workers arguably being more likely than high-skilled workers to perceive the use of TMC to be legitimate.

Finally, as noted above, for gig economy firms, the use of gamification elements is a quite common strategy to invoke desired worker behaviors and positively influence their work experience. Still, the actual ***degree of gamification*** can vary considerably across gig economy platforms. For example, when asked about the driver app, a veteran Uber driver stated, "*The whole thing is like a video game*" (Scheiber 2007). By gamifying the driving experience, Uber gives drivers the impression that their 'destiny' is in their own hands, fueling perceptions of high autonomy. For instance, the app shows drivers the number of trips they have completed in the current week, the money they have earned, and the time they have spent logged on. Conveying a feeling of work autonomy, all of these video-game like metrics "can stimulate the competitive juices that drive compulsive game-playing" (Scheiber 2017). Adding to this, the gamification elements included in Uber's driver app have the potential to alleviate drivers' privacy concerns by putting them into a mental state known from video gaming and referred to as "ludic loop" (Scheiber 2007). On this basis, it can be argued that the deployment of a high gamification degree is an effective strategy in masking the exercise of (tight) control, as well as in trivializing the associated collection of sensitive data, and thus in increasing gig workers' perceptions of TMC legitimacy. This is largely in keeping with Rosenblat and Stark's (2016) argument about the "prominence of control [being] not as perceptible" for Uber drivers and other gig workers whose work is primarily mediated electronically.

Taken together, the key antecedents, consequences, and boundary conditions of TMC legitimacy can be integrated into a nomological network (see Figure 3 below) that can guide future research in the area.
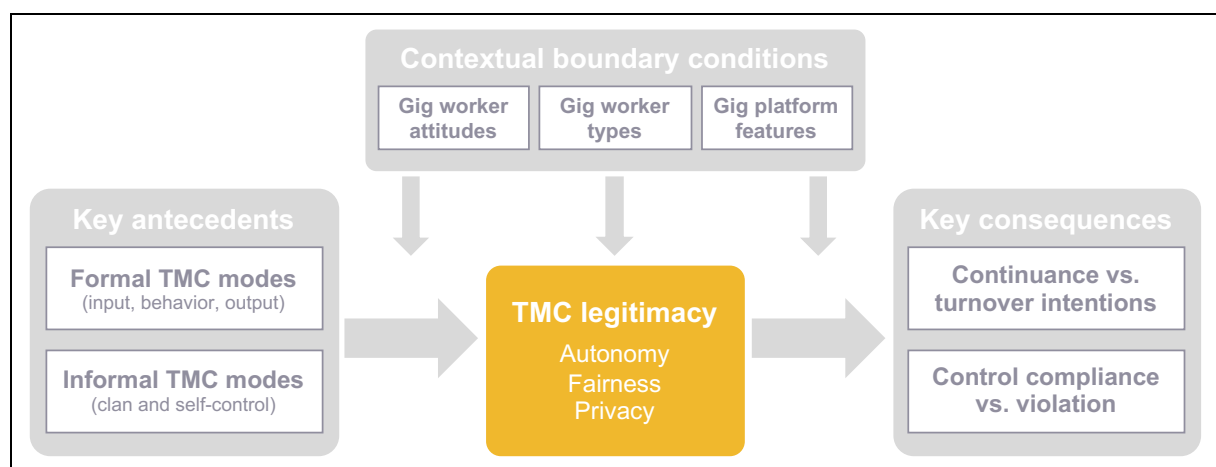
Figure 3. Nomological network of TMC legitimacy

5   Conclusion

In this chapter, we build on extant research to derive a three-dimensional conceptualization of TMC legitimacy (i.e., in terms of autonomy, fairness, privacy) attuned to the specific context and unique challenges of the gig economy. Future research can use this conceptualization to extend prior studies on the gig economy, which have typically focused on the first legitimacy dimension, namely, perceived autonomy (e.g., Goldbach et al. 2018; Möhlmann & Zalmanson 2017). Further, by exploring the nomological network of TMC legitimacy (perceptions), and in particular by identifying a set of key antecedents, consequences, and contextual boundary conditions, our study provides direction and inspiration for future research on the control strategies used by gig companies. For example, our study contributes to extant research on platform/ecosystem 'health' by pointing to the importance of TMC legitimacy in explaining gig workers' continuance or turnover intentions, on one hand, and their control compliance or violation (including the use of workarounds), on the other hand (cf. Benlian et al. 2015; Iansiti & Levien 2004).

On this basis, our study also offers important implications for practice. Most notably, low retention rates represent a key challenge for Uber and other gig economy platforms. For example, an Uber-internal study shows that only about 55% of the drivers "who started in the first half of 2013 remained active a year after starting" (Hall & Krueger 2015, p. 16). For gig companies, it is thus imperative to understand what factors influence workers' continuance intentions. As such, the concept of TMC legitimacy along with the theoretical relationships proposed in this chapter offer important 'food for thought' on how gig economy companies can improve the design of their platforms whose success ultimately depends on an effective TMC approach and a 'happy' workforce that perceives this approach to be legitimate.

6   Acknowledgements

7   References

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