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RESEARCH PAPER

IT Professionals in the Gig Economy

The Success of IT Freelancers on Digital Labor Platforms

Lisa Gussek · Manuel Wiesche

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Abstract When IT work is performed through digital labor markets, IT professionals have a high degree of personal responsibility for their careers and must use appropriate strategies to be successful. This paper investigates the success of IT freelancers on digital labor platforms. Drawing on signaling theory, a dataset of 7166 IT freelancers is used to examine how activating, pointing, and supporting signals lead to success. Analysis was carried out using negative binomial regression. The results indicate that the three signaling types positively influence the objective career success of IT freelancers. This paper contributes to the literature by testing signaling theory in the new context of digital labor platforms, investigating IT specifics, and proposing support as a new type of signal for IT professionals on digital labor platforms. In practice, the results provide guidelines for IT freelancers to improve their success within their careers.

Keywords IT work · IT freelancer · Signaling theory · Digital labor platforms · Career success · Gig economy

1 Introduction

As an additional, fast-growing labor market, the gig economy has changed the way people work and is attracting increasing numbers of academic investigations (Jabagi et al. 2019; Kuhn 2016). In 2020, about 36% of the U.S. labor force (59 million people) worked as freelancers (Upwork 2020). Online freelancing plays an important role, especially in professions such as software engineering, digital marketing, design, image editing, writing and translating (Blaising et al. 2021). Moreover, the number of qualified freelancers is increasing, e.g. in the field of computer programming and IT (Upwork 2021).

Particularly for IT work, digital labor markets offer new opportunities to tackle the increasing need, the chronic skills shortage, high turnover rates and the growing talent gap in IT (Apfel et al. 2020; Fuller et al. 2020; Wiesche et al. 2019). IT freelancers perform software development work online as independent contractors rather than as employees of a permanent company (Sison and Lavilles 2018). The field of IT freelancing must be distinguished from other freelancing areas because IT work itself exhibits specific characteristics that demand further investigation in the context of digital labor markets. IT freelancers differ from other online freelancers in two main aspects.

First, the breadth of knowledge and skills required, the constant change and development, and the need to learn and adapt knowledge in an intellectually demanding work context are characteristics that distinguish the IT profession from other professions (Riemenschneider and Armstrong 2021). IT freelancers must particularly respond to the threat of skill obsolescence, especially in the context of digital labor platforms, as they face a high level of personal responsibility for continuous training, updating, and learning (Graham et al. 2017; Kost et al. 2020; Spreitzer et al. 2017). On digital labor platforms, these characteristics additionally pose a particular challenge to the success of IT freelancers, as they must further differentiate themselves from the global competition by meeting high skill

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L. Gussek · M. Wiesche (✉)
Chair of Digital Transformation, TU Dortmund Business School, Dortmund, Germany
e-mail: manuel.wiesche@tu-dortmund.de

L. Gussek
e-mail: lisa.gussek@tu-dortmund.de

requirements (Gandini 2016; Jarrahi et al. 2020). Compared to other freelancing fields, IT tasks are more complex, interdependent and constantly evolving (Stol and Fitzgerald 2014). In particular, the aspect of skill obsolescence is less relevant for freelancers in, for example, the areas of design or translation (Gussek and Wiesche 2022b).

Second, IT work often requires collaborative efforts in designing architectures and integrating components as well as teamwork (Ang and Slaughter 2001; Kudaravalli et al. 2017; Levina 2005; Majchrzak et al. 2005). On digital labor platforms, meanwhile, freelancers usually work alone and teamwork is not common, e.g., for image editing, translation, or simple design tasks (Ashford et al. 2018). But for IT freelancers, some collaboration or teamwork can boost careers and help with advancement (Gussek and Wiesche 2022b).

On the one hand, collaboration within organizations is becoming more intense (Maruping and Matook 2020), but IT workers also value freedom and self-determination in their careers (Gol et al. 2018). In comparison, the traditional understanding of career success refers to the perceived or actual achievements of individuals (e.g., Judge et al. 1999). To succeed in digital labor markets despite the described characteristics of IT work, however, IT freelancers must independently apply suitable strategies. Due to the digital organization of work, the geographical distribution of freelancers and clients, and the resulting strong competition, IT freelancers need to convince potential new clients through their profiles on a platform to acquire projects (Agrawal et al. 2015). To improve trust and reduce uncertainty among potential clients, IT freelances can display signals about their achievements and skills (Connelly et al. 2011; Hukal et al. 2020; Kathuria et al. 2021).

Previous studies on careers in the gig economy suggest that a high level of expertise as well as a wide range of skills and resources and self-expression are necessary for workers to be successful (Ashford et al. 2018; Damarin 2006; Petriglieri et al. 2019; Van den Born and Van Witteloostuijn 2013). Some studies have already investigated the sending of signals on online labor markets. Durward et al. (2016) present signaling behavior as a mechanism that influences bargaining power and thus success in crowdsourcing. Yoganarasimhan (2013) finds that buyers are predictive, that they place significant weight on seller reputation, and that failure to account for momentum and choice can bias estimates of reputation. Horton (2019) examines the introduction of a new signaling feature into the context of a market design platform. In addition, Kathuria et al. (2021) investigate the effectiveness of skill and achievement signals. Moreover, only a few studies have focused on IT work in the gig economy and examined, for example, IT crowdsourcing (Stol and Fitzgerald 2014; Taylor and Joshi 2019) or the characteristics of online software development freelancers (Sison and Lavilles 2018; Watson Manheim and Ahuja 2019). In combination, however, it remains unclear how signaling differs for freelancing in the IT field and in online labor markets given the specific characteristics of IT work and digital labor platforms described earlier. This makes the signaling of IT freelancers on digital labor platforms not well comparable to signaling in other fields.

We test signaling theory in the new context of digital labor platforms, investigating IT specifics, and proposing a new typology of signals. Therefore, this research seeks to answer the research question: *How do different signals on digital labor platforms affect the career success of IT freelancers?* Using a quantitative analysis of 7,166 IT freelancer profiles from the freelance platform Upwork, we investigate the relationship between the use of signals and the career success of IT freelancers. Specifically, we study how three types of signals influence the career success of IT freelancers: activating signals, pointing signals, and supporting signals. The activating signals are related directly to the person and illustrate their skills, characteristics and human capital independent of the digital labor platform (e.g., education or programming skills). The pointing signals describe some kind of behavior and are therefore not directly related to the person; they are specific to the platform market and refer to the presentation of a certain image to convince clients and stand out from the competition on the platform (e.g., ratings of platform clients or a profile badge). Finally, the supporting signals are related to beyond the person and therefore indicate a certain form of team or group support (e.g., agency support on the platform).

The rest of the paper is organized as follows. First, the theoretical background and the state of the literature are explained, which leads to the development of the hypotheses. We then describe the data, the sample and the methodology. Finally, we report the results, discuss the main findings, and conclude.

2 Theoretical Background

2.1 IT Freelancing

This research focuses on freelancers who work in the gig economy and are classified as independent contractors who complete and coordinate their work online through digital labor platforms (Popiel 2017). These online labor markets are defined as digital matching platforms that facilitate work allocation in the global economy (Agrawal et al. 2015). These markets provide the digital infrastructure for payment, communication, search, feedback and ranking and they mediate the interaction between employers and employees (Rai et al. 2019). IT freelancers perform software development work through such platforms as independent contractors rather than as employees of a permanent company (Sison and Lavilles 2018). This work environment, where developers are involved in multiple, concurrent projects on various digital labor platforms, creates a complex and fragmented work environment (Watson Manheim and Ahuja 2019). IT freelancing requires special considerations due to the specific characteristics of both IT work and classic freelancing. In general, the characteristics of classic freelancers also apply to IT freelancers. However, some characteristics of IT work reinforce these special features (see Table 1).

IT professionals require a high skill level (Zhang et al. 2012), as well as a certain breadth of knowledge, skills and abilities. Unique IT related skills, both technical skills as well as soft and interpersonal skills such as communication skills, are important (Guzman et al. 2008). Moreover, these skills must always be kept up-to-date. IT work is driven by fast technological change, resulting in rapid knowledge obsolescence and a constant need for training and updating (Gussek et al. 2021; Matook and Blasiak 2020; Zhang et al. 2012). Furthermore, IT work requires collaborative efforts to integrate components and design architecture (Levina 2005), as well as teamwork (Ang and Slaughter 2001).

In terms of freelancing, there is no long-term connection between employee and employer (Friedman 2014; Gussek and Wiesche 2022a). Furthermore, unlike traditional workers, who are covered by relevant employment laws, freelancers are effectively self-employed and are thus responsible for their own career planning (Graham et al. 2017; Kost et al. 2020; Spreitzer et al. 2017). In addition, it is important for freelancers to present their skills on the digital platform, as they will be evaluated as individuals in the selection process based on the information available on the platform (Ashford et al. 2018; Roberts 2005). Thus, the success of gig workers depends on how successfully they develop a positive brand image (Hennekam and Bennett 2016; Vallas and Christin 2018).

The IT freelance sector should be distinguished from traditional freelancing in the sense that a broad range of skills and high-level skills are particularly important for IT gig workers. IT work itself requires highly advanced skills, which are even more important on digital labor platforms, where workers need to stand out from the competition (Gandini 2016; Heimburg and Wiesche 2022; Jarrahi et al. 2020). Furthermore, IT freelancers do not work exclusively on repetitive, small tasks that require low skill levels but also perform more complex tasks with higher skill requirements. In this context, software development tasks are more complex and interdependent compared to classic freelancing work (Stol and Fitzgerald 2014). Moreover, IT freelancers work collaboratively and often in teams, which is uncommon in classic freelancing (Ashford et al. 2018; Friedman 2014).

Few studies have focused on IT work in the gig economy. Such studies have, for example, examined IT crowdsourcing (Stol and Fitzgerald 2014; Taylor and Joshi 2019) or the practices and characteristics of online software development freelancers (Sison and Lavilles 2018; Watson Manheim and Ahuja 2019). In addition, Frenzel-Piasentin et al. (2022) examine the importance of improving non-technical skills for the development of information systems in the gig economy. Lastly, Kanat et al. (2018) address survival in global online labor markets for IT services.

2.2 Signaling Theory

Signaling theory describes the process by which one party (referred to as the agent) uses signals to credibly convey various information about themselves to another party (the principal) (Matsubara and Kagifuku 2016). A signal can be defined as a visible characteristic of an object, person, or organization (Spence 1973). These signals, in turn, reduce the information asymmetry between the parties and are

Table 1 IT work and classic freelancing characteristics

Category	Characteristics	Source
IT work	High skill level	Niederman et al. (2016); Zhang et al. (2012)
	Skill diversity	Guzman et al. (2008); Niederman et al. (2016)
	Constant skill change	Niederman et al. (2016); Zhang et al. (2012)
	High collaboration, teamwork and communication	Ang and Slaughter (2001); Kudaravalli et al. (2017); Levina (2005); Meyer et al. (2021)
Classic freelancing	High degree of individual responsibility for career management	Graham et al. (2017); Kost et al. (2020); Spreitzer et al. (2017)
	High competition and required image presentation on the digital labor platform	Ashford et al. (2018); Roberts (2005); Hennekam and Bennett (2016); Vallas and Christin (2018)

considered beneficial for the formation of contracts. Accordingly, signaling theory has been explored in different contexts, such as in e-commerce (Mavlanova et al. 2016; Wells et al. 2011), marketing (Kirmani and Rao 2000; Robbins and Schatzberg 1986) and the labor market (Spence 1973). In traditional labor markets, there are many possible signals, such as different personal characteristics, education, job experience, race (Spence 1973), or cognitive and social skills (Piopiunik et al. 2020).

Previous research has mainly focused on signals that can be distinguished according to their associated costs and thus credibility, called assessment and conventional signals (Donath 2007; Holthaus and Stock 2018), or according to whether they are self-reported or from a third party, called internal and external signals (Mavlanova et al. 2016; Spence 1973). In addition, prior research lacks a consensus on signal effectiveness in online freelance job markets (Durward et al. 2016; Gefen and Carmel 2008; Hukal et al. 2020). However, these two signal distinctions may not be sufficient for the context of IT work on digital labor platforms.

2.3 A Typology of Signals on Digital Labor Platforms

In the particular environment of digital labor platforms, significant information asymmetries prevail, as the low entry costs and purely digital interactions in online markets create additional uncertainties. Potential clients only have the profile information of online freelancers to assess their quality (Agrawal et al. 2015; Claussen et al. 2018). Freelancers on digital labor platforms can use signals to reduce the lack of trust and uncertainties of potential clients and obtain jobs, consequently increasing their earnings and success (Durward et al. 2016; Gefen and Carmel 2008; Hukal et al. 2020). For these reasons, we propose to structure the signals on digital labor platforms into activating signals, pointing signals, and supporting signals. We define the three types of signals as follows.

Activating signals relate directly to the person and illustrate the person's skills, attributes, and human capital independent of the digital labor platform (e.g., education or programming skills). **Pointing signals** describe a type of behavior and are therefore not directly related to the person. They are specific to the platform market and refer to the presentation of a certain image to convince clients and stand out from the competition on the platform (e.g., reviews from platform clients or a profile badge). **Supporting signals** refer beyond the individual and indicate a specific form of team or group support (e.g., agency support on the platform). This typology is consistent with other research on signals (Bianchi et al. 2019; Connelly et al. 2011; Durward et al. 2016; Schulz et al. 2015).

Activating signals are related to the person individually and illustrate the skills, attributes and human capital the person possesses. In this context, they signal characteristics of the person that distinguish the signaler from the competition and that is also essential for activating or performing the signaler's quality (Hasson 1997). These signals are inherently related to the quality of the individual freelancer and also exist outside the platform (Bianchi et al. 2019; Durward et al. 2016; Schulz et al. 2015). For example, the communication of skills or education could be considered as an activating signal.

However, given the high number of competitors in a global, anonymous market, it is insufficient to send these activating signals alone. **Pointing signals** refer not to the personal characteristics or skills themselves, but to a corresponding image presentation or behavior of the IT freelancer on the platform (Bianchi et al. 2019; Connelly et al. 2011). For online freelancers, these additional pointing signals are very important to differentiate from the global competition present on the platforms. For example, a platform-specific profile badge or ratings already received on the platform can be classified as pointing signals. While this information relates to the freelancer, it denotes his or her behavior on the platform (e.g., providing information on the profile) rather than a direct characteristic, such as education or skills (Durward et al. 2016). The need to distinguish these types of signals becomes especially clear when considering the difficult situation of starting a freelancing career on platforms (Claussen et al. 2018; Frenzel-Piasentin et al. 2022). At the beginning, freelancers can only demonstrate activating signals, as they already possess the platform-independent personal characteristics and skills, but they cannot yet demonstrate the platform-specific pointing signals such as good ratings (Rahman 2021; Stanton and Thomas 2016; Tóth et al. 2022). In this context, it is particularly difficult for these freelancers to be seen by clients on the platform and to gain their trust without being able to "point" to their existing skills. Since algorithmic ranking systems are supposed to facilitate matching of clients and freelancers in online labor markets, IT freelancers need to aim for a higher listing to be seen by the clients, which may be only possible through the use of pointing signals (Durward et al. 2016; Möhlmann et al. 2021).

In order to capture specifics of IT work on digital labor platforms, we add a new third type of signal that is relevant for IT freelancers: **Supporting signals**. These extend beyond the individual and signal some support from groups or teams. This signal is not related to the person, so does not describe any direct characteristics, or related to beyond the person, so does not describe any behavior related to the platform. Such supporting signals apply particularly to IT freelancers. Freelancers in other areas usually work alone on the digital labor platform (Ashford et al. 2018); for IT freelancers, however, some collaboration or teamwork can boost careers and help with advancement (Gussek and Wiesche 2022b). The detailed motivation of this new type of signaling follows in the hypothesis development.

Table 2 summarizes the current body of knowledge on the use of signaling theory in online labor markets (a complete overview can be found in Table A1 in the Appendix; available online via http://link.springer.com). In Table 2, we structure the current state of knowledge regarding both signals and signal outcomes based on our typology of signals. It is clear that, when the sources are assigned to our signaling types, the pointing signals dominate. Few papers integrate multiple signal types in their research and supporting signals were only studied in one source. In addition, few papers use samples from the IT field. Consequently, no study has yet investigated all three types of signals, considered supporting signals as a new signal type, and explored the characteristics of IT workers on digital labor platforms as IT freelancers.

Figure 1 illustrates our research construct regarding the signaling timeline. As described earlier, the central actors within the signaling theory are the signaler (in our case the IT freelancer), and the receiver (the potential client), as well as the signals themselves (the three signal types: activating, pointing, and supporting signals) (Connelly et al. 2011).

The IT freelancers send certain signals to indicate their quality. The potential clients evaluate the validity of the quality of the signalers based on these signals and decide to book the IT freelancer for a project or not, which has a direct impact on the IT freelancer's subsequent earnings and success (Pavlou et al. 2007). The three types of signals presented must be considered in the environment in which they are used. Therefore, this study also examines the signals' applicability in the digital labor platform environment and the IT domain. The signaling environment is

Table 2 Overview of literature on signaling in online labor markets

Assignment to signaling types	Reference	Signal	Signal outcome
Activating signals	Seifried (2021)	Skill value & portfolio, offline skills	Skill distance
	Pallais (2014)	Personal information	Hiring probability
	Kässi and Lehdonvirta (2018)	Certification	Earnings
	Kokkodis and Ipeirotis (2016)	Skills	
Pointing signals	Hong and Pavlou (2017)	Reputation	Buyer selection
	Yoganarasimhan (2013)	Price, reputation	
	Hong and Pavlou (2012)	Average ratings, project experience	Provider pricing
	Assemi and Schlagwein (2016)	Reviews, average rating, comments	Customer decision
	Horton (2019)	Capacity of workers	Hiring probability
	Benson et al. (2020)	Reputation	Jobs, rejection rate, time to payment
	Lin et al. (2018)	Reputation, portfolio items	
	Moreno and Terwiesch (2014)	Reputation	Selection probability
	Rahman (2018)	Ratings	Reputation
Pointing and activating signals	Durward et al. (2016)	Pointing and activating signals	Bargaining power
	Kathuria et al. (2021)	Skill and achievement signals	Supplier quality
	Holthaus and Stock (2017)	Character traits, conventional and assessment signals	Earnings
	Holthaus and Stock (2018)	Tests, portfolio items, rating, self-promotion, price	
	Claussen et al. (2018)	Skills, self-description, project experience	
	Banker and Hwang (2008)	Performance, achievements, skill certifications, badge	Sales performance
	Lehdonvirta et al. (2019)	Platform-generated, platform-verified and unverified signals	Pay rate
Supporting and pointing signal	Stanton and Thomas (2016)	Outsourcing agency affiliation, feedback score	Hiring probability, wages

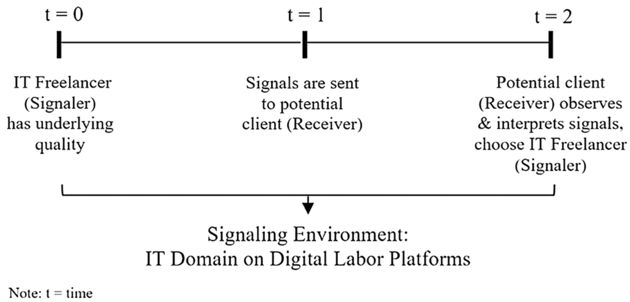


Fig. 1 Signaling timeline

overall an under-researched aspect of signaling theory (Connelly et al. 2011) and only a few research papers have investigated the signaling context so far (Kathuria et al. 2021).

3 Hypotheses

Based on the presented theoretical background, this study investigates how the three proposed signaling types affect the success of freelancers in the IT domain on digital labor platforms. In particular, we present the specifics of the aspects for IT professionals.

In the psychological literature, career success is defined as the perceived or actual achievements an individual has made in their career (e.g., Judge et al. 1999). A distinction can be made between subjective and objective career success (Hughes 1937; Judge et al. 1995; Wang and Wanberg 2017). In this context, Hughes (1937) defines objective success as directly observable, measurable, and verifiable by third parties, whereas subjective success means the individual's reactions to their career experiences.

3.1 Activating Signals: Human Capital

As described, signals can reduce the information asymmetry between parties on digital labor platforms, thus leading to online freelancers generating more projects and therefore higher earnings (Matsubara and Kagifuku 2016). First, this increased success can be enabled by activating signals that affect the skills and human capital of signal senders (Connelly et al. 2011). These skill signals can help signal senders provide better quality solutions to meet buyers' needs (Kathuria et al. 2021; Lee et al. 2004). In this regard, human capital can be defined as a signal, as it indicates that potential workers possess personal characteristics desired by potential clients, such as intelligence, effort, and self-motivation (Howard 1986; Strober 1990; Swenson-Lepper 2005).

In digital labor markets, a long-term, pre-planned career in a single organization is not guaranteed. There is a high degree of uncertainty about future work due to the highly transient nature of work, which results from mostly short-term projects (Ashford et al. 2018; Ibarra and Obodaru 2016). This requires building core competencies, such as communication skills and up-to-date skills. These competencies make freelancers more qualified to perform different types of work roles, constantly able to apply their expertise to new tasks, thus making them more attractive to clients (Damarin 2006).

Since, as described, the constant changes and complexity of tasks in IT place extreme and unusual demands on the profession, a high level of qualification is particularly important for IT professionals (Guzman et al. 2008). For IT freelancers, the importance of sending activating signals concerning human capital becomes even more important. On the one hand, a relatively high skill level is required to participate in IT freelancing (Taylor and Joshi 2019). On the other hand, there is a constant change in the required skills, which is amplified especially on digital labor platforms by a frequently changing market and variable work requirements (Ashford et al. 2018; Niederman et al. 2016).

Related research suggests possible relationships between skill development and performance among online freelancers (e.g., Anderson 2017; Huang et al. 2019). For example, Anderson (2017) and Huang et al. (2019) found correlations between performance, earnings, and different skillset combinations in two large-scale case studies on Fiverr and Upwork. Anderson (2017) also found that workers with various skillsets earn higher wages than those with more specialized skills. Freelancers need to self-initiate the development of skills that will enable them to adapt to a frequently changing market and variable work demands (Ashford et al. 2018).

We therefore posit that activating signals positively influence the objective career success of IT freelancers. Firstly, the amount of skills indicated on the profiles serves as a quality indicator and is related to the acquisition of new contracts (Kathuria et al. 2021). Offering a variety of skills is very advantageous for interactions with clients (Durward et al. 2016). Based on these assertions, the following hypothesis is proposed:

H1a The amount of IT freelancer skills is positively related to objective career success.

Since we focus on IT freelancers, IT specific skills may play a particular role for success. IT freelancers deliberately use their skills to present themselves as experts in a specific field. For this reason, we further propose that the number of top IT skills an IT freelancer masters likewise has a positive impact on the success (Durward et al. 2016;

Taylor and Joshi 2019). For these reasons, we propose the following:

H1b The number of IT top skills of an IT freelancer is positively related to objective career success.

Furthermore, since communication with clients is essential due to frequent interaction between IT freelancers and their clients, we suggest that the better the IT freelancer's command of the English language, the more successful they will be. Since English is an international language, the IT freelancer may receive more orders and the quality of their work may increase due to better communication (Popiel 2017; Taylor and Joshi 2019). Thus, we hypothesize the following:

H1c Higher English skills of an IT freelancer are positively related to objective career success.

Lastly, the education of IT freelancers could be a strong activating signal to reduce the lack of information regarding the quality of IT freelancers. Consequently, the educational background could be used to demonstrate expertise. The academic degrees achieved enable IT freelancers to perform better compared to competitors on the digital labor platform and thus potentially lead to more success (Durward et al. 2016). Hence, we posit:

H1d A higher level of education of an IT freelancer is positively related to objective career success.

At this point, we also introduce an IT specific variable and consider that education in an IT related field sets IT freelancers even more apart from the competition and signals special skills in their field of activity. For example, Setor and Joseph (2016) find evidence that formal IT education provides an advantage over non-IT education in terms of wages in early IT careers. Therefore, we propose the following hypothesis:

H1e An IT education of an IT freelancer is positively related to objective career success.

3.2 Pointing Signals: Image Presentation Specific to Digital Platforms

Greater success of IT freelancers through more projects, achieved by reducing information asymmetries, can also be realized through platform-specific pointing signals. These do not refer to the person but clarify the image the IT Freelancer has built on the platform to stand out from competition (Connelly et al. 2011; Matsubara and Kagifuku 2016). In online labor markets, algorithmic ranking systems facilitate the matching of clients and freelancers (Durward et al. 2016; Möhlmann et al. 2021). Therefore, to be more visible and get more projects, IT freelancers need to improve their image on the platform and aim for higher listings on digital labor platforms, which is possible through pointing signals. However, IT freelancers have no direct influence on these pointing signals; they can only influence them indirectly (Durward et al. 2016; Möhlmann et al. 2021).

IT professionals typically do not have to compete for jobs because the market demand for skilled IT professionals is very high and employers compete aggressively for workers to meet the demand for IT services (Taylor and Joshi 2019). Other reasons for this IT workforce shortage include declining numbers of students studying technology-related majors and poor career development, which is exacerbated by pending retirements in the existing IT workforce (Bitkom 2022; Bosworth et al. 2013; Prommegger et al. 2020; Setor and Joseph 2021). In contrast, workers in the gig economy, including IT freelancers, must compete on digital labor platforms to get jobs. This situation is new for IT professionals, which is why it is particularly interesting to examine the second signaling type, pointing signals. On digital labor platforms, IT freelancers' success depends on how successfully they develop a positive brand image on the platform (Hennekam and Bennett 2016; Vallas and Christin 2018).

We therefore propose that pointing signals positively influence the objective career success of IT freelancers. Firstly, we posit that the number of jobs on the IT freelancer's profile (portfolio items) as a pointing signal is crucial for career success (Holthaus and Stock 2018; Lin et al. 2018). Such references can signal a record of efficient client relationships. Moreover, they serve as figureheads or advertisements to promote the IT freelancer's skills and to help them stand out from the competition on the platform (Durward et al. 2016). In the light of this, we hypothesize that:

H2a A higher number of jobs of an IT freelancer is positively related to objective career success.

In addition, the review quality of these completed jobs is also considered as a pointing signal. On digital labor platforms, a certain number of stars are given as ratings to each of the IT freelancers' projects (Ashford et al. 2018; Jarrahi et al. 2020). The IT freelancers cannot directly influence these ratings, as the clients give the feedback. However, feedback can be positively influenced indirectly by successful project completion (Moreno and Terwiesch 2014). This individual success record serves as a status indicator and affects future project acquisition. Therefore, the quality of these evaluations is precious for IT freelancers and a good rating must be developed and maintained (Durward et al. 2016; Rahman 2021). Thus, we hypothesize the following:

H2b A higher review quality of an IT freelancer is positively related to objective career success.

Furthermore, IT freelancers can build up their image by providing as much information as possible on their profiles on the digital labor platform. By the pointing signal of a complete profile, freelancers can reduce many client uncertainties (Holthaus and Stock 2018; Ludwig et al. 2022; Sison and Lavilles 2018). Based on these assertions, the following hypothesis is proposed:

H2c A higher profile completeness of an IT freelancer is positively related to objective career success.

Finally, a profile marker through a badge can help the IT freelancers to improve their image and thus improve their success by signaling high quality. These badges are displayed to potential clients directly on top of the profiles and signal a special status of the IT freelancer compared to the competition (Assemi and Schlagwein 2016). For these reasons, we propose the following hypothesis:

H2d A profile badge of an IT freelancer is positively related to objective career success.

3.3 Supporting Signal

Since we focus on IT professionals as freelancers on digital labor platforms, we additionally consider the impact of supporting signals, related to group or team support of the IT freelancer. We consider this type separately because it is a signal that is valid beyond the person, the support from outside. What is important here is not the person itself, but the team or the people who stand behind them. Through this signal, therefore, the deviant organizational form of the work is embodied. Therefore, it is neither about the skills or the human capital of the IT freelancer (activating signals) nor the behavior on the platform (pointing signals) (Stanton and Thomas 2016).

Collaboration, communication and teamwork are of great importance in IT work (Kudaravalli et al. 2017; Meyer et al. 2021). IT freelancers are often interdependent due to the collaborative nature of work. This fact is made difficult on digital labor platforms and in the context of freelancing scenarios, which is why IT freelancers need to put more effort into building a functioning community and some support. In the area of agile methods, for example, pair programming leads to intensive collaboration and communication among IT professionals (Kude et al. 2019; Matook et al. 2016). Also, in software development teams, there are different members (project managers, developers and testers) who have different roles and perceptions and are dependent on each other (Ghobadi and Mathiassen 2016). Following this line of reasoning, we suggest that a lot of coordination and a collaborative way of working is also important for IT freelancers.

In classic freelancing, however, work is performed alone, which makes the necessary collaboration and cooperation between IT freelancers difficult. Freelancers are physically separated from each other and their clients on digital labor platforms. They lack relationships with work colleagues with whom they can exchange ideas or whom they can use as sources of support (Ashford et al. 2018; Kunda et al. 2002). This separation can further challenge IT freelancers, as they lack role models or career mentors and therefore have few practical opportunities to develop themselves and be successful (Grugulis and Stoyanova 2011). As described, the online nature of the digital platform makes IT freelancing more difficult due to the classic freelancing barriers to collaboration and communication. For these reasons, we propose that dedicated support is especially important for IT freelancers.

Such support can come for IT freelancers in two forms. In the first, several freelancers on the platform can associate to create groups, teams or collaborative communities. In the second, support can come from an agency to which the IT freelancers belongs (Kost et al. 2020). Agency support for freelancers is similar to sponsorship by organizations. For freelancers, support from agencies is essential (Barley and Kunda 2011). In the process, many of the workers develop close relationships with external agencies, which are important partners for them in their search for new jobs. Thus, these relationships positively influence IT freelancers' success (Van den Born and Van Witteloostuijn 2013). On the basis of these assertions, the following hypothesis is proposed:

H3 Support from agencies or groups of an IT freelancer is positively related to objective career success.

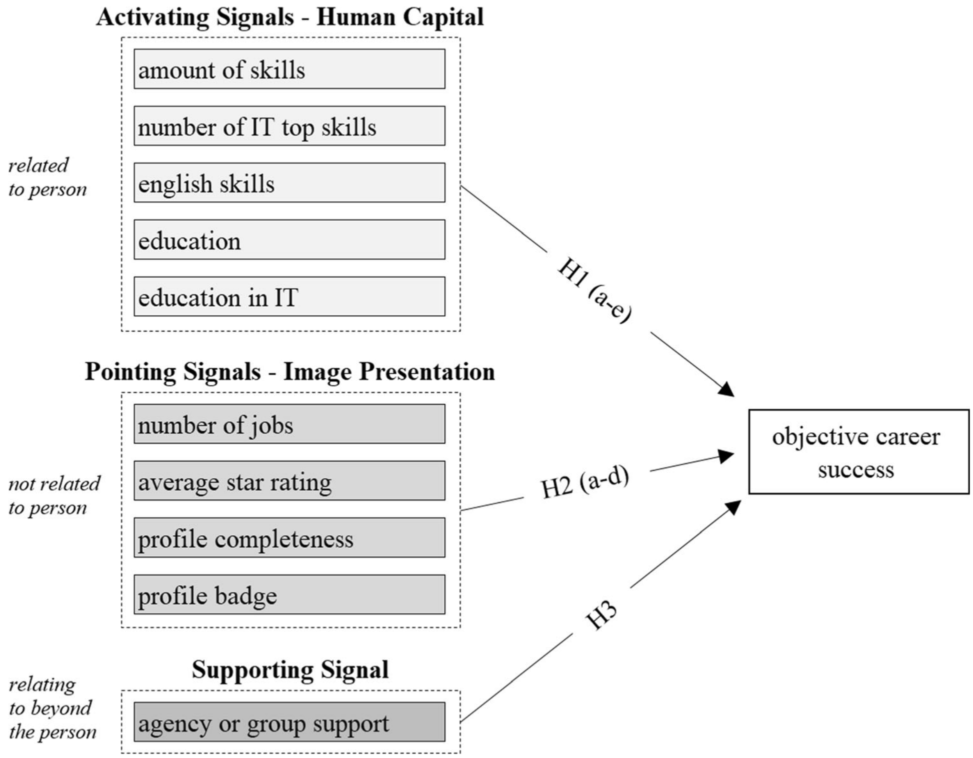
Based on the background and hypotheses section, our research model is illustrated in Fig. 2.

4 Method

4.1 Data and Sample

We use digital trace data on IT freelancers to answer our research question (Howison et al. 2011). Digital trace data are records of activities (traces) performed through an online information system (digital). They have two important properties. First, they are existing data, not data produced for research. Second, they are event-based rather than summarized data (Howison et al. 2011). Because digital trace datasets are not collected primarily for research purposes, researcher-induced bias is eliminated (Lindberg 2020). In analyzing the secondary data, we

Fig. 2 Research model



follow the methodological approach of working with digital trace data (Holthaus and Stock 2017; Howison et al. 2011; Vial 2019). First, we (i) saved each freelancer's publicly available information in a local database. Then, we (ii) removed all personal information from the data set and anonymized it by assigning random numbers to the freelancers. Finally, we (iii) analyzed the data points in aggregated form to avoid possible conclusions about individual freelancer profiles.

For each profile, we use the description, job history and career progress of IT freelancers on the digital labor platform Upwork to test the hypotheses developed above. This freelancing platform was chosen as the empirical context because it is the largest freelancing website in the world (Claussen et al. 2018; Seifried et al. 2020). This allows for a variety of jobs from the IT context in terms of diversity in task, duration, and freelancer skill level. This guarantees a heterogeneous dataset that includes differently successful workers. The data was collected for the first time in February 2021 and for the second time in February 2022 to examine the career development of IT freelancers over one year. The dataset contains data from 36,661 freelancers working in the IT industry. More precisely, we used profile data of freelancers who work in categories *IT & Networking, Data science & analytics, Web, mobile & software development* as well as *Project Management (Admin support)* and *Tech support (Customer service).* After including those profiles that match with the variables of interest and that were active within the observation period of one year, our final sample consists of 7,166 IT freelancer profiles. We have additionally illustrated the data structure in Fig. A1 (in the Appendix).

4.2 Measures

4.2.1 Dependent Variable

Earnings or salary are commonly used criteria of objective career success (Judge et al. 1995, 1999). Measuring earnings as an indicator of career success has significant advantages compared to other measures of success. For one, earnings are measured in a natural unit that is easy to interpret. In addition, there is less bias than with single-source or dyadic data. Lastly, it provides an approximation of many dimensions of success in a single measurement, such as client satisfaction and successful management and sales activities (Healy et al. 1992; Holthaus and Stock 2018). Therefore, we measure the variable of *objective career success* using the earnings, rounded to integer values, earned by each IT freelancer on the digital labor platform over one year between February 2021 and February 2022. Accordingly, we were able to collect objective 1-year earnings information for each IT freelancer for the year after using the different signals. Information about the earnings is automatically calculated on the profiles in dollars.

4.2.2 Independent Variables

All independent variables are based on the dataset at the first point of data collection in February 2021, as we want to test the impact of the different signals (see Table 3) on one-year earnings. Accordingly, our goal was to model the earnings for each freelancer for the year after the signaling information.

We use five variables related to activating signals. The freelancer's *amount of skills* (H1a) is the number of the self-reported skills on the freelancer profile (Jarrahi et al. 2020). The *number of IT top skills* (H1b) is the number of top IT skills reported on the freelancer profile. We focused on the top 10 programming skills in 2021 (observation year): Python, Java, C, C + + , JavaScript, C#, R, Go, HTML and Swift (Cass 2021). Furthermore, Upwork offers freelancers the possibility to indicate their language skills and the respective level on their profiles. Thus, there are the variants "basic", "conversational", "fluent" or "native or bilingual". The variable *English skills* (H1c) is therefore ordinally scaled and can take on values between 0 (no English skills) and 4 (highest possible English skills), depending on the existing levels of the platform. The variable *education* (H1d) is also ordinally scaled and can take the values 0 (no education specified), 1 (bachelor's degree), 2 (master's degree) or 3 (Ph.D. education) (Seifried et al. 2020). Lastly, the variable *education in IT* (H1e) is a dummy equal to 1 if the freelancer has completed an education in an IT related field and 0 if not. For example, academic degrees in information technology, computer science, software engineering or software development were considered.

Regarding pointing signals, four variables are included in the model. The variable *number of jobs* (H2a) is the (log) number of previously completed jobs scaled logarithmically that the freelancer has undertaken (Claussen et al. 2018). Next, we measure the variable *review quality* (H2b) of an IT freelancer as the calculated average overall feedback score of their entire work history, with individual ratings provided by the employer of each project. These ratings are based on a ranking from 0 (worst) to 5 (best) stars. Here, the rating indicates how satisfied an employer was with the project outcome overall (Claussen et al. 2018). Additionally, the variable *profile completeness* (H2c) measures the number of completed fields in the IT freelancer's profile. The following nine filling options that Upwork offers are taken into account: availability information, response time, skills information, language skills,

Table 3 Illustration of the used signals

Signal type	Definition	Signal	Description
Activating signal	Related to the person's human capital that is essential to activating the person's quality, independent of digital platforms	Amount of skills	The number of self-reported skills reported on the freelancer profile
		Number of IT top skills	The number of top IT skills reported on the freelancer profile. Top 10 IT skills in 2021 (observation year): Python, Java, C, C + + , JavaScript, C#, R, Go, HTML, Swift
		English skills	The indicated language skills on the freelancer profile. There are the variants "basic", "conversational", "fluent" or "native or bilingual". Range from 0 (no English skills) and 4 (highest possible English skills)
		Education	The indicated education on the freelancer profile. Range from 0 (no education specified), 1 (bachelor's degree), 2 (master's degree) or 3 (Ph.D. education)
		Education in IT	Indicates whether the freelancer has academic degrees in information technology, computer science, software engineering or software development
Pointing signal	Related to the person's behavior and a corresponding image presentation specific to digital platforms	Number of jobs	The number of previously completed jobs displayed on the freelancer profile
		Average star rating	The calculated average overall feedback score over the entire work history with which the employer rated the project, range from 1–5 stars
		Profile completeness	The number of completed fields of the freelancer profile, range from 0–9
		Profile badge	Indicates whether the freelancer has a profile badge like "Rising Talent", "Top Rated" or "Top Rated Plus"
Supporting signal	Related to beyond the person independent of the human capital or behavior	Agency or group support	Indicates whether the freelancer is represented by an agency or member of a group of freelancers

skill certificates information, education information, information about work experience outside the platform, other experiences, and testimonials from clients. Finally, the variable *profile badge* (H2d) is a dummy variable equal to 1 if the IT freelancer has a profile badge, and equals to 0 if not. The markers "Rising Talent", "Top Rated" or "Top Rated Plus" can appear at the top of the IT Freelancer profile.

Finally, we measure the support system using the variable *agency or group support* (H3), which is a dummy equal to 1 if the freelancer is represented by an agency or member of a group of freelancers and equal to 0 if not (Claussen et al. 2018; Stanton and Thomas 2016; Van den Born and Van Witteloostuijn 2013). This information is reported on the profile.

4.2.3 Control Variables

We first control for the job categories in which an IT freelancer works. We use four dummy variables, which are equal to 1 if the IT freelancer mainly does jobs in that category and equal to 0 if not. More specifically, we include the variables (1) *IT & Networking,* (2) *Web, mobile & software development,* (3) *Project Management,* and (4) *Technical Support*. The Data Science & Analytics category serves as the reference category.

Second, we control for the geographical origin of the IT freelancer (Claussen et al. 2018; Holthaus and Stock 2018; Seifried et al. 2020). We use four dummy variables, which are equal to 1 if the freelancer is from the specific area and equal to 0 if not. More precisely, we use the variables *Subcontinent India* (India, Pakistan, Bangladesh, etc.)*, Asia* (Philippines, Indonesia, etc.)*, Developed countries* (Western Europe, Australia, USA) and *East Europe* (Russia, Ukraine, Poland, Baltic States, etc.). Other regions serve as a reference category (Egypt, Nigeria, Serbia, Brazil, etc.).

4.3 Data Analysis

Our dependent variable of interest, objective career success measured by the earnings each IT freelancer earns within one year (rounded to integer values), is a non-negative integer with a limited range and therefore represents count data. Our dependent variable is therefore not normally distributed. We confirm this via three checks. This is evident firstly from the histogram of the dependent variable. Second, the value for the skewness of the distribution of the dependent variable is positive. Third, we performed a Kolmogorov–Smirnov normality test, which proves, with a *p*-value less than 0.001, that there is no normal distribution of the dependent variable. These results additionally suggest a right-skewed distribution. Parametric tests, such as linear regression, are not sufficient in this case and violate the assumptions of ordinary least squares regression. Under these conditions a transformation (e.g., log transformation) of the dependent variable can be used, but the interpretation of these transformed values can be difficult and statistical power would be lost. Poisson regression models and negative binomial models better approximate a right-skewed distribution, as is the case for count outcomes, and are the most applicable econometric approaches (Coxe et al. 2009; Wooldridge 2016).

In this regard, a Poisson regression model is based on the equivalence between the mean and the variance of the dependent variable. However, we detected overdispersion in our dependent variable, which means that the employed regression approach should control for overdispersion. The standard deviation (Stdv = 13,278) was almost three times higher than the mean (mean = 4534). Therefore, we select negative binomial regression (Gardner et al. 1995). Crucially, unlike Poisson regression, negative binomial regression corrects for overdispersion by calculating an additional parameter in the regression (Wooldridge 2016).

We performed the negative binomial regression in SPSS and calculated the Exp(b) coefficients for a better interpretation of our results. The latter represent odds ratios that can be interpreted by multiplying them by the dependent variable to approximate the effect of increasing the independent variable by one unit. Thus, any value greater than 1 represents a positive impact and any value less than 1 represents a negative impact on the outcome variable. The decision steps for the model choice are shown in Fig. A2 (in the Appendix). The path in bold reflects our choice for data analysis.

5 Results

5.1 Descriptive Statistics

The means, standard deviations, and Pearson intercorrelations of the independent measures used in the regression analysis are shown in Table 4. The variance inflation factors (VIF) associated with the predictors range from 1.079 to 2.133, indicating that the results are not biased due to instances of multicollinearity (Hair et al. 2012). Furthermore, the correlations between the independent variables (see Table 4) are below the limit of 0.70, which reduces concerns about multicollinearity (Cohen et al. 2013).

In our sample, the average 1-year earnings is $4534. The average number of skills reported on the profiles is 8.86 and the average number of IT top skills of the IT freelancers is 0.71. Furthermore, most of the IT freelancers speak English fluently (mean = 3) and the majority has at least a bachelor's degree, as indicated by the mean value of the variable education of 1.05. Additionally, 62% of IT

Table 4 Variable descriptive statistics and intercorrelations

	Min	Max	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 IT and networking	0	1	0.11	0.310																	
2 Web, mobile, software dev.	0	1	0.66	0.474	−.484**																
3 Project management	0	1	0.04	0.194	−.070**	−.282**															
4 Technical support	0	1	0.01	0.117	−.041**	−.165**	−.024*														
5 Subcontinent India	0	1	0.48	0.500	−.054**	.120**	−.091**	−.045**													
6 Asia	0	1	0.15	0.353	.022	−.082**	.088**	.100**	−.400**												
7 Developed countries	0	1	0.08	0.266	.043**	−.083**	.050**	−.021	−.279**	−.179**											
8 East Europe	0	1	0.13	0.331	−.009	.069**	−.027*	−.038**	−.367**	−.156**	−.109**										
9 Amount of skills	0	10	8.86	1.948	−.003	.024*	.006	−.003	.056**	−.049**	−.019	−.006									
10 Number fo IT top skills	0	6	0.71	0.952	−.081**	.050**	−.117**	−.072**	−.055**	−.041**	.005	.039**	.140**								
11 English skills	0	4	3.00	0.646	−.008	−.059**	.094**	.027*	.121**	−.085**	.188**	−.275**	.086**	−.043**							
12 Education	0	3	1.05	0.751	−.002	−.071**	.038**	−.025*	.009**	−.072**	.037**	−.013	.056**	−.008	.089**						
13 Education in IT	0	1	0.62	0.486	.020	.054**	−.095**	.017	.236**	−.060**	−.077**	−.126**	.046**	.113**	.049**	.229**					
14 Number of jobs (log)	0	8.41	1.75	1.429	−.033**	.116**	−.029*	−.009	.067**	−.048**	−.051**	.050**	.137**	−.035**	.078**	.091**	−.000				
15 Review quality	0	5.00	4.61	1.106	−.026*	.166**	.016	.017	.002	−.030*	−.022	.063**	.024*	.012	−.015	−.002	.025*	.265**			
16 Profile completeness	3	9	5.69	0.935	.069**	.026*	−.024*	.021	.105**	−.026*	−.046**	−.036**	.181**	−.066**	.104**	.060**	.050**	.383**	.046**		
17 Profile badge	0	1	0.30	0.457	−.020	.091**	−.025*	.025*	−.019	−.018	−.015	.076**	.112**	−.020	.040**	.056**	−.000	.394**	.114**	.292**	
18 Agency or group support	0	1	0.11	0.313	−.006	.066**	.016	.004	.093**	−.049**	−.056**	.026*	.067**	−.028*	.065**	.062**	.029*	.285**	.045**	.138**	.182**

N = 7166

*$p < .05$; **$p < .01$

freelancers have a degree from the IT domain. Furthermore, IT freelancers completed an average of 18 jobs on the platform. The average review quality is 4.61 out of 5 stars. This high average score is common in marketplaces with implemented reputation systems and can be explained by the survival behavior of users in online communities. When they receive low feedback scores, they have difficulty re-engaging and often leave the platform (Kokkodis and Ipeirotis 2016). Additionally, IT freelancers completed an average of 5.69 out of 9 fields on their profiles and 30% have a profile badge. It is also notable that only 11% of IT freelancers receive support from agencies or groups.

In addition, 11% of the studied IT freelancers work in the job category IT & Networking, 66% in Web, mobile and software development, 4% in Project management, 1% in Tech support and 18% in Data science & analytics. Almost half of IT freelancers are working from the subcontinent India (48%), followed by Asia (15%), East Europe (13%) and the developed countries (8%). In addition, 16% of IT freelancers come from other regions. The top five countries are India (25%), Pakistan (16%), Ukraine (5.4%), Philippines (5%) and Bangladesh (4.9%), which aligns with previous studies (Claussen et al. 2018; Seifried et al. 2020).

5.2 Regression Analysis

5.2.1 Main Effects

Table 5 shows the negative binomial regression results for the dependent variable 1-year earnings. Model 1 is the baseline model. Model 2 additionally includes the variables concerning the activating signals and Model 3 those of the activating and pointing signals. Model 4 shows the full model. Inspection of the Log-likelihood reveals that the different signals add explanatory value compared to Model 1. We discuss below the results of the independent and the control variables in the full model (Model 4). We check the robustness of our results by using the number of stated hours on the platform that an IT freelancer could work for acquired projects within a year as an alternative measure of objective career success. The results are very similar to those obtained by using 1-year earnings as a measure of objective career success.

For activating signals regarding the human capital of IT freelancers, we found that the number of IT top skills ($p < 0.05$) and the English skills ($p < 0.01$) had a positive and significant effect on the 1-year earnings. Therefore, H1b and H1c were supported. Accordingly, as shown by the odds ratio in Table 5, adding one IT top skill to the profile increases earnings by 10.4% and improving English skills by one level increases earnings by 30%. However, H1a, H1d and H1e concerning the amount of skills and the (IT) education could not be confirmed in our analysis.

Concerning pointing signals regarding the image presentation, we found that all four variables had the expected significant positive effect on 1-year earnings. The results were consistent with H2a-d. The number of jobs ($\mathrm{Exp}(b) = 1.520$, $p < 0.01$) and the review quality of completed projects ($\mathrm{Exp}(b) = 1.081$, $p < 0.1$) showed significant positive associations with 1-year earnings. Furthermore, the additional filling of a field of the IT freelancer profile increases earnings by 19.6% ($p < 0.01$) and IT freelancers who have a profile badge earn much more than those without a badge ($\mathrm{Exp}(b) = 2.490$, $p < 0.01$).

Lastly, regarding the supporting signal, the variable agency or group support showed a positive and significant effect on the 1-year earnings. Thus, H3 was supported. In detail, it becomes clear that belonging to a group or agency increases IT freelancer's earnings by 60.9% ($p < 0.01$). Table 6 shows an overview of the supported and not supported hypotheses.

5.2.2 Control Effects

In addition, our results regarding control effects show that the job category of freelancers and the region from which the IT freelancer comes are significant. Freelancers earned more in the category IT & Networking ($\mathrm{Exp}(b) = 1.543$, $p < 0.05$) and in Technical support ($\mathrm{Exp}(b) = 3.239$, $p < 0.01$) compared to the reference category Data science & analytics. Moreover, IT freelancers from East Europe ($\mathrm{Exp}(b) = 1.495$, $p < 0.05$) earn more than IT freelancers from other regions.

6 Discussion

Prior research calls for studying the influence of signal types and signal environment on the effectiveness of signals (Connelly et al. 2011; Durward et al. 2016; Kathuria et al. 2021). Our results advance this discussion by examining the impact of three signaling types in the context of digital labor platforms on the career success of IT freelancers. Our study suggests that different activating signals related to human capital, pointing signals related to image presentation specific to digital platforms and supporting signals positively predict the objective career success of IT freelancers on digital labor platforms.

This improves our understanding of the recent technological and economic changes in the employment environment. The workplace is experiencing rapid digitalization, exemplified by the digital labor platforms where new, digital forms of communication and work processes are the norm. This digital work execution and mediation leads to uncertainties between parties, which can

Table 5 Regression analysis results

	Model 1		Model 2		Model 3		Model 4	
Intercept	2.854,413***	(0.1477)	239,277***	(0.3380)	62,993***	(0.4477)	65,138***	(0.4464)
Control variables								
IT & networking	1.742***	(0.1812)	1.835***	(0.1825)	1.600***	(0.1761)	1.543**	(0.1763)
Web, mobile, software dev.	1.473***	(0.1266)	1.557***	(0.1281)	1.136	(0.1248)	1.123	(0.1248)
Project management	1.410	(0.2603)	1.335	(0.2644)	1.081	(0.2602)	1.027	(0.2607)
Technical support	2.932***	(0.4145)	3.139***	(0.4166)	3.192***	(0.4024)	3.239***	(0.4018)
Subcontinent India	1.017	(0.1337)	0.934	(0.1369)	0.872	(0.1320)	0.830	(0.1326)
Asia	1.009	(0.1674)	1.085	(0.1680)	1.077	(0.1635)	1.089	(0.1634)
Developed countries	1.069	(0.2048)	0.845	(0.2087)	0.987	(0.2044)	0.992	(0.2046)
East Europe	1.737***	(0.1762)	2.135***	(0.1802)	1.552***	(0.1727)	1.495**	(0.1728)
Independent variables								
Amount of skills			1.114***	(0.0246)	1.034	(0.0239)	1.031	(0.0239)
Number of IT top skills			1.022	(0.0532)	1.104**	(0.0498)	1.104**	(0.0497)
English skills			1.520***	(0.0806)	1.311***	(0.0769)	1.300***	(0.0768)
Education			1.138**	(0.0649)	0.985	(0.0634)	0.978	(0.0633)
Education in IT			1.063	(0.1031)	1.062	(0.0990)	1.061	(0.0988)
Number of jobs (log)					1.565***	(0.0438)	1.520***	(0.0445)
Review quality					1.078*	(0.0432)	1.081*	(0.0430)
Profile completeness					1.186***	(0.0559)	1.196***	(0.0557)
Profile badge					2.574***	(0.1105)	2.490***	(0.1105)
Agency or group support							1.609***	(0.1501)
Model performance								
Log-likelihood	−38,751		−38,722		−38,509		−38,503	
Chi2	32.270***		90.061***		516.896***		527.954***	
Number of observaions	7166		7166		7166		7166	

Standard deviations are shown in parentheses; dependent variable = 1-year earnings; Exp(B) values are displayed

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

be reduced by IT enabled signals and thus lead to success in these new digital environments. Thus, this paper shows how technology can be built and used on digital labor platforms, especially in the form of signals. However, we also illustrate that digital labor platforms still need to be improved regarding available signals to build technology for humanity.

6.1 A Typology of Signals to Explain Career Success of IT Freelancers on Digital Platforms

Previous research has mostly focused on signals that can be distinguished according to their associated costs (assessment and conventional signals) (Donath 2007; Holthaus and Stock 2018), or according to whether they are self-reported or from a third party (internal and external signals) (Mavlanova et al. 2016; Spence 1973). In addition, prior research lacks a consensus on signal effectiveness in online freelance job markets (Durward et al. 2016; Gefen and Carmel 2008; Hukal et al. 2020). The previous signal distinctions, therefore, are not sufficient for the context of IT work on digital labor platforms. Furthermore, since we focus on digital labor platforms in the IT domain, we investigated the support signal as a third new signal type relevant for IT freelancers. Therefore, we focused on three signaling types: activating signals, pointing signals, and supporting signals (Bianchi et al. 2019; Connelly et al. 2011; Durward et al. 2016; Schulz et al. 2015).

Our data show that all three signal types positively influence the success of IT freelancers. More specifically, the proof of skills in the IT field and the English skills are relevant for success. The indication of an additional currently requested IT skill on the IT freelancer profile can increase the earnings by 10.4%. In addition, the improvement of English skills by one level can even result in a 30% increase in earnings. Furthermore, the number of jobs in the work history and the resulting review quality also has a positive impact on the success of IT freelancers, as well as the completeness of the profile and the receipt of a profile badge for self-promotion. Finally, IT freelancers who

Table 6 Results of hypotheses tests

	Hypotheses	Variable	Results
Activating signals – human capital	H1a (+)	Amount of skills	Not supported
	H1b (+)	Number of IT top skills	Supported
	H1c (+)	English skills	Supported
	H1d (+)	Education	Not supported
	H1e (+)	Education in IT	Not supported
Pointing signals – image presentation specific to digital platforms	H2a (+)	Number of jobs	Supported
	H2b (+)	Review quality	Supported (marginal)
	H2c (+)	Profile completeness	Supported
	H2d (+)	Profile badge	Supported
Supporting signal	H3 (+)	Agency or group support	Supported

receive and signal social support are more successful than those who work alone without any support (Exp(b) = 1.609, $p < 0.01$).

6.2 The Role of the Signaling Environment: The IT Domain on Digital Labor Platforms

Overall, the signaling environment is an under-researched aspect of signaling theory and only a few research papers have investigated the signaling context so far (Connelly et al. 2011; Kathuria et al. 2021). We contribute to this literature by testing signaling theory in the new context of IT work on digital labor platforms. The three types of signals presented must be considered in the environment in which they are used. Besides, it also plays a role who sends the signals. Therefore, this study also examined the applicability of signals in the digital labor platform environment and the IT domain.

Through our analysis, the interplay between the characteristics of online freelancing on digital labor platforms and the characteristics of IT work became clear. The use of signals is special in this context due to the nature of the work relationship because freelancers work independently and are thus responsible for their own career. Moreover, work coordination and execution occurs completely online via the digital platform. In addition, we were able to show that different IT characteristics affect the effectiveness of the signals.

First, the characteristics of online freelancing and IT work regarding activating signals become clear. We were able to show in this paper that IT freelancers need to build human capital themselves in order to be successful. Above all, this illustrates the diversity of skills needed. For example, we showed that general skills are important for success, like English skills (Exp(b) = 1.300, $p < 0.01$), while, simultaneously, the specific expertise for IT jobs, such as the amount of top IT skills the freelancer indicates in the considered year, is important for success (Exp(b) = 1.104, $p < 0.05$). However, we did not find that the amount of skills listed on the IT freelancer profiles significantly influences 1-year earnings. A possible explanation could lie in the associated costs for the signals. These are possibly higher for IT specific signals and thus have a stronger impact on success. Furthermore, from the results, it can be concluded that skills in the specific skill environment are essential for career success. IT work is driven by fast technological change, which leads to rapid knowledge obsolescence and a constant need for training and skill development (Zhang et al. 2012). We support these findings because signaling mastery of currently in-demand IT skills, in particular, had a positive effect on IT freelancers' earnings. Lastly, we did not find that IT freelancers' education significantly impacted earnings. A possible explanation for this result could be that IT work is constantly changing and IT freelancers do not necessarily learn the skills required for a project in their basic education. Therefore, the qualifications that had been acquired some time ago are not necessary for success. Consequently, anyone can enter the platform and be successful if they adapt their skills to current market demands. Concrete skills in the field of activity, such as the programming skills, are therefore particularly important (Fuller et al. 2022).

Second, the characteristics of online freelancing and IT work also become clear in terms of pointing signals. In the traditional labor market, the demand for IT professionals is very high. Moreover, the constant technological change makes it difficult to find replacements for IT professionals who have left a team (Bosworth et al. 2013; Thibodeau 2012). For this reason, image presentation on the digital platform and the associated use of platform-specific pointing signals is usually not necessary for IT professionals outside of digital labor platforms. However, within the context of digital labor markets, self-promotion is mandatory due to global competition and IT freelancers are self-responsible for this promotion (Ashford et al. 2018;

Hennekam and Bennett 2016; Roberts 2005; Vallas and Christin 2018). IT freelancers need to deal with algorithmic labor management for a successful image presentation because career success especially depends on the logic of the algorithms on the digital labor platforms. Here, we contribute to the literature on the use and handling of algorithms and matching (Cram et al. 2020; Möhlmann et al. 2021; Straub et al. 2015). Freelancers are highly dependent on and driven by established metrics. For example, Uber measures availability, jobs accepted, jobs completed, and customer reviews (Kalleberg and Dunn 2016). Consequently, the platform's mechanisms are important and must be used and influenced or addressed by IT freelancers. Regarding the platform-specific pointing signals concerning image presentation, we could show through our study that it is important for successful careers of IT freelancers to actively use certain mechanisms of the digital labor platform. The platform offers various possibilities, which IT freelancers should use. We observed significant effects from the number of completed jobs (Exp(b) = 1.520, $p < 0.01$), the quality of reviews in the work history (Exp(b) = 1.081, $p < 0.1$), the completeness of profile information (Exp(b) = 1.196, $p < 0.01$) and the achievement of a profile badge (Exp(b) = 2.490, $p < 0.01$). By using such signals, IT freelancers can move up the lists of available freelancers and thus be more visible to potential clients. In addition, it could be interesting to develop additional platform features for IT freelancers to support image development and more platform-specific pointing signals.

Third, the characteristics of online freelancing and IT work additionally become clear regarding supporting signals. In IT, collaboration, communication and teamwork are of great importance for the successful completion of tasks (Ghobadi and Mathiassen 2016; Kudaravalli et al. 2017; Meyer et al. 2021). Consequently, IT freelancers are also often interdependent during their work. This reality is made difficult on digital labor platforms and in the context of freelancing scenarios, so IT freelancers must make more efforts to build an active community and some support. This is because in traditional freelancing, work is usually done alone and freelancers are separated from each other and clients (Ashford et al. 2018; Kunda et al. 2002). We contribute to this literature by showing that IT professionals can be more successful in teams or groups than alone, even on digital labor platforms. Accordingly, the signaling of support from groups or agencies has a positive impact on an IT freelancer's earnings (Exp(b) = 1.609, $p < 0.01$). This result provides a starting point for future research, as the investigated team or group support of IT freelancers can be used as a baseline for development of further supporting signals.

6.3 The Need to Improve Digital Labor Platforms for Humanity

Through our investigation, it became clear that digital platforms still need to be improved in terms of available signals to actually build "technology for humanity". Surprisingly, we found that many signals used in traditional labor markets could not be observed in our dataset, as globalized, anonymous digital labor platforms do not provide space for this type of holistic assessment of a person. In Table 7, we have listed possible signals that might be particularly relevant on digital platforms within the three signal types in addition to those we found.

The detected and analyzed activating, pointing and supporting signals are very limited. Consequently, truly meaningful signals on digital platforms are very limited. In their current form, platforms enormously degrade the ways in which people can be evaluated. All the signals on the profiles tend to be transaction-based and signals related to individual situations and personality (e.g., Ashford et al. 2018; Van den Born and Van Witteloostuijn 2013) are not available. One possible reason could be that the inherent goal of digital platforms is to capture value (Schreieck et al. 2021). The information control of freelancers is therefore limited because they cannot communicate and signal many dimensions of their identity in any way on the digital platforms (Averill 1973). Thus, they have a very limited ability to influence or control the decisions of the people who assess them. Therefore, to build technology for humanity and be fairer, digital labor platforms would need to be improved in the future to give space to more relevant and differentiated signals.

6.4 Practical Contributions

This research has practical implications as well. First, our results on activating signals referring to human capital show that IT freelancers need to keep their skills up to date. The fast pace of information technology leads to rapid obsolescence of technologies and skills. Obsolescence is particularly relevant for IT professionals, which is why freelancers should invest heavily in their human capital to keep it current, especially in their professional domain. It also became clear that (IT) education has no significant impact on success. Consequently, platform work in the IT field is attractive for everyone, even if they were not educated in classic IT fields. Secondly, IT freelancers should consider and implement various factors of image presentation through platform-specific pointing signals. Our results show that it is crucial for the career success of IT freelancers to have a high review quality, many completed jobs in the work history, a profile badge and overall a complete profile. Therefore, they should actively fight for

Table 7 Potential relevant but unavailable signals on digital labor platforms

Signaling type	Potential relevant but unavailable signals on digital labor platforms	Illustrative references
Activating signal	Personality traits, character traits	Van den Born and Van Witteloostuijn (2013)
	Ethical sensitivity, moral, intelligence	Swenson-Lepper (2005)
	Motivation	Van den Born and Van Witteloostuijn (2013)
	Social skills	Gandini (2016)
	Interpersonal and verbal skills	Howard (1986)
	Cognitive capabilities (flexibility, agility)	Ashford et al. (2018); Strober (1990)
	Emotional capabilities (regulating emotions, tolerating ambivalent and conflicting emotions)	Ashford et al. (2018)
Pointing signal	External certifications the platform does not support	Kässi and Lehdonvirta (2018)
	Ratings from other platforms (which are not portable between platforms)	Wohlfarth (2019)
	Training, learning and updating activities	Gussek and Wiesche (2022b)
Supporting signal	Networks independent of the platform	Gold and Fraser (2002)
	Size of the network	Van den Born and Van Witteloostuijn (2013)
	Offline support from friends and family	Gussek and Wiesche (2022b)

a good rating from the clients or a profile badge to stand out from the competition. Third, the results underline the importance of IT freelancers actively searching for support on the digital labor platform to receive content support for completing their tasks and an emotional network in order to be more successful. Lastly, digital labor platforms could solve the problem of high demand for IT professionals, as digital labor platforms always have many IT professionals available (Popiel 2017). Furthermore, the international use of the platform provides access to IT professionals from all over the world. Thus, the platforms are a potential new source of skilled IT workers for organizations.

6.5 Limitations and Future Research

Our research has some limitations that need to be considered. First, we only study IT freelancers on the platform Upwork, which means that we cannot draw a comparison between different digital labor platforms. In future work, it would be interesting to explore whether our results also apply to other online freelancing platforms, such as Fiverr. Second, we do not differentiate between different skills or the degree to which skills are mastered (depth) but only use the total amount of skills as a measure of human capital. Future research could therefore investigate whether some (IT) skills are more relevant than others for specific tasks and thus the degree to which various skills and the respective breadth and depth of a freelancer's skillset influence career success. Third, through the profile data of IT freelancers, we can only study the objective career success. Therefore, the individual's reactions to their career experiences should be considered in more detail in future work (Hughes 1937; Judge et al. 1995). Subjective success and other enriched insights into the careers of IT freelancers can be considered through targeted surveys or interviews. Therefore, more causal inferences could be drawn regarding the results. Fourth, the final analyzed dataset (7166 profiles) includes only a subset of the originally scraped freelancer profiles (36,661 profiles). This is mainly due to the choice of the dependent variable. In order to determine a meaningful value for objective success as a way to interpret the effect of the different signals, we use success over the one year period after the signals are sent. As a result, many profiles that left the platform market during this year or set their profiles to private for the second data collection point are not included in the analysis. In addition, there are many incomplete profiles. As with any empirical data collection of this kind, these circumstances could lead to a bias in the results due to survivorship bias. Lastly, other effects regarding IT freelancers' career success could be considered, such as the application of different business strategies, gender or age. For example, a low-cost strategy or an industry specialization strategy could contribute to the success of IT freelancers on digital labor platforms (Van den Born and Van Witteloostuijn 2013). In addition, the issue of obsolescence is significant to the success of IT freelancers. It is exciting to investigate in the future how the strategy of unlearning works to ensure the ability to innovate and remain responsive (Matook and Blasiak 2020).

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