YOU ARE WHAT YOU TURK: EMPIRICALLY TESTING AN ELANCE WORK DESIGN MODEL

by

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ABSTRACT

As the completion of short-term tasks on online work platforms such as Amazon Mechanical Turk (MTurk; i.e., eLancing) continues to increase in popularity, it is important to establish an understanding of how traditional work design principles manifest in a digital, transient workforce (Colbert et al., 2016). Therefore, the present effort aimed to do so by empirically testing aspects of Schroeder et al.'s (2021) eLance work design theoretical model through the lens of the Attraction-Selection-Attrition (ASA) model (Schneider, 1987). Data were collected from 325 MTurk workers to examine the mechanisms by which eLancers are attracted to tasks with specific work characteristics, select tasks to design their work, and intend to leave the eLance work role. Results of a path analysis indicated that a number of personality factors (e.g., prosociality) were predictive of increased attraction to specific task characteristics (e.g., task significance). With the exception of feedback from the job, attraction to all task characteristics was predictive of increased selection of tasks with those same characteristics. However, only one selection factor (i.e., feedback from the job) predicted turnover intentions from the eLance role, which was, unexpectedly, a positive effect. No indirect effects emerged for the full mediation model, but two perceptions of work factors (i.e., viewing MTurk work as a calling and a career) were found to interact with specific attraction factors (i.e., task significance and task variety) to predict selection of tasks. These results provide support for some aspects of both the ASA model in this context and Schroeder et al.'s (2021) eLance work design model. The findings of this study have important implications, as they provide information that MTurk requesters can use to attract desirable workers to their tasks (e.g., those high in conscientiousness). The findings are also beneficial to eLancers in that they are provided with increased insight into how to select tasks that align with their personal desires and characteristics.

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DEDICATION

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CHAPTER ONE: Introduction

In recent decades, continuous technological and economic advancements have led to substantial changes in the manner in which work is conducted (Kalleberg, 2000), resulting in the creation of a "new world of work" (Ashford et al., 2018, p. 2). For instance, an influx of novel Internet-enabled forms of work have emerged, such as the enablement of any individual to complete small freelance tasks posted on online work platforms, referred to as eLancing (Aguinis & Lawal, 2013). eLancing is unique in that it offers a seemingly endless pool of work opportunities with a wide variety of task characteristics, therefore gives workers an opportunity to select which tasks to complete and to engage in work design behaviors. As such, eLancing shares minimal similarities with the standard workplace (i.e., full-time, steady employment conducted at the hiring organization's location; Kalleberg et al., 1997), which has been the focus of most workplace research to date. Therefore, scholars have noted that due to the novelty of a fully digital workforce comprised of individuals with a wide array of competencies, research investigating what work design looks like in this unprecedented work environment is crucial (Colbert et al., 2016).

Notably, in an effort to better understand eLance work design, recent work has begun to investigate the applicability of standard work theories and models to the eLance work environment. Namely, Schroeder, Bricka, and Whitaker (2021) presented a theoretical eLance work design model, tailored from standard work design models, to specifically consider the eLance work environment. However, this model has not been empirically tested; therefore, the literature is lacking metrics to represent the factors influencing eLancer selection of work and its impact on important outcomes. A theory commonly used to explain the mechanisms by which standard workers select work is the Attraction-Selection-Attrition (ASA) model (Schneider, 1987), which may also explain the attraction, selection, and attrition patterns of eLancers. Thus, the purpose of the present effort is to empirically test Schroeder et al.'s (2021) model through the lens of the ASA framework. More specifically, this paper investigates the mechanisms by which eLancers on the online platform Amazon Mechanical Turk (MTurk) are attracted to tasks, select tasks, and intend to leave the eLance work role, which provides the information necessary to improve eLancer experiences and outcomes.

Nonstandard Work

For the majority of the 20th century, standard employment was the predominant work arrangement in the U.S. (Kalleberg, 2000). However, recent estimates suggest that between 10% and 20% of today's U.S. workforce engages in work arrangements that fall outside of the standard employment structure (Appelbaum et al., 2019; Cappelli & Keller, 2013), referred to as nonstandard work (Ashford et al., 2007; Kalleberg et al., 2000). Further, due to the influx of individuals completing nonstandard work arrangements in the wake of COVID-19-related job layoffs (Semuels, 2020), it is likely that the number of individuals presently engaging in nonstandard work exceeds previous estimates.

As nonstandard work encompasses all forms of work that differ from standard employment, there are a wide array of highly diverse work arrangements that fall within the umbrella of nonstandard work (Bricka & Schroeder, 2021). For example, nonstandard arrangements can range from long-term, stable roles which differ from standard work in terms of work location or hours worked (e.g., telecommuting, part-time work) to isolated, contingent roles that an individual is hired to complete on an as-needed basis, referred to as gig work (Torpey & Hogan, 2016). Further, among the types of arrangements that are classified as gig work, there is wide variation in types of roles as well. More specifically, as gig work encompasses all forms of on-demand projects or tasks, individuals such as independent contractors, subcontracted vendors, rideshare drivers, Airbnb hosts, and online task workers are all completing various forms of gig work. The demand for gig work continues to increase, with projections that customers will increase their spending in the gig economy by 17% by 2023, resulting in an estimated $455 billion industry (MasterCard, 2019).

The continual shift from standard employment to more nontraditional roles is redefining work, thereby garnering attention in academic communities and the media. For instance, the changing nature of work (e.g., novel approaches in regard to who completes work, such as the rise of contractors and temporary workers) has been on the Society for Industrial and Organizational Psychology's list of top 10 work trends for the past five years (Stark, 2021), and the gig economy was ranked third on the 2020 list (Haynes, 2020). In addition, the rapid growth of the gig economy has been the focus of articles from many mainstream popular press outlets (see, e.g., Arruda, 2020; Conklin, 2019; Eidelson, 2021; Iacurci, 2020), making claims such as "the gig economy is coming for your job" (Kim, 2020, para. 1).

The popularization of gig work has also resulted in interest from parties such as government and international agencies (see, e.g., International Labour Organization, 2021; United Kingdom Parliament, 2017) in regard to factors such as labor rights and welfare benefits. For example, there have been recent controversial legal rulings regarding the labor rights of rideshare drivers in California and the United Kingdom (see, e.g., Browne, 2021; Conger, 2020), highlighting that gig work is a phenomenon of interest to a large number of differing entities. As such, this sector of work is becoming increasingly prevalent and garnering interest from many parties, which is a trend that is likely to continue in the future.

eLancing

Due to the wide variety of work arrangements that fall under the umbrella of the gig economy, grouping together these diverse work roles in an unspecific "gig work" category is problematic (Bricka & Schroeder, 2021). More specifically, as there is great discrepancy among these forms of work in regard to work environments and tasks, it is imperative to examine the subsets of gig work independently in order to avoid overgeneralization errors. One popular form of gig work is online task work, which has been referred to by terms such as crowdsourcing (Howe, 2008) or eLancing (Aguinis & Lawal, 2013).

These terms are differentiated in that crowdsourcing refers to the general act of redistributing tasks once internally completed at an organization by making them publicly available to an external group of unspecified individuals (Howe, 2008). In turn, eLancing narrows in on this concept by describing a specific type of crowdsourcing work environment (Ford et al., 2015) in which individuals complete freelance tasks on a platform facilitated by the Internet (Aguinis & Lawal, 2013). Stated differently, eLancing is a form of crowdsourcing in which tasks are outsourced to a group of Internet-based workers (Ford et al., 2015), colloquially referred to as freelancing in a digital space (Cascio & Boudreau, 2017).

eLance tasks can either be small-scale in nature (i.e., microwork), in which workers complete short, manual tasks such as image tagging or audio transcription that do not require specific knowledge or abilities, or large-scale projects that rely on niche professional skills (Webster, 2016). There are a number of online platforms on which eLance work is conducted, including sites that cater specifically to microwork tasks (e.g., MTurk), survey completion (e.g., Prolific), or longer-term projects for individuals with specific skills (e.g., Upwork). Taken together, the eLance work environment consists of boundless opportunities for workers and offers tasks of any nature; therefore, workers have an opportunity to design their work in a way that adheres to their desired characteristics.

Microwork represents a particularly interesting avenue of eLancing, as it often involves minimal or no interaction with the person requesting the work and entails anonymously completing work for very small sums of money (Webster, 2016). In contrast, project-based eLance work is often more similar in nature to standard work in which eLancers may be professionals in their field who work closely with the client for a long duration (Aguinis & Lawal, 2013). Due to the specific challenges posed for individuals completing microwork and the novelty of the work environment, the present effort focuses on eLancers completing microwork rather than project work. Further, as MTurk has been identified as one of the largest and most popular microwork platforms (Difallah et al., 2015; Smith & Leberstein, 2015), eLancers completing work on MTurk are the population of interest in the present effort.

MTurk functions as a virtual marketplace in which parties that have work to be completed (i.e., requesters) post it in the form of a small, isolated task (i.e., human intelligence tasks; HITs) to be completed by workers (Amazon Mechanical Turk, 2018). Requesters upload information about the HIT for worker evaluation, such as a HIT title, summary of the task, amount of time allowed to complete work, and keywords or tags depicting the subject or nature of the HIT. The subject of each HIT typically can be categorized into seven key areas: data processing (e.g., entering data or verifying data entry), categorization (e.g., sorting products in catalog into similar groups), sentiment (e.g., evaluating tweets or comments for expressed attitudes), tagging (e.g., creating keywords for advertisements), content (e.g., creating, revising, or critiquing writing samples), business feedback (e.g., evaluating a new product), and academic research (e.g., engaging as a participant in a study; Deng & Joshi, 2016). As such, workers are provided with information that suggests the task characteristics that may be present or absent in the work prior to selecting the HIT (e.g., a task categorized as data processing may signal to workers that autonomy will be low).

After a worker has completed a HIT, requesters must review each submission and decide whether to accept the HIT, thereby paying the worker for completing the task, or rejecting the HIT, declining to pay the worker for reasons such as incorrect completion of the task, not adhering to instructions, or low-quality responses (Amazon Mechanical Turk, 2018). Workers remain anonymous while completing tasks on MTurk, as they are identifiable to requesters only by an MTurk identification number. High performing workers can achieve an exclusive status on the platform (i.e., master worker) by successfully completing a large number of accepted tasks for a variety of requesters, thereby receiving the ability to access HITs that require a master-level qualification to complete (Amazon Mechanical Turk, 2018).

Due to MTurk's unique work environment in which work is sliced into the smallest possible increments, some have referred to such online work contexts as reflecting Taylor's (1911) principles of scientific management, which endorse task simplification (Deng et al., 2016; Duggan et al., 2020; Williams et al., 2019). However, in contrast to the scientific management perspective, MTurk also allows for work enrichment as individuals are able to design their work to fit their desired specifications (Deng et al., 2016). As such, the work design behaviors of workers functioning in an innately Tayloristic work environment offers a particularly interesting avenue for exploration.

Notably, eLance work has been examined in previous empirical work, but the primary focus of a large subset of research on eLancers has been determining the quality of survey data collected from eLancers via sites such as MTurk (see, e.g., Buhrmester et al., 2011; Chmielewski

& Kucker, 2020; Smith et al., 2016). However, the departure of the eLance work context from standard workplace norms warrants specific investigation into this form of work in order to avoid disregarding eLancer work conditions and experiences (Webster, 2016). As such, additional research is needed on eLancers, aside from examining their utility as research participants. Further, as the eLance workforce is comprised of individuals with an array of skills, abilities, and digital experiences, research examining how individuals with diverse backgrounds design work in the face of innumerable opportunities is necessary (Colbert et al., 2016). Emphasizing this point, others have noted that the lack of attention given to online platform work and its notable contrast to standard work in the human resources and organizational behavior literature is surprising and should be rectified (Kuhn & Maleki, 2017).

As such, recent work has begun to discuss the eLance work experience from a human resource management (HRM) perspective, exploring how crucial HRM functions such as work design, recruitment, and selection manifest in this work context. The first effort to specifically examine online platform work through an HRM lens was led by Aguinis and Lawal (2013), introducing a research agenda for eLancing research which called for a need to examine key HRM areas in this segment of the workforce. In later work, Meijerink and Keegan (2019) highlighted that HRM and online platform work are contradictory in that HRM is typically an activity executed by an employer to oversee their relations with their employees, yet online platforms do not engage in a formal employment relationship with workers. As such, they argue that HRM in this work context should be conceptualized as consisting of separate yet related entities (e.g., workers, platforms) functioning within a single ecosystem (Meijerink & Keegan, 2019). Other efforts have similarly discussed the challenges of managing non-employees (Ford et al., 2015) and examined the relevance of existing HRM studies to an online platform work environment (Buettner, 2015). In sum, the practice of HRM in online work environments poses significant challenges to existing HRM frameworks and conceptualizations; therefore, work is needed to determine the applicability of HRM concepts to emerging work contexts (Aguinis & Lawal, 2013; Cascio & Boudreau, 2017; Kuhn & Maleki, 2017).

Additional work has been done to determine what is known about the key HRM functions of attraction and selection in online platform work and the generalizability of such concepts to new work contexts. Notably, Cascio and Boudreau (2017) examined the state of the literature in regard to overlap between nonstandard work and typical HRM functions. Their results indicated that the majority of literature examining HRM activities pertains to more longstanding forms of nonstandard work such as part-time workers and workers hired through temp agencies (Cascio & Boudreau, 2017). Further, they discovered that research on online platform workers has rarely investigated worker attitudes or actions taken by individuals completing such forms of work, whereas this was frequently the focus of research that focused on more common forms of nonstandard work (Cascio & Boudreau, 2017). This demonstrates that the focus of HRM research in regard to nonstandard workers has varied in scope depending on the form of work being examined and that research on eLancer attitudes and behavior is lacking.

In addition, Williams et al. (2021) used the ASA model as a framework to examine the actions online platforms take to attract and select workers, making an important note that the attrition component of the ASA framework is less visible in this context. More specifically, a worker's decision to stop engaging with a given work platform is typically not formally investigated or logged in the manner that an organization would handle a worker's exit from a standard position (e.g., exit interviews, surveys). As such, attraction and selection may be more relevant to an online platform work context than attrition (Williams et al., 2021). Similarly, Dan et al. (2021) discussed considerations for attracting and selecting digital talent, highlighting specific strategies that can be taken to attract digital workers (e.g., advertising the specific tasks that can be selected in the role as a mechanism to attract workers).

Further, Bush and Balven (2021) discuss that in an online platform work context, the pairing of qualified workers with appropriate tasks is often up to the discretion of the worker, therefore the risk of misalignment between worker competencies and task requirements is high. As such, they recommend using increased vetting procedures to aid the worker's ability to self-select into tasks that are aligned well with their expertise and interests (Bush & Balven, 2021). However, on this note, it is important to highlight that HRM functions in this work context could have several conceptualizations. For instance, Kuhn and Maleki (2017) made an important observation that the meaning of selection in online platform work may range from receiving approval to begin work on a platform to worker selection of tasks from those available to them on the platform. As the present effort is focused on eLancers on MTurk who have conducted work on the site rather than those seeking a site to complete work on, selection in the present effort refers to worker selection of tasks on the MTurk platform.

In other efforts discussing HRM in online work, scholars have noted that across many online labor platforms, HRM functions including selection are often carried out by pre-programmed algorithms rather than following the standard workplace model of designating individuals to conduct such activities (Duggan et al., 2020; Kuhn & Maleki, 2017; Waldkirch et al., 2021). As such, Waldkirch et al. (2021) proposed that the use of algorithmic management on online work platforms has introduced a hybrid approach to HRM, such that workers are responsible for managing some of their own HRM functions (e.g., work design, training), yet are simultaneously under a level of intense algorithmic scrutiny in regard to other areas of HRM (e.g., performance management). This use of algorithms to manage HRM activities has been argued to directly impact work design considerations (Parent-Rochelau & Parker, 2021). For instance, it has been posited that greater use of algorithmic management may have differential effects on job design, possibly resulting in less worker autonomy, yet greater feedback from the job (Parent-Rochelau & Parker, 2021). Such discussions highlight the potentially impactful role that algorithms may be playing in HRM in online platform work.

Another disconnect between traditional HRM and HRM in online platform work pertains to work design. Several papers have acknowledged this difference, highlighting that the nature of the small, parsed apart tasks completed in online platform work settings are fundamentally different in nature from the way that the same work would be designed in standard work contexts (Durward et al., 2020; Kittur et al., 2013). Further, in traditional work settings, job design is often executed as an HRM function when recruiting for and selecting individuals for specific, pre-determined roles (Connelly et al., 2021). However, due to the lack of formal employment relationships in an online platform work context, task characteristics are often instead the mechanisms through which eLancers design their own work (Bush & Balven, 2021; Connelly et al., 2021).

Similarly, others have noted the entrepreneurial nature of some forms of gig work, such as eLancing and app-based work, in which workers may be responsible for self-selection of tasks or upgrading their resources (e.g., vehicle) to offer better services (Barratt et al., 2020; Bricka & Schroeder, 2019). In doing so, workers are able to craft jobs that are specifically tailored to their criteria (Connelly et al., 2021; Ellmer & Reichel, 2018), whether that may be their available resources or their personal considerations and interests. As such, work design in online platform work represents a significant departure from work design in standard workplaces. Taken together, much recent work has focused on the nuanced topic of HRM in online platform work. However, despite such efforts, there has been no empirical evidence demonstrating how selection takes places in this context, referring to how individuals select which work tasks to complete on sites such as MTurk.

Although this lack of empirical knowledge on how individuals select roles or tasks to complete extends to all forms of gig work, it is important to note that there has been investigation into the job search process for individuals engaging in nonstandard roles that fall outside of the gig work definition (i.e., part-time, temporary, and temporary-to-permanent positions). More specifically, Pedulla and Mueller-Gastell (2019) examined sociodemographic differences in applications to nonstandard work roles, finding that women and the youngest and oldest members of the workforce (i.e., ages 18-24 and 55-64) are the most likely to apply to nonstandard positions. In contrast, individuals with a college degree were more likely to apply for standard work roles than nonstandard positions, demonstrating that applications to nonstandard and standard work roles are disproportionately skewed towards certain subgroups. Despite this initial empirical investigation into the factors influencing selection of work for nonstandard workers, there is much work to be done to fully understand the mechanisms by which eLancers select which tasks to complete on platforms such as MTurk.

Theory Relevant to eLancer Selection of Tasks

Due to the recency of the emergence of gig work, there is a lack of existing theories specifically pertaining to such novel work contexts (Ryan & Wessel, 2015). Thus, it is often necessary to consider the applicability of standard workplace theories to nonstandard work contexts (Brawley, 2017). As such, in order to develop a greater understanding of the process by which eLancers select work on platforms such as MTurk, it is important to turn to theories considering how individuals select work in standard work contexts. Namely, the ASA model is a person-centered framework (Schneider et al., 1995) that has commonly been used to explain the process by which people enter standard work arrangements. The ASA framework theorizes that individuals who are attracted to, selected by, and retained by organizations are likely to be similar in nature due to the selection of work environments that are congruent with their personalities. The theory also posits that individuals who are attracted to and selected by an organization that is not compatible with their personalities will voluntarily leave the organization (Schneider, 1987).

The ASA theory builds upon earlier conceptual work pertaining to an individual's fit with their work environment, such as person-environment (P-E) fit theory. P-E fit theory posits that behavior is determined by the fit of a person to their work environment (Schneider et al., 2000). This theory is derived from seminal work by researchers such as Lewin (1935) and Murray (1938), who introduced the rudimentary concept of behavior being determined by the interaction between a person and a given environment. P-E fit theory has been applied in a number of work contexts, including virtual organizations, to determine an individual's fit with a virtual work environment (Shin, 2004). The literature has identified many forms of P-E fit, including person-organization (P-O) and person-job (P-J) fit, with P-O fit referring to the congruence between an individual and an organization and P-J fit referring to the congruence between an individual and the tasks involved for a specific job (Carless, 2005).

Discussions of the relevance of concepts such as P-O and P-J fit in online platform work contexts have highlighted some important considerations. Namely, Bush and Balven (2021) emphasized that in such forms of work, P-O fit is a rare consideration when matching individuals with tasks to complete due to worker anonymity. In turn, others believe that P-J fit is particularly relevant to an MTurk work context, such that the fit between the worker and MTurk tasks has been theorized to predict intention to select tasks (Schulze et al., 2012). However, Buettner's (2015) review of the crowdsourcing literature concluded that the lack of empirical research linking P-J fit to crowdsourcing outcomes limits the strength of conclusions that can be made about the applicability of P-J fit to crowdsourcing environments.

It is important to note that there have been numerous criticisms of P-E fit theory, including the vague manner in which fit is operationalized, disagreement over best measurement practices, the lack of consideration of individual attributes in conceptualizing the work environment, and the neglect of any negative consequences that may arise from P-E fit, among many others (Schneider et al., 2000). As such, Schneider's ASA model is proposed as an alternative to P-E fit theory that does not have such limitations.

The first stage in the ASA model is the attraction stage, in which the founder of the organization determines its overarching goals, structure, and functions, thereby laying the groundwork for organizational attraction by creating factors that individuals can determine to be alike or dissimilar from their personalities (Schneider et al., 1995). Thus, recruitment activities are key to attracting candidates that align with the hiring organization (Schneider, 1987). In an eLance context, this first stage may be akin to an MTurk requester designing the task and creating the HIT description that workers evaluate when considering whether to select a HIT.

The second phase of the ASA model, selection, refers to the process of determining which individuals in the pool of interested candidates have the organization's desired attributes (Schneider et al., 1995). The ASA model posits that both the attraction and selection stages are the mechanisms by which organizations end up with a group of people that have similar personalities, but various competencies and skills (Schneider, 1987). Stated differently, at this point organizations have selected a pool of individuals who are more similar to each other than they are to individuals employed at other organizations. As discussed previously, in an eLance work context, workers are responsible for designing their work experience by selecting work tasks of their choosing. Therefore, among eLancers, the selection phase of the ASA model is likely within the realm of control of the worker rather than an organization.

However, as it is posited that workers select tasks that align with their personal characteristics, requesters may still obtain a pool of workers that are similar in nature in regard to personality, skill, or competency. Additionally, as requesters have the ability to accept or reject completed work, it is possible that rejected work may belong to individuals with characteristics that are dissimilar to those who had approved work (e.g., low conscientiousness for a data entry task). In such an instance, the selection phase would still parallel ASA's initial conceptualization in which the authoritative party plays a role in curating a similar workforce.

Lastly, the attrition phase of the ASA model describes the process by which individuals who are incongruent with the work environment realize that they were mistakenly attracted to the organization and exit the role (Schneider, 1987). Among eLancers, this is likely most similar to the point at which an individual exits the eLance work role by deciding to discontinue the completion of all work on the platform. Taken together, the ASA framework suggests that the attraction, selection, and attrition stages are affiliated mechanisms taking place over an extended period of time (Muchinsky, 2000) that collectively establish which types of people exist in an organization, which then impacts organizational characteristics, such as procedures and culture (Schneider et al., 1995).

The ASA model has been empirically supported, as personality has been demonstrated to be related to organizational choice or preference (Judge & Cable, 1997; Lievens et al., 2001;

Schneider et al., 1998), and similarity in personality between members of the same organization has been established (Jordan et al., 1991; Schneider et al., 1998). Further, empirical studies have determined that job applicants often associate organizations with specific personality traits (e.g., identifying an organization to be helpful or creative) and use those traits to assess fit (Slaughter et al., 2004) and to determine whether to seek employment at that organization (Slaughter & Greguras, 2009).

In addition, several studies have demonstrated that individuals with congruence between their personality and organization are more likely to remain at the organization than those with incongruence (O'Reilly et al., 1991; Posner, 1992; Posner et al., 1985). In sum, the ASA model is a useful framework for examining the general processes by which people are attracted to, selected at, and remain at an organization, as demonstrated by the vast number of research efforts that have used the ASA model to examine attraction, selection, and retention processes (see, e.g., Choi & Chung, 2017; Judge & Cable, 1997; Slaughter et al., 2005; Wilson, 2016; Wright & Christensen, 2010).

Despite the utility of the ASA framework in explaining these mechanisms, the theory was developed in reference to this process occurring at one standard organization for a specific job role. As such, the tenets of this theory do not directly translate to an eLance work context due to the lack of a consistent organizational culture and work environment, which is dissimilar to standard workplaces. However, aspects of the ASA framework have been determined to be applicable to an eLance work context, as demonstrated by Williams et al.'s (2021) use of the ASA model to examine which HRM practices digital platforms implement to attract and select workers. Taken together, although the traditional manner in which the ASA model conceptualizes relations between workers and organizations is not identical to an eLance work context, there are important tenets of ASA theory that can be used to examine the attraction, selection, and attrition patterns of eLancers.

eLance Work Design

As highlighted previously, recent efforts have discussed the disparate nature of work design in traditional and online platform work contexts, yet more work is needed to provide empirical evidence of the work design process among eLancers. Thus, it is necessary to draw from existing work design principles to understand the considerations of eLancers in designing their work (i.e., choosing which HITs to complete). One popular work design principle in a standard work context is job crafting (i.e., a bottom-up process in which an employee modifies their role to more closely align with their desired tasks), which often results in greater perceptions of meaningfulness and the employee identifying more strongly with their work (Tims & Bakker, 2010; Wrzesniewski & Dutton, 2001).

There is notable overlap between job crafting principles and the eLance work role, in which work design is entirely under the discretion of the eLancer who selects each task (Schroeder et al., 2021). To this point, work examining job crafting behaviors among online platform workers has found job crafting to be positively linked to worker outcomes such as increased career commitment and resilience (Wong et al., 2021). As such, the personality factors that have been demonstrated to be related to job crafting behaviors are likely to be similarly predictive of eLancer work selection behaviors (Schroeder et al., 2021).

In order to develop a greater understanding of the mechanisms by which eLancers engage in digitized work, Schroeder et al. (2021) set forth a theoretical model of eLance work design that built upon previous standard work design frameworks (Morgeson & Campion, 2003; Morgeson & Humphrey, 2006) to specifically consider this novel work context (see Figure 1). In this model, the authors proposed that several categories of eLance work antecedents (i.e., social [e.g., eLance network social cues], structural [e.g., technology], and personal [e.g., proactive personality]) influences predict work characteristic design factors (i.e., motivational [e.g., feedback from the job] and social [e.g., social support] characteristics). These work characteristic design factors were expected to predict several key mediating mechanisms (e.g., meaningfulness), with that relationship being moderated by relevant contextual characteristics (e.g., work conditions).

Lastly, the mediating mechanisms were posited to predict several categories of outcomes (i.e., behavioral [e.g., turnover intentions], attitudinal [e.g., job satisfaction], role perception [e.g., role ambiguity], and well-being [e.g., stress]). However, this model has not been empirically tested to verify the proposed mechanisms of eLance work design. Nevertheless, aspects of this work design model may offer crucial insight into the factors involved in worker selection of tasks on MTurk. As such, the present effort aims to conduct an initial empirical test of specific aspects of this eLance work design framework that pertain to worker attraction to and selection of tasks.

Revisions to Schroeder et al.'s (2021) Framework

Examination of Schroeder et al.'s (2021) eLance work design model through the lens of the ASA framework suggests that revisions to the model may be necessary in order to adhere to the scope of the present effort. Therefore, a modified version of Schroeder et al.'s (2021) model was tested in this paper in order to focus on the factors most relevant to the ASA theory and to incorporate important additional theoretical considerations. As depicted in Figure 2, the proposed model for the present effort involves Schroeder et al.'s (2021) personal growth and prosociality factors (referred to subsequently as personality factors) predicting attraction to task characteristics (i.e., autonomy, task variety, task significance, task identity, feedback from the job, task clarity). Attraction to these six task characteristics is expected to predict actual selection of tasks with these characteristics, with this relationship being moderated by work essentiality factors (i.e., financial need and perceptions of work). Lastly, selection of tasks with those characteristics is posited to predict turnover intentions from the eLance role. Justification for this proposed model is provided below, along with the study hypotheses.

Personality Predicting Attraction to Tasks

Consideration of this work design model from an ASA theory perspective reveals that certain subsets of Schroeder et al.'s (2021) work design framework are likely to be more relevant to the attraction, selection, and attrition processes of eLancers than other aspects of the model. For instance, as the premise of the ASA model is that an individual's personality is predictive of attraction to an organization, the personality factors (i.e., proactive personality, learning goal orientation, need for achievement, self-efficacy, psychological capital, the Big Five traits, prosociality) of the antecedents proposed by Schroeder et al. (2021) are particularly relevant in the context of the ASA framework. Additionally, as the emphasis of the ASA model is on an individual's homogeneity with their work environment, the motivational characteristics most consistent with the ASA theory in this work design framework are task characteristics (i.e., autonomy, task variety, task significance, task identity, feedback from the job, task clarity).

Notably, as Schroeder et al. (2021) emphasized, knowledge-related factors may be more relevant to high-skilled project-based eLance work rather than microwork on MTurk. As such, the knowledge characteristics subfactor of the motivational characteristics category is less appropriate to assess in an MTurk setting, as it is a platform that facilitates the completion of small, individual tasks. Further, as the purpose of the present effort is to empirically test

Schroeder et al.'s (2021) model through the lens of the ASA framework, the mediating mechanisms section of the original model and the moderating contextual characteristics have been excluded, as they fall outside of the guiding framework of the ASA model.

The most significant revision to the original eLance work design model is the insertion of attraction to task characteristics in between the personal influences antecedents category and selection of tasks with specific characteristics. The ASA process has been established to be linear, in that attraction to a role must precede selection and attrition (Muchinsky, 2000). This suggests that attraction should predict selection of tasks, rather than the direct link between specific personality traits and relevant task characteristics depicted in Schroeder et al.'s (2021) model. As such, the incorporation of this ASA theory tenet into Schroeder et al.'s (2021) eLance work design model is necessary in order to fully understand the mechanisms by which eLancers are attracted to and select work.

The rationale for adding attraction to tasks as a mediator between personality characteristics and selection of tasks is further supported by the many instances in the literature of personality factors predicting an individual's attraction to an organization or specific tasks. In addition to personality factors being predictive of organizational attraction, Kristof-Brown et al.'s (1996) meta-analytic findings demonstrated that compatibility between an individual's characteristics and the characteristics of a specific job predicted greater attraction to the organization. A description of each of each task characteristic of interest in this study, as well as the personality factors and their relations to attraction is included below.

The six motivational task characteristics compiled by Schroeder et al. (2021) are autonomy (i.e., the extent to which a worker has freedom and discretion over the completion of a task; Hackman & Oldham, 1976), task variety (i.e., the extent to which a wide array of work activities are involved in a job; Hackman & Oldham, 1976), task significance (i.e., the degree to which the job tasks are believed to impact the lives of others; Hackman & Oldham, 1976), task identity (i.e., the extent to which a job involves completing an easily identifiable task in its entirety; Hackman & Oldham, 1976), feedback from the job (i.e., the degree to which information about a worker's performance is clearly communicated in the job; Hackman & Oldham, 1976), and task clarity (i.e., the extent to which a task's instructions are clearly denoted; Schroeder et al., 2021).

Notably, these characteristics, with the exception of task clarity, have long been factors of interest among workplace researchers. More specifically, these five task characteristics were central to Hackman and Oldham's (1976) Job Characteristics Theory, in which they were considered to be core job dimensions that impacted psychological states (e.g., work meaningfulness), which then impacted relevant work outcomes (e.g., turnover). These characteristics were also included in later standard work design models (e.g., Morgeson & Campion, 2003; Morgeson & Humphrey, 2006), demonstrating their centrality to work design efforts. Task clarity was included in Schroeder et al.'s (2021) model as a task characteristic alongside the five core task characteristics, as many efforts have noted its important role in an eLance work environment. Further, many of these factors have been reported as desirable characteristics of eLance work that encourage participation in this form of work (Deng & Joshi, 2016).

Previous research has demonstrated links between each of these personality factors and organizational or task attraction. For instance, proactive personality, referring to the tendency to take action to introduce meaningful change in one's environment (Bateman & Crant, 1993), has been positively linked to job search behaviors (e.g., preparing application materials), job search effort, and entrepreneurial intentions (Brown et al., 2006; Prieto, 2010). Likewise, some have posited that individuals with high levels of proactive personality will experience greater organizational attraction, as they will envision opportunities in which they can be of service to the organization (Zhang et al., 2019).

Another personality factor that has been linked to task and organizational attraction is learning goal orientation, which refers to one's desire to seek out opportunities to complete difficult tasks that enhance learning (Wood & Bandura, 1989). Notably, one's intention to learn has been positively linked to task attraction (Seegers & Boekaerts, 1993). In addition, learning goal orientation was found to be an important moderator of the relationship between mentorship programs and organizational attraction, such that individuals with a greater learning orientation reported greater attraction to organizations that offered formal mentoring programs than those that did not (Allen & O'Brien, 2006).

Similarly, need for achievement, which is characterized by a tendency to push oneself to accomplish challenging tasks and meet a high performance standard (Jackson, 1974), has been found to predict attraction to an organization or a specific field (Turban & Keon, 1993; Wilson, 2016). Further, organizational attraction has been found to differ according to an individual's levels of need for achievement (Bretz et al., 1989; Slaughter et al., 2005).

In turn, self-efficacy refers to an individual's belief in their capabilities to perform well in a specific area (Bandura, 1997). Scholars have posited that self-efficacy is likely to play an important role in an individual's attraction to an organization, as those with high levels of self-efficacy will have an expectation of succeeding at the organization, and therefore will likely evaluate it more critically (Ehrhart & Ziegert, 2005). Further, an individual's knowledge self-efficacy for a particular task has been positively linked to both personal interest in the task and motivation to contribute to task completion (de Vreede, 2016).

Psychological capital, a composite factor that encompasses an individual’s self-efficacy, hope, optimism, and resiliency (Luthans & Youssef, 2004), is also an important factor in determining organizational attraction. As psychological capital has been found to moderate the relationship between work engagement and organizational commitment, scholars have argued that organizations that value work engagement and organizational commitment should invest in development of psychological capital in order to increase organizational attraction (Robyn & Mitonga-Monga, 2017).

The Big Five traits include neuroticism (i.e., a predisposition to have high anxiety), openness to experience (i.e., a propensity to be imaginative and demonstrate originality), extraversion (i.e., one’s tendency to be sociable and talkative), agreeableness (i.e., one’s inclination to be cooperative and courteous), and conscientiousness (i.e., one’s tendency to be organized and responsible; Barrick & Mount, 1991). The Big Five traits have been linked to differences in organizational attraction and have been shown to predict attraction to organizations (Judge & Cable, 1997; Slaughter et al., 2005). In addition, the Big Five traits have been found to interact with variables such as organizational personality and characteristics to predict greater attraction to the organization (Lievens et al., 2001; Slaughter & Greguras, 2009).

Lastly, prosociality refers to the extent to which an individual desires to aid others (Grant, 2008a). Notably, organizational engagement in prosocial attitudes and behavior was found to predict greater organizational attraction via the mediating mechanism of applicant perceived fit with the organization's values, highlighting that applicants shared a prosocial orientation with the organization (Jones et al., 2014). Further, roles that were perceived by applicants to consist of prosocial characteristics (e.g., helping others, contributing to society) were positively linked with greater applicant intentions to apply (Asseburg et al., 2020).

As eLancers engage in job crafting practices and have significant autonomy over which tasks to select, Schroeder et al. (2021) argued that average levels of task characteristics present in work may be reflective of a worker's personal characteristics, such as their goals and preferences. As such, it is likely that the aforementioned personality factors will not only predict attraction to tasks, but more specifically will predict attraction to tasks with high levels of generally desirable task characteristics. Taken together, the following is hypothesized:

> *Hypothesis 1 (H1):* Personality factors will predict attraction to task characteristics, such that individuals with high levels of proactive personality, learning goal orientation, need for achievement, self-efficacy, psychological capital, the Big Five traits, and prosociality will experience greater attraction to the specified task characteristics.

As it is expected that personality factors will predict attraction to the specified task characteristics, below is a discussion of evidence that personal influence factors are linked to specific eLance task characteristics.

Scholars have argued that proactive personality is likely to influence the levels of task characteristics present in one's work (Tornau & Frese, 2013). This proposition has been supported, as a meta-analysis demonstrated a positive relationship between proactive personality and autonomy (Tornau & Frese, 2013). Further, learning goal orientation has been positively linked to feedback seeking behaviors (Whitaker & Levy, 2012), as individuals with a high learning goal orientation rely on feedback as a critical tool to improve performance (VandeWalle et al., 2001). In addition, learning goal orientation has been positively linked to job autonomy (Zhang et al., 2017). In turn, individuals with a high need for achievement have been found to have higher performance on work that requires autonomy and task variety (Steers & Spencer, 1977) and require greater feedback on tasks (Steers, 1987) compared to those with a low need for achievement.

Further, self-efficacy and psychological capital have been found to be positively related to autonomy, task variety, task significance, task identity, and feedback (Cai et al., 2019; Kao, 2017; Malik & Dhar, 2017; Todd & Kent, 2006). Various relationships have been demonstrated between the Big Five traits and task characteristics, such as the relationships between emotional stability and autonomy (Barrick & Mount, 1993) and conscientiousness and skill variety (Kim et al., 2009). In addition, Grant (2007) posited that completing work with high levels of task significance may be related to an individual's prosocial orientation. Therefore, in light of both the ASA theoretical tenet of personality driving attraction to work roles and Schroeder et al.'s (2021) eLance work design framework that expected personality traits to be linked to specific task characteristics, the question is proposed on an exploratory basis:

> *Research Question 1 (RQ1)*: Which specific work characteristics (i.e., autonomy, task variety, task significance, task identity, feedback from the job, and task clarity) are predicted by personality factors?

Attraction to Tasks Predicting Selection of Tasks

Further, there is evidence to suggest that work attraction is predictive of work selection. Namely, Tikhonov (2019) found that one of the most important considerations for workers when selecting a work role is the attractiveness of the specific tasks offered in that position. Further, previous work has demonstrated that attraction to work roles with high levels of job security is predictive of working in an employment sector that provides job security (Choi & Chung, 2017). In the same vein, individuals who reported attraction to work that is beneficial to others were more likely to be employed in a job that provides an opportunity to help others than one that does not (Wright & Christensen, 2007). In addition, Carless (2005) found that during a selection process, attraction to the organization was positively related to job acceptance intentions. These findings demonstrate the likelihood of attraction to specific task characteristics predicting selection of tasks with those same characteristics (e.g., attraction to tasks with autonomy predicting selection of tasks with autonomy). As such, the following hypothesis is proposed:

Hypothesis 2 (H2): Attraction to task characteristics will predict selection of tasks with corresponding characteristics, such that a) autonomy attraction will predict greater selection of tasks with autonomy, b) task variety attraction will predict greater selection of tasks with task variety, c) task significance attraction will predict greater selection of tasks with task significance, d) task identity attraction will predict greater selection of tasks with task identity, e) feedback from the job attraction will predict greater selection of tasks with feedback from the job, and f) task clarity attraction will predict greater selection of tasks with task clarity.

In addition to the personality factors discussed previously, Schroeder et al. (2021) also included two work essentiality factors (i.e., financial need and perceptions of work) in their personal influences antecedents category. Although they fall outside of the personality considerations suggested by the ASA framework, they are important factors that are likely to impact the relationships between attraction to tasks and actual selection of tasks. For instance, in an eLance work context there is a potential for variation between attraction to and actual selection of tasks, such as an individual being attracted to tasks with desirable work characteristics, yet selecting undesirable tasks that offer greater compensation due to financial need. This demonstrates just one instance in which the relationships between attraction and selection may be impacted by work essentiality factors.

Financial need refers to the role of monetary income in a worker's life, such as the extent to which an individual relies upon a source of income to meet basic needs (Shaw & Gupta, 2001). As may be expected, a desire to earn money has been identified as the greatest motivator for participating in platform work (Chen et al., 2019). However, it is important to note that not all MTurk workers are completing such work due to financial motives. Financial need among MTurkers has been demonstrated to vary, such that perhaps up to one-third of workers on the platform are largely dependent on MTurk for income (Berg, 2016; Kuhn & Maleki, 2017). However, others with presumably lower levels of financial need participate on the site for purposes such as entertainment (Ipeirotis, 2010), learning potential (Chen et al., 2019), or to experience a break from the pressures of daily life or standard employment (Gray & Suri, 2019).

Previous work has argued that an individual's level of financial need may impact the extent to which individuals are accessible for work opportunities, such that those with higher levels of financial need are less likely to uphold personal boundaries on digital connectivity (Ollier-Malaterre et al., 2019). For example, Gray and Suri (2019) labeled one subset of platform workers as "always on," referring to individuals that remain constantly tethered to the platform in order to avoid missing new work opportunities, often due to high levels of financial need. Further evidence for Ollier-Malaterre et al.'s (2019) proposition is provided through interviews with one form of gig workers (i.e, rideshare drivers), discussing the dilemma many drivers face in which they must choose between spending the most profitable hours (i.e., 6 – 9 am, 5 – 7 pm) driving or with their children (Rosenblat, 2018).

Financial need has been shown to impact the type of work an individual is drawn to (Vohs et al., 2006) and has been determined to be the most common motivation for individuals to pursue eLance tasks (Deng & Joshi, 2016). Further, among a sample of gig workers, the extent to which an individual was dependent on that source of income was found to have a direct impact on work experiences, such that those with lower financial dependence had greater satisfaction and control over work hours (Schor et al., 2020). Notably, the amount of financial compensation provided in a task has been shown to moderate previous relationships in an online platform work context, such as the relationships between task characteristics (i.e., autonomy, task variety, task identity, feedback) and satisfaction (Durward et al., 2020).

Attraction to tasks may differ among individuals with various levels of financial need, as workers seeking supplemental income may value favorable work practices (e.g., high levels of communication) more than those completing work out of dire financial need (Cassady et al., 2018). In other words, individuals who have high financial need are likely to place greater emphasis on the income received than the characteristics of the work, whereas workers low in financial need can afford to select attractive work tasks rather than strictly completing tasks with high compensation to meet income needs. As such, high levels of financial need may weaken relationships between attraction and selection.

Perceptions of work refers to the meaning that a work role holds in one's life (Rosso et al., 2010). Work meaning has been categorized into three conceptualizations: viewing work as a job (i.e., a focus on rewards rather than personal fulfillment), a career (i.e., a focus on progressing to higher status positions), and a calling (i.e., a focus on completing fulfilling work; Wrzesniewski et al., 1997). Although conceptualizing the term "job" slightly differently than Wrzesniewki et al.'s (1997) categorization, Keith et al. (2019) explored whether or not MTurk workers viewed their work on the platform as a job, in contrast to viewing MTurk work as a gig or side hustle. Results indicated that viewing MTurk work as a job was related to having a set schedule for work and completing more HITs per week and hours per week on the site than those who did not (Keither et al., 2019). As such, the way an individual views their MTurk work has been demonstrated to impact their behavior on the site.

In turn, scholars have argued that individuals may experience attraction to a specific field or type of work due to experiencing a sense of calling (Thompson & Christensen, 2018), with this sense of calling allowing individuals to focus on the innate meaning and value of their work (Hakala, 2009). Whereas individuals who view their work as a calling are likely to only select tasks that they experience strong attraction to, workers who view their work as a job or career may demonstrate a weaker relationship between attraction to and selection of tasks. As the interactions between attraction to task characteristics and work essentiality factors on selection of specific task characteristics has not been explored in previous research, the following research question is proposed on an exploratory basis:

> *Research Question 2 (RQ2):* Do work essentiality factors (i.e., financial need and perceptions of work) interact with attraction to task characteristics to predict selection of task characteristics?

Selection of Tasks Predicting Turnover Intentions

Recent work discussing the inconsistent nature of HRM in online platform work (i.e., high performance monitoring yet self-managed work design and training) has emphasized that research examining worker outcomes is imperative to monitor the effects of such work environments (Waldkirch et al., 2021). A variable that is of utmost interest in a traditional HRM environment is employee turnover, yet the applicability of turnover to nonstandard work contexts has been questioned (Cappelli & Keller, 2013). As such, the turnover intentions of individuals participating on online platforms has not received much attention to date (Ma et al., 2018). However, Kuhn and Maleki (2017) purport that the inflow and outflow of workers on such platforms is important to consider. For instance, they suggest that the global nature of MTurk in which large volumes of workers are constantly both entering and exiting the platform could be seen as a natural work cycle rather than high levels of turnover (Kuhn & Maleki, 2017).

In regard to Schroeder et al.'s (2021) proposed eLance work design outcomes, this effort will focus specifically on turnover intentions in the behavioral outcomes category in order to examine the attrition behavior of eLancers. Notably, in an online platform work context, some previous work has conceptualized turnover intention as a worker's desire to discontinue work on a specific platform entirely, rather than the discontinuation of a task for one requester to begin work for another (Ma et al., 2016). As such, the current effort adopts this perspective, with turnover intentions referring to intent to discontinue the completion of eLance work on MTurk entirely.

Turnover intentions are a construct of interest in the context of the ASA model and eLance research efforts alike. For instance, Shin (2004) theorized that in virtual organizations, compatibility between the characteristics of the person and their organization, work group, or job would result in decreased turnover intentions. In addition, Ma et al. (2018) found that active participation on MTurk (e.g., communicating with other members of the MTurk community, providing information to other MTurk workers) was negatively related to turnover intentions, which is a trend that continued across a period of several months.

From an eLance work design perspective, there is evidence to suggest that eLancers find certain work characteristics desirable, and therefore may be less likely to leave the role if those characteristics are present. For instance, Brawley and Pury (2016) found that task feedback predicted greater job satisfaction among some eLancers, which, in turn, predicted lower turnover behavior. As autonomy, task variety, task significance, and task clarity have been reported by eLancers as factors that motivate their participation and engagement in an eLance work environment (Deng & Joshi, 2016), it is likely that similar trends will occur for each task characteristic, such that higher levels of these characteristics will result in lower turnover intentions. As such, the following hypothesis is proposed:

Hypothesis 3 (H3): Selection of tasks with autonomy, task variety, task significance, task identity, feedback from the job, and task clarity will predict turnover intentions, such that performing work with higher levels of these characteristics will be linked to lower turnover intentions.

Mediating Effects

A key aspect of Schroeder et al.'s (2021) framework is the mediation effect that is expected to occur between phases of the eLance work design model. More specifically, the model is arranged such that the antecedent variables are proposed to predict worker outcomes via work characteristic design factors and mediating mechanisms. As the present effort aims to incorporate core ASA theory principles into this eLance work design model, thereby following the overall structure set forth by Schroeder et al. (2021), the following indirect effect is proposed:

Hypothesis 4 (H4): Personality factors are expected to predict turnover intentions via the mediating mechanisms of attraction to task characteristics and selection of task characteristics.

CHAPTER TWO: Method

Participants

Data were collected from 343 MTurk workers in the United States across two separate data collection efforts conducted 14 days apart. After removing outliers, the final sample was comprised of 325 individuals with an average age of 41.42 (*SD* = 12.11). The sample had almost equivalent representation of gender (52.6% male, 45.8% female), but not race (80.3% white). The most common education level was attainment of a Bachelor's degree (45.5%), followed by a Master's degree (16.9%) and having attended some college, but not obtaining a degree (15.1%). The sample was comprised of highly experienced MTurk workers, with the average number of approved HITs being 36,083.31 (*SD* = 144,204.81).

In order to account for attrition, the first round of data collection garnered approved responses from 524 individuals, ultimately retaining 343 of those respondents in the second survey effort, or 65% of the sample. This aligns with Keith et al.'s (2017) findings that longitudinal studies on MTurk typically experience an attrition rate around 30%. This sample size was determined based on the results of an a priori power analysis conducted using G*Power (Faul et al., 2009), which indicated that a sample of 242 participants was necessary to detect a medium effect size ($f^2 = 0.15$) with an alpha level of .05 and power level of 0.95. As the number of participants that would complete both surveys was unknown a priori due to attrition, the final sample size of 325 participants exceeds the minimum requirements of the power analysis.

As suggested by Deng et al. (2016), the sample was restricted to individuals in the United States in an effort to mitigate any confounds that many occur from cultural influences due to the fact that the desirability of task characteristics may differ across cultures. Further, in order to increase the likelihood that the sample would be representative of the eLancer work population and to avoid the risk of range restriction that arises from only sampling experienced, high-performing workers, minimal restrictions were applied for individuals to participate in the study. More specifically, in order to ensure that workers had experience evaluating and selecting tasks on MTurk, the only eligibility requirement for participants was the completion of 50 approved HITs in order to participate in the study. However, as the lack of enforcing strict performance requirements in order to participate in the study was likely to drastically increase the number of poor submissions and illegitimate survey completions by bots, a number of quality control assessments were included in various formats (see Appendix A). The final sample of participants includes only individuals who passed the screening measures implemented in Appendix A.

In addition, measures were taken in the survey to discourage bot participation, such as requiring respondents to complete a reCAPTCHA verification question and enabling a feature to prevent ballot box stuffing (i.e., several survey responses from the same IP address). Survey responses that failed two or more of the quality control questions by providing an incorrect survey response or an incoherent open-ended response were rejected and not included in the final sample. Each participant with an approved submission by the researcher was paid $1.80 upon completion of the first survey, which adheres to U.S. federal minimum wage standards, as the survey took the majority of respondents approximately 15 minutes to complete. For the second survey, workers with approved submissions received $1.20 for completing the survey, which took 10 minutes to complete, on average. Taken together, respondents who completed both surveys were compensated $3 each.

Design and Procedure

This study assessed participant demographics, personality, work essentiality, attraction to tasks, selection of tasks, and turnover intentions by way of a two-wave survey study design. Data were collected from participants at two different time points approximately 14 days apart, as longitudinal study designs are necessary when testing for mediation effects (Cole & Maxwell, 2003). The latency period between participant completion of both surveys was on par with the intended 14-day gap, as results indicated that an average of 14.28 days (*SD* = 0.64) elapsed between participant completion of both surveys.

It is important to note that in an eLance context there are unique concerns when conducting a time-series study, particularly in regard to measurement of turnover intentions. For example, high levels of turnover intentions in the first survey could result in eLancers exiting the work role prior to completion of the second survey, or range restriction of turnover intention scores may occur in the second survey, as all participants will have been eLancers for a continued period of time, therefore collectively exhibiting low turnover intentions.

In an attempt to mitigate these confounds, the first survey included measures of all variables (i.e., demographics, personality factors, attraction to task characteristics, selection of task characteristics, work essentiality factors, and turnover intentions), and the second survey assessed attraction to task characteristics, selection of task characteristics, work essentiality factors, and turnover intentions. Additional analyses, described below in the results section, were conducted to determine if turnover intentions in the first survey predicted completion of the second survey and to assess range restriction in turnover intentions during the second survey.

Measures

A description of each measure that was used is included below. Unless stated otherwise, each measure used a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Intercorrelations between all variables are provided in Table 1.

Personality Factors

For each personality factor, participants were asked to assess the extent to which each item described them in general. All personality factor measures are provided in Appendix B. Proactive personality was assessed with Seibert et al.'s (2001) 10-item scale. An example item is "I am constantly on the lookout for new ways to improve my life," and the Cronbach's alpha reliability coefficient for the scale was 0.90. Learning goal orientation was measured with the five-item scale developed by Brett and VandeWalle (1999), which had an alpha coefficient of 0.90. An example item is "I am willing to select a challenging work assignment that I can learn a lot from."

Need for achievement was assessed using Eisenberger et al.'s (2005) eight-item measure, which had an alpha reliability coefficient of 0.90. An example item is "I get the most satisfaction when completing job assignments that are fairly difficult." Self-efficacy was measured using Chen et al.'s (2001) eight-item New General Self-Efficacy Scale, which had an alpha reliability coefficient of 0.93. An example item is "I will be able to achieve most of the goals that I have set for myself." Psychological capital was assessed with a modified version of Luthans et al.'s (2006) Psychological Capital Questionnaire, which consists of 24 items and had a reliability coefficient of 0.93. Some items were modified in order to generally pertain to work, rather than context-specific statements such as "this job." An example item is "There are lots of ways around any problem."

The Big Five traits were evaluated using the Mini-IPIP developed by Donnellan et al. (2006). This scale consists of 20 items, with four items measuring each of the Big Five dimensions, and Cronbach's alpha reliability coefficients ranged from 0.70 to 0.80 for each subscale. Notably, the originators of this scale titled the construct traditionally referred to as "openness" instead as "intellect/imagination," but note that the intellect/imagination factor maps onto the construct of openness and that previous work has used the two terms interchangeably (John & Srivastava, 1999). In the present effort, the construct is referred to as openness for the sake of familiarity. Example items include "I sympathize with others' feelings" (agreeableness) and "I have a vivid imagination" (openness). Lastly, prosociality was measured using Grant's (2008b) three-item prosocial motivation scale, which demonstrated an alpha reliability coefficient of 0.94. An example item is "It is important to me to make a real difference in people's lives through my work."

Work Essentiality Factors

Financial need was assessed both using an objective metric and a self-report measure. The objective metric was calculated using an index developed by Shaw and Gupta (2001) evaluating relevant factors assessed in the demographic questions (i.e., marital status, number of children under the age of 18 in the household, other sources of income and financial support). The index scoring involved weighting married participants and those with children more heavily than single, non-parent respondents (i.e., respondents are assigned a score of 1 for being married and for each child in the household). In addition, a value of 0.5 was subtracted from the total for each individual in the house that works at least 20 hours per week and for each 20 hours worked by the participant in a role other than their MTurk work. After scoring took place, these values were summed for each participant, with scores ranging from -3.50 to 3.50, in which higher scores indicated greater financial need.

Participants were also asked to indicate their financial need on a self-report measure by indicating how they would classify their financial need without the income provided by their work on MTurk. The question was preceded with directions stating that when answering the question, they should consider essential expenses to be bills such as utilities or rent/mortgage, and nonessential expenses to be voluntary expenditures such as concert tickets. They were then provided with the statement “I would be able to pay for…,” with response options for essential and nonessential expenses listed separately, ranging from “no essential [nonessential] expenses” to “all essential [nonessential] expenses”, which were combined to represent an average self-reported financial need score. See Appendix C for all work essentiality items.

Perceptions of work were measured using the Work-Life Questionnaire developed by Wrzesniewski et al. (1997). Participants were provided with three separate paragraphs describing a job, career, and calling perspective of work, then rated their similarity to the situation on a scale from 1 (very unlike me) to 7 (very like me). For example, a section of the calling paragraph states, "Person C feels good about their work because they love it, and because they think it makes the world a better place."

Attraction to Task Characteristics

Attraction to task characteristics was measured by administering a measure for each characteristic and asking participants to indicate how attractive they find each of the HIT characteristics on MTurk on a scale ranging from 1 (not at all attractive) to 7 (extremely attractive). Autonomy (consisting of work scheduling, decision-making, and work methods subscales), task variety, task significance, task identity, and task feedback were measured using a modified version of Morgeson and Humphrey’s (2006) Work Design Questionnaire scale, which was revised to reference HITs rather than a specific job role and to add item stems that were germane with the prompt. Cronbach’s alpha reliability coefficients ranged from 0.88 to 0.95 for each of Morgeson & Humphrey’s five task characteristic scales across both survey efforts. Task clarity was assessed using a modified five-item role ambiguity scale from Peterson et al. (1995), with a reliability coefficient of 0.91 for both surveys. Each of these measures are provided in Appendix D.

Selection of Task Characteristics

To assess average selection of task characteristics, the same measures located in Appendix D were administered, but participants were instead instructed to indicate how often they complete tasks with those characteristics in the first survey and how often they had done so over the past 14 days in the second survey. Participants responded to these questions on a scale from 1 (never) to 7 (always). Cronbach's alpha reliability coefficients ranged from 0.91 to 0.96 for all task characteristic scales across both survey efforts. Notably, following the administration of these items in the second survey, participants were given an opportunity to note if there were factors that had prevented them from participating in HITs with certain characteristics (e.g., no HITs that allowed for decision-making were available in the past 14 days).

Turnover Intentions

Turnover intentions were measured using an adapted version of Nissly et al.'s four-item scale (2005; see Appendix E). This measure was revised to reference intentions to stop working through MTurk, rather than intentions to quit a job role. The Cronbach's alpha reliability coefficients across both survey efforts was 0.77.

Demographics

Basic demographic information was also collected from participants, such as age, gender, race, and education level. In addition, the previously mentioned information necessary to calculate the financial need index (i.e., marital status, number of children under the age of 18 in the household, number of individuals in house working 20 hours per week, number of sources of income outside of MTurk, hours per week individual has worked in non-MTurk jobs) was included in the demographic questions. Participants were also asked to provide details about what types of HITs they typically complete on MTurk (e.g., surveys, image tagging). Further, in the first survey, individuals were asked to provide the number of approved HITs they have completed on MTurk in order to meet eligibility criteria, and in the second survey were asked to provide the number of approved HITs they have completed in the last 14 days in order to be included as a covariate in analyses. In order to increase the likelihood that the reported number of HITs completed in the last 14 days was accurate, both survey phases were initially posted on MTurk on a Sunday, and participants were instructed to check their worker dashboard for accurate numbers, which shows HITs completed Sunday through Saturday of each week. All demographic questions are provided in Appendix F.

CHAPTER THREE: Results

Preliminary Analyses

Several preliminary analyses were conducted prior to testing hypotheses. Namely, it was important to confirm that the aforementioned complications with turnover intentions did not occur. Therefore, a logistic regression was conducted to determine if high turnover intentions in the first survey resulted in lower completion rates of the second survey. In examining the results, several indicators suggested that the logistic regression model was a poor fit for the data. For instance, turnover intention scores from the first survey were found to explain only 3% of variance in whether the second survey was completed (Nagelkerke $R^2 = .03$) and the Hosmer and Lemeshow Test yielded a significant chi-square, $\chi^2(8) = 18.21$, $p = .02$, indicating that the data (i.e., observed frequencies) were a poor fit to the model (i.e., estimated expected frequencies).

This poor fit between observed and expected frequencies is exemplified by the classification table, which demonstrated that the model only accurately predicted 0.6% of cases in which the second survey was not completed and predicted 100% of cases in which the second survey was completed, resulting in an overall classification accuracy rate of 65.6%, which falls below the typically acceptable threshold of 80% (Heidel, 2022). This poor model fit is problematic in that inferences drawn from such models may be incorrect due to unreliable estimates (Hosmer et al., 1991). This may be attributed to the low mean of turnover intent in the first survey (*M* = 2.84, *SD* = 1.35), indicating that there was limited variance in intent to turnover. In addition, the poor fit of this model could be due to the large number of factors that could contribute to failure to complete the second survey aside from having turned over in the survey timeframe, such as disliking the survey content or length.

Although logistic regression did not produce an interpretable result, the turnover intention scores from the second survey were examined for evidence of range restriction. This is likely to occur if all participants who completed the second survey demonstrated low intent to turnover. It was determined that turnover intention scores from the second survey did not demonstrate additional evidence of range restriction when compared to those from the first survey, as turnover intentions from the second survey effort (*M* = 2.85, *SD* = 1.41) demonstrated the same range in scores (i.e., scores ranged from 1 to 5.75 in both efforts) as the first survey effort (*M* = 2.84, *SD* = 1.35). As such, both efforts depicted a similarly wide array of perspectives regarding intent to turnover. Taken together, these results suggest that the turnover intention scores from the second survey were satisfactory to use in subsequent analyses.

Further, to determine if the number of paths in the model could be reduced, the dimensionality of the independent variables was tested to determine if parceling of variables was appropriate. Parceling (i.e., the combination of items) involves testing a group of items to determine if there is a unidimensional factor structure (Holt, 2004). If the items are determined to comprise one factor, all items can be parceled; however, if the items are determined to have a multidimensional factor structure, the items may be parceled into their appropriate factors or remain unparceled (Holt, 2004). Parceling is considered to be a valuable practice for testing models, as parceling can increase the stability of parameter estimates (Bandalos & Finney, 2001).

Notably, this approach has been used in instances of multicollinearity among variables in order to avoid reduced statistical power (Rosopa et al., 2013). As such, the personality factors (i.e., proactive personality, learning goal orientation, need for achievement, self-efficacy, psychological capital, the Big Five traits, and prosociality) and the work essentiality factors (i.e., financial need and perceptions of work) were tested for unidimensionality to determine if parceling was appropriate. Results of the tests of dimensionality indicated that the work essentiality items loaded on two disparate factors, therefore should not be parceled. In turn, examination of the factor loadings of all personality items revealed that the only constructs in which all items loaded onto the same factor with loadings greater than .30 were learning goal orientation and need for achievement. Therefore, those two constructs were parceled in subsequent analyses.

Model Comparisons

After these preliminary analyses were completed, a number of alternative path models were tested to determine which one represented the best fit to the data. Path analysis is an advanced form of multiple regression which permits testing of complex models (Streiner, 2005), and is a form of structural equation modeling that examines relationships between observed variables (Barbeau et al., 2019). Path analysis was determined to be more appropriate in the present effort than structural equation modeling (i.e., modeling latent factors) for a number of reasons. Namely, path analysis is recommended when testing models with smaller sample sizes, as it results in a smaller number of parameters estimated than a structural model, which includes additional paths between indicator and latent variables (Zacher & de Lange, 2011). In addition, all multi-item scales used in the study had been previously validated, therefore the structural equation modeling approach of testing the integrity of the measurement model through confirmatory factor analysis prior to the structural model was not necessary.

Prior to testing the path model, it was necessary to determine which measures of moderating variables collected should be used in the analyses (i.e., financial need index versus self-reported scores and job, career, or calling perceptions of work). Unexpectedly, as displayed in Table 1, the calculated financial need index and the self-reported financial need measure were found to be unrelated to one another (i.e., correlation coefficients ranged from .03 to .06 between measures at both time points). Examination of the relationships for each measure revealed that the self-reported financial need measure displayed expected trends across both survey waves (e.g., positively related to perceptions of MTurk work as a job, negatively related to attraction and selection of some task characteristics, positively related to turnover intentions).

This aligns with expectations, as people with high levels of financial need are likely to view MTurk as just a source of income that they plan to stop completing after financial needs are met, and it is likely less of a priority to them to ensure that their work is enriched with desirable task characteristics. However, in contrast, the financial need index demonstrated inconsistent findings across survey efforts (e.g., being positively related to viewing MTurk work as a calling in the first survey only and a career in the second survey only). As the former demonstrated a more reliable, anticipated pattern of results across surveys and as an individual’s perceptions of financial need are likely more relevant to their work selection decisions than objective metrics of need, the self-reported measure of financial need was used in subsequent analyses.

For the sake of parsimony in the number of paths estimated, it was also necessary to determine which variable should be used to test the moderating effects of perceptions of work (i.e., viewing MTurk work as a job, career, or calling). As noted previously, individuals who view their work as a calling may be likely to only select tasks that they experience strong attraction to, whereas workers who view their work as a job or career may demonstrate a weaker relationship between attraction to and selection of tasks. As self-reported financial need was found to be positively related to holding a job perspective on MTurk work, therefore demonstrating some level of similarity between those factors, calling was selected as the variable that would be used in analyses in order to diversify the moderating factors. Notably, following the methodology set forth by Konze et al. (2017) in which a similar analysis was conducted, the interaction terms to test moderation were created by multiplying the centered independent variables by the centered selected moderator variables from the first survey effort.

It is also critical that to ensure that six key assumptions of path analysis have been met prior to model testing (Barbeau et al., 2019). First, the data must consist of endogenous variables that are continuous or categorical in nature. This assumption is met in the present study as all endogenous variables were continuous. Second, there is an assumption that missing data have been deleted or imputed to ensure that same sample size for all regression equations. In the present study, the dataset was comprised only of participants that had completed both survey waves and had no missing data in responses.

Third, there is an assumption of normality. With the exception of the covariate (i.e., number of HITs completed in the last 14 days), the data were determined to be normal, with all variables adhering to the skewness (i.e., values ranging from -2 to 2) and kurtosis parameters (i.e., values ranging from -7 to 7) established in several efforts (Byrne, 2010; Hair et al., 2010; Kim, 2013). The covariate demonstrated indicators of non-normality, with a skewness value of 4.82 and a kurtosis value of 31.42. As these values of HITs completed in the last 14 days provide potentially valuable information about the activity level of participants during the survey latency period, a log transformation was conducted on this variable in order to ensure that it met the assumptions necessary for it to be incorporated into analyses. This transformation resulted in normality statistics within the acceptable range; therefore, the transformed variable was included as a covariate in subsequent analyses.

Fourth, there is an assumption that there are no outliers in the data. Examination of the Mahalanobis values indicated that there were 18 multivariate outliers, or cases that were outliers when accounting for multiple variables at once (Leys et al., 2019). These cases were removed from the dataset, resulting in a final sample size of 325. Notably, deletion of outliers was deemed appropriate for these cases, as they were determined to not be erroneous values due to data-entry or transcription errors (i.e., all outliers stemmed from scale-based variables in which an option was selected by participants rather than those in which they an open-ended text response; Aguinis et al., 2013).

Fifth, there is an assumption of low collinearity between variables. As no variables included in the path analysis had correlation coefficients greater than .85 (Kline, 2005), it was determined that multicollinearity was not a concern. It is important to note that the correlation coefficient between learning goal orientation and need for achievement exceeded this threshold, but those variables were previously determined to be unidimensional and were parceled in path analyses. As both the original and parceled versions of the variables appear in Table 1, those correlations also exceed .85, yet only the parceled variable was used in analyses. The parceled variable did not demonstrate correlation coefficients exceeding .85 with any other variables. Finally, the last assumption is that of adequate sample size, which was taken into consideration via the power analysis. Taken together, these assumptions were determined to be met.

All path analyses were conducted in R with the lavaan package (Rosseel, 2012), and models were tested using the maximum likelihood estimator, as is appropriate when normality of variable distributions has been demonstrated (Hayashi et al., 2010). In addition, parameter estimates were generated via 1000 bootstrapped iterations. Further, as was recommended by Konze et al. (2017), the alternative model testing process took place to determine the best-fitting structural model prior to adding code to test more advanced hypotheses (e.g., indirect effects). A summary of the model comparisons discussed below is provided in Table 2.

Models were evaluated on a number of fit statistics, including the comparative fit index (CFI), Tucker-Lewis Index (TLI), standardized root mean square residual index (SRMR), and root mean square error of approximation (RMSEA). Higher CFI and TLI values indicate better fit, with acceptably fitting models represented by values of .90 or higher, whereas lower SRMR and RMSEA values indicate better fitting models, with values below .08 considered to be acceptable (Bentler, 1990; 1995; Hu & Bentler, 1999; Kline, 2005; Steiger, 1990). The chi-square goodness-of-fit statistic is also reported and used to compare alternative models; however, there are some issues with using this test as a basis to evaluate models (e.g., sensitivity to sample size) without also considering the indices discussed previously (Bentler, 1990). With that being said, the lower the chi-square to degrees of freedom ratio is, the better the model fit is considered to be.

The first series of models tested were intended to examine substantive effects of the proposed model, prior to examining changes in effects over time. The first model tested, Model 1a, tested the fit of the model without moderation paths added, following suit with Konze et al. (2017). More specifically, in this model, personality and attraction to task characteristic scores from the first survey were used to predict selection of task characteristics and turnover intention scores from the second survey. The lapse between surveys was modeled between attraction to and selection of characteristics, as there was no reason to expect that the relationships between personality and attraction to task characteristics would vary over time. However, attraction to a characteristic and actual selection of that characteristic is a relationship that needs time to take place, as the ASA framework is a process that takes place over an extended period of time (Muchinsky, 2000).

As such, participants reported their baseline attraction, then the extent to which they actually selected that characteristic over a 14-day period. In addition, the number of HITs completed in the last 14 days was included as a covariate on the paths predicting variables collected in the second survey. All exogenous variables (i.e., personality) were allowed to covary, and the residual covariances between relevant endogenous variables were modeled (i.e., attraction variable residuals covaried with one another, as did selection variables).

The results of Model 1a indicated that this model demonstrated an excellent fit to the data: $\chi^2(46) = 80.95$, $p < .001$, CFI = .99, TLI = .95, SRMR = .03, RMSEA = .05. Examination of general trends across the parameter estimates indicated that various personality factors predicted attraction to task characteristics (e.g., prosocial orientation predicted greater attraction to task significance), and that attraction to task characteristics predicted increased selection of corresponding task characteristics, with the exception of feedback from the job. The only selection variable that predicted turnover intentions was feedback, which interestingly, had a positive coefficient.

The next model tested, Model 1b, was the originally hypothesized moderated serial mediation model (see Figure 2), which built upon Model 1a by incorporating the hypothesized moderating variables. Subjective financial need and calling were modeled as moderators on the relationship between attraction to and selection of task characteristics. In addition to the model covariances described in Model 1a, this model was specified such that additional exogenous variables were allowed to covary within their relevant groups (i.e., interaction terms including calling, interaction terms including financial need), in addition to specified covariation between interaction terms and variables that contained the same task characteristics. For example, the interaction term between calling and attraction to autonomy was specified to covary with the interaction term between financial need and attraction to autonomy.

Paths between disparate sets of exogenous variables (e.g., personality and the interactions between perceptions of work and attraction to task characteristics) were fixed to zero (i.e., covariances between these variables were not estimated in the model), as there is no theoretical reason to expect that there was a relationship that should be accounted for in the model. Results indicated that the initially hypothesized moderation model (Model 1b) represented a good fit to the data: $\chi^2(340) = 544.01$, $p < .001$, CFI = .97, TLI = .94, SRMR = .05, RMSEA = .04. Examination of the interaction terms revealed that the only significant interaction term was that between calling and attraction to task significance in predicting selection of tasks with task significance.

Notably, it is customary when testing complex models to test several competing versions of the model and compare the output to determine which represents the best fit to the data

(Werner & Schermelleh-Engel, 2010). Thus, in order to determine if steps could be taken to specify a model that represented a better fit to the data, the modification indices were examined. It is important to note that in the lavaan package, the modification indices only provide suggestions of parameters that are currently fixed in the model that can be freed to improve model fit (Rosseel, 2022). The modification indices output suggested modeling variables within relevant predictor groups to predict one another (e.g., selection of task clarity predicting selection of task identity), which does not have theoretical backing according to ASA or Schroeder et al.'s (2021) frameworks. As such, there was no theoretical justification to make these modifications to Model 1b in order to improve model fit.

However, in addition to examining which fixed paths can be freed to improve model fit, it is also important to consider which freely estimated paths can be fixed to determine if it results in a better fitting model. Examination of the parameter estimates revealed that psychological capital and the covariate variable (i.e., number of HITs completed in the last 14 days) did not significantly predict any paths in Model 1b. Therefore, Model 1c was tested in which these non-significant paths were fixed to zero (i.e., not estimated) to determine if it resulted in improved model fit. Results indicated that there was a significant difference between the models, $\Delta\chi^2 = 530.71$, $\Delta df = 28$. Model 1c resulted in a much larger chi-square value (1074.71) compared to the previous model (544.01). Therefore, Model 1b with these paths freely estimated was retained moving forward, as smaller chi-square to degrees of freedom ratios are indicative of better model fit.

On an exploratory basis, in order to confirm that the placement of the moderators in the model represented to the best fit to the data, an alternative model (Model 1d) was tested in which work essentiality variables were specified to moderate both the a paths (personality factors predicting attraction to task characteristics) and the b paths (attraction to task characteristics predicting selection of task characteristics). This recommendation was not made by the modification indices discussed for Model 1b, as it requires the addition of specific interaction terms between the moderating variables (i.e., calling and financial need) and personality factors into the model that were not previously present in Model 1b.

With the exception of the addition of the new interaction terms on the a paths and the specification of covariances between the personality moderators, personality moderators and personality variables, all calling moderators, and all financial need moderators, the remainder of the model was specified exactly the same as Model 1b. As the inclusion of the additional personality and moderator interaction variables resulted in an increased covariance matrix, thereby changing the degrees of freedom in the model, conducting a chi-square difference test between Model 1b and this model was not appropriate, as the models were not nested. However, the fit statistics for this model indicated that the Model 1d had worse fit than Model 1b, $\chi^2(890) = 1434.97$, $p < .001$, CFI = .95, TLI = .91, SRMR = .08, RMSEA = .04. Therefore, Model 1b was retained over Model 1d, and the additional moderation paths were not added.

After determining the best-fitting version of the originally hypothesized path model, more complicated models testing cross-lagged effects were examined. Cross-lagged path analysis is a form of path analysis that allows for examination of directional relationships between variables across time periods using longitudinal data (Kearney, 2017). Previous work has identified cross-lagged modeling as one of the most common approaches for analyzing longitudinal data (Jöreskog, 1970; 1979), offering benefits such as the ability to make stronger inferences about directionality of variables than cross-sectional models and the reduction of parameter bias (Selig & Preacher, 2009). Following the methodology set forth by Hakanen et al. (2008), a series of competing structural models were tested in order to investigate the nature of effects across time points. As the purpose of testing these competing models was to examine how to most appropriately model cross-lagged effects, Konze et al.'s (2017) methodology was mirrored, in which moderation effects were excluded from the model comparison process until the best-fitting model was selected.

The first time-series model tested was the stability model, which tested the effects of autoregressive paths between variables over time without any cross-lagged relations. Autoregressive paths in cross-lagged path analysis refer to the modeling of previous values of each variable as a predictor of later values to control for those effects and provide information on construct stability over time (Cain et al., 2018). Therefore, in this model, each variable collected across time points (i.e., all attraction and selection factors and turnover intent) was modeled such that the scores from the first survey predicted scores from the second survey. Variables within time points were allowed to covary, following Hakanen et al.'s (2008) and Konze et al.'s (2017) methodologies.

The stability model (Model 2a) demonstrated less than acceptable fit, $\chi^2(156) = 429.77$, $p < .001$, CFI = .92, TLI = .88, SRMR = .10, RMSEA = .07. Examination of the autoregressive effects indicated that each variable from the first survey significantly predicted their subsequent values. The autoregressive effects were moderate to strong, with regression coefficients ranging from 0.39 (attraction to task identity) to .80 (turnover intent). This indicates that variance between time points was minimal; therefore, variables were relatively stable over time (Kearney, 2017).

The next model tested was the causal model (Model 2b), in which the causal paths were added to the autoregressive effects from the stability model. It is important to note that personality factors were added to the following models to allow for examination of all modeled predictive effects, which had only been measured in the first survey. As such, subsequent models were non-nested from Model 2a. Exogenous variables and residuals of endogenous variables were specified to covary within their relevant groups (e.g., personality factors, time one attraction factors, time one selection factors) and corresponding attraction and selection factors were allowed to covary (e.g., attraction to autonomy at time one and selection of autonomy at time one). The causal model was determined to have less than acceptable fit, $\chi^2(374) = 1260.61$, $p < .001$, CFI = .89, TLI = .80, SRMR = .20, RMSEA = .09.

Next, a reverse causality model (Model 2c) was tested in which the ordering of the mediator and outcome variables were switched. More specifically, this model examined if personality predicted turnover intentions, which then predicted attraction to and selection of tasks. The reverse causality results revealed that there was no significant difference between this model and the causal model, $\Delta\chi^2 = 2.43$, $\Delta df = 0$. Therefore, the causal model was retained, as it had stronger theoretical backing than the reverse causality model. This adheres to Kline's (2005) recommendation that in the event of models fitting the data similarly, the model that aligns with theoretical expectations is preferable.

Finally, a reciprocal model was tested (Model 2d), which combines the causal and reverse causality models. The reciprocal model was not determined to be significantly different from the causal, $\Delta\chi^2 = 10.49$, $\Delta df = 12$, or reverse causality, $\Delta\chi^2 = 12.92$, $\Delta df = 12$, models. Therefore, it was determined that neither the reverse causality nor the reciprocal model improved model fit beyond the causal model. This adheres to the logic used by Hakanen et al. (2008) and Konze et al. (2017) in similar efforts, in which the causal model was selected when neither alternative model significantly improved fit; therefore, it was determined to be the best fitting model due to the law of parsimony. However, it is important to note that none of the cross-lagged models tested represented a particularly good fit to the data.

Thus, in order to determine if combining the best-fitting cross-lagged model with the best-fitting previously tested set of models resulted in acceptable model fit, Model 3a was tested. More specifically, this model combined the best-fitting originally proposed model (Model 1b) and the causal cross-lagged model (Model 2b). This model resulted in the best-fitting cross-lagged model, yet still fell below acceptable fit cutoffs, $\chi^2(824) = 1813.04$, $p < .001$, CFI = .89, TLI = .85, SRMR = .16, RMSEA = .06. Despite the methodological advantages offered by the cross-lagged analysis, Schimmack (2020) purports that it is difficult to justify interpreting parameters and drawing conclusions from a model that has been demonstrated to be a poor fit to the data. Therefore, the best-fitting model, Model 1b, was selected to test the hypotheses.

Hypothesis Testing

After the best-fitting model was selected, the hypotheses and research questions were tested. In testing *H1* (i.e., anticipating that personality factors would predict attraction to task characteristics, such that individuals with high levels of proactive personality, learning goal orientation, need for achievement, self-efficacy, psychological capital, the Big Five traits, and prosociality would experience greater attraction to tasks with more positive work design characteristics), the a paths in the path analysis were examined.

Results indicated that *H1* was partially supported, as almost all personality factors predicted attraction to at least one task characteristic (see Table 3 and Figure 3). However, unexpectedly, extraversion predicted decreased attraction to specific task characteristics (i.e., task identity and task clarity). Notably, psychological capital and proactive personality did not predict attraction to any task characteristics. All other personality factors significantly predicted increased attraction to at least one task characteristic. The learning goal orientation and need for achievement parceled variable and agreeableness were the factors that predicted attraction to the greatest number of characteristics, as they predicted attraction to four out of the six task characteristics. Again, these findings demonstrate partial support for *H1*.

These relationships were examined more closely in relation to *RQ1*, which sought to explore which specific attraction work characteristics (i.e., autonomy, task variety, task significance, task identity, feedback from the job, and task clarity) were predicted by personality factors. Results revealed that all six task attraction characteristics were significantly predicted by a minimum of two personality factors, although those factors differed across task characteristics. More specifically, increased attraction to autonomy was predicted by the learning goal orientation/need for achievement parceled variable and openness. In turn, increased attraction to task variety was predicted by greater learning goal orientation/need for achievement, self-efficacy, agreeableness, and prosociality. Further, increased attraction to task significance was predicted by greater agreeableness and prosociality. In turn, when examining attraction to feedback from the job, results indicated that greater learning goal orientation/need for achievement, self-efficacy, and neuroticism predicted increased attraction.

However, a few situations demonstrated differing effects of personality factors on attraction to task characteristics. For example, agreeableness and prosociality predicted increased attraction to task identity, whereas extraversion predicted decreased attraction to task identity. Likewise, agreeableness and conscientiousness predicted increased attraction to task clarity, whereas extraversion predicted decreased attraction. However, as discussed in more detail below, it is likely that this effect was spurious in nature. As such, in answering *RQ1*, all attraction work characteristics were predicted by select personality factors, although effects pertaining to extraversion were in an unanticipated direction.

Next, the results were examined in relation to *H2,* which proposed that attraction to task characteristics would predict selection of tasks with corresponding characteristics, such that a) autonomy attraction will predict greater selection of tasks with autonomy, b) task variety attraction will predict greater selection of tasks with task variety, c) task significance attraction will predict greater selection of tasks with task significance, d) task identity attraction will predict greater selection of tasks with task identity, e) feedback from the job attraction will predict greater selection of tasks with feedback from the job, and f) task clarity attraction will predict greater selection of tasks with task clarity. As depicted in Table 3 and Figure 3, the results indicated that each of the attraction characteristics positively predicted their corresponding selection characteristic, with the exception of feedback from the job. As such, *H2* was partially supported, as *H2a, H2b, H2c, H2d,* and *H2f* were supported, but *H2e* was not.

Next, to examine *RQ2*, which questioned if work essentiality factors (i.e., financial need and perceptions of work) interact with attraction to task characteristics to predict selection of task characteristics, the interactions between the attraction factors and moderators were tested. One significant interaction emerged, which was the interaction between calling and attraction to task significance in predicting selection of task significance.

In order to examine the possibility of additional untested significant interactions, Model 1b was rerun with the remaining perceptions of work variables included (i.e., interactions between holding a career perspective of MTurk work and attraction to task characteristics and those between holding a job perspective and attraction to task characteristics). This analysis resulted in one significant interaction term, which was that between having a career perspective of MTurk work and attraction to task variety in predicting selection of task variety (*p* = .03). There were no significant interactions involving holding a job perspective on work.

The simple slopes of both significant interactions were plotted to probe these interactions at low (-1 SD) and high (+1 SD) levels of calling and career perceptions of work. Results indicated that attraction to task significance was significantly related to selection of task significance at low, $\beta = .84$, $p < .001$, mean, $\beta = .75$, $p < .001$, and high levels of calling, $\beta = .66$, $p < .001$ (see Figure 4). However, these results are surprising in that they demonstrate that attraction to task significance became a weaker predictor of selection of task significance as perceptions of viewing MTurk work as a calling increased. In turn, attraction to task variety was found to be significantly related to selection of task variety at low, $\beta = .71$, $p < .001$, mean, $\beta = .75$, $p < .001$, and high levels of the career perception of work, $\beta = .79$, $p < .001$ (see Figure 5). This indicates that viewing MTurk work as a career strengthened the relationship between attraction to and selection of task variety, such that attraction to task variety became a stronger predictor of selection of task variety as career perceptions increased. Taken together, these results aid in answering *RQ2*, revealing that specific perceptions of work factors (i.e., calling and career perceptions) interacted with attraction factors (i.e., task significance and task variety, respectively) to predict selection of those task characteristics.

In turn, *H3* proposed that selection of tasks with autonomy, task variety, task significance, task identity, feedback from the job, and task clarity would predict turnover intentions, such that performing work with higher levels of these characteristics would be linked to lower turnover intentions. Interestingly, the results indicated that only selection of one task characteristic, feedback from the job, predicted increased turnover intentions. This represented a departure from the expected trend of this relationship, which was that increased feedback from the job would predict decreased turnover intentions. Therefore, *H3* was not supported.

Next, *H4* was tested, which proposed that personality factors would predict turnover intentions via the mediating mechanisms of attraction to task characteristics and selection of task characteristics. To test this, indirect effects involving only significant paths were examined, which resulted in the testing of 19 indirect effects. Examination of the results (see Table 4) revealed that there were no significant indirect effects. This is not surprising, as only one selection factor (i.e., feedback from the job) was predictive of turnover intentions, and selection of tasks that provided feedback from the job was not predicted by attraction to that task characteristic. As such, *H4* was not supported.

However, given the strength of predictors in the portions of the mediation model prior to the paths predicting turnover intentions, additional indirect effects were tested on an exploratory basis. More specifically, abbreviated versions of the previous indirect effects were tested that only included personality traits, attraction, and selection factors, thereby removing the latter paths to turnover intentions. This revealed a number of significant indirect effects. Namely, the learning goal orientation/need for achievement parcel, self-efficacy, and extraversion each individually predicted selection of task variety via attraction to task variety. Further, learning goal orientation/need for achievement, agreeableness, and prosociality predicted selection of task identity via attraction to task identity, and extraversion and agreeableness predicted selection of task clarity via attraction to task clarity. Finally, prosociality predicted selection of task significance via the mediating mechanism of attraction to task significance. Although these findings do not provide support for *H4*, they do reveal important information about the nature of the personality, attraction, and selection links.

CHAPTER FOUR: Discussion

The purpose of the present effort was to empirically test Schroeder et al.'s (2021) eLance work design theoretical model through the lens of the ASA framework. More specifically, the mechanisms by which eLancers on MTurk are attracted to tasks, select tasks, and intend to leave the eLance work role were investigated. Study results indicated that an eLancer's personality was predictive of attraction to specific task characteristics in a number of cases and that attraction to a given task characteristic was predictive of greater selection of that characteristic, with the exception of one factor (i.e., feedback from the job).

However, selection of desirable task characteristics did not predict decreased turnover intentions. There were no indirect effects of personality on turnover intentions via attraction and selection factors, but there were indirect effects of personality on selection factors via attraction. Finally, two significant interactions emerged, demonstrating that one's perceptions of work (i.e., holding a calling or career perspective on MTurk work) can, in certain cases, impact the relationships between attraction and selection of task characteristics. Taken together, this information begins to demonstrate the extent to which ASA theory is applicable to an eLance work context and serves as an initial empirical test of Schroeder et al.'s (2021) theoretical eLance work design framework.

However, there were some unexpected results that warrant discussion. For instance, variable intercorrelations revealed that the two financial need measures (i.e., an objective index and a subjective self-rating) had different effects and were not significantly related to one another. Roll et al. (2019) note that most research examining financial need uses objective metrics, but argues that this is problematic because subjective evaluations may be more accurate because they allow participants to assess factors that may fall outside of the data points used to calculate financial need. Further, self-evaluations of financial need may be more impactful on work decisions than objective factors, as an individual's perceptions of the severity of their financial state presumably impacts their work selection behaviors to a greater extent than clear-cut facts about income. Therefore, the objective index used in the present effort may not have captured all necessary information needed to align with subjective assessments, and the use of the subjective measure in analyses likely was more relevant because it captured participant perceptions, which is likely to impact behavior. However, even the subjective measure did not result in any significant interactions involving financial need, which may be due to the low levels of financial need and minimal variation between participants reported in the sample (i.e., average scores of 2.34 and 2.36 with standard deviations of 0.85 on a 7-point scale).

Furthermore, an iterative model testing process revealed that models including cross-lagged effects demonstrated poorer fit than non-cross-lagged models. This is likely because of the high stability of effects over time that were demonstrated, such that minimal changes in scores occurred across study time periods. As such, it was not necessary to model the variables across time points, and doing so resulted in a less parsimonious model without much value added. Stated differently, it complicated the model without adding additional explanatory information regarding changes in effects over time. Therefore, the better-fitting model without autoregressive paths was used to test hypotheses.

In turn, the nature of the predictive effects of extraversion on attraction factors was contrary to expectations, with extraversion predicting decreased attraction to task identity and task clarity. As extraversion was not predictive of increased attraction to any task characteristics, it is possible that the sociable and talkative nature of extraverts resulted in decreased attraction to the MTurk work environment in general, which manifested in these specific relationships.

However, as these relationships were not significant in Table 1, it is likely that extraversion served as a suppressor effect in the path analysis. Stated differently, the negative predictive effects of extraversion on attraction to task identity and task clarity may be spurious in nature, therefore should be interpreted with extreme caution. On another note, Table 1 demonstrated that the mean for extraversion was notably lower than the means for the remainder of the Big Five items (excluding neuroticism), therefore there may have been range restriction of extraversion in this sample.

Another surprising finding was that feedback attraction was the only attraction task characteristic that did not predict subsequent selection of that task characteristic. When indicating if there were any factors that prevented them from selecting a specific type of HIT over the past 14 days, a number of participants noted that there were few HITs available to them in that time frame in general, which could have impacted their ability to select HITs that provide feedback from the job. In addition, it is possible that even if HITs were available to workers, there was still a lack of HITs specifically providing feedback from the job. Alternatively, as feedback in standard roles is often sought out in order to improve performance, it is possible that HITs offering feedback from the job were not selected by workers as they do not have an incentive to improve (e.g., promotion) or a consistent party monitoring for improvement in task performance over time.

An additional unexpected finding pertaining to feedback from the job was that it predicted increased turnover intent. Related to this, it is interesting to note that attraction to feedback was the only attraction characteristic to predict turnover intent, and it predicted decreased intent to turnover, whereas selection of feedback was the only significant selection characteristic, which predicted increased intent to turnover. It is possible that desired feedback from the job (e.g., a signal at the end of a HIT indicating performance) is attractive to participants, thereby decreasing turnover intent, whereas actual feedback received from the job is not what participants anticipated, thereby increasing turnover intent. An example of this may be if feedback on HIT performance was only received in the event of rejected work, therefore resulting in frustration and increased intent to stop completing work on MTurk. Stated differently, the nature of feedback received could result in differential effects, such that desired feedback (i.e., attraction to feedback) may differ from actual feedback received (i.e., selection of feedback). This may explain these differential effects of attraction to and selection of feedback on turnover intent.

It was also contrary to expectations that the majority of selection factors did not predict turnover intent. However, given that Williams et al. (2021) noted in their investigation of the ASA framework within eLance work that the attrition aspect of the ASA model is less visible in this work context, it is not entirely surprising that there were not strong links to intent to turnover from the eLancer role. These findings provide support for Williams et al.'s (2021) conclusion that attraction and selection are more relevant to an eLance work context than attrition. Another potential explanation for this finding could be that there are external factors impacting intent to turnover from the eLancing role that were not assessed in this study (i.e., those outside of work design or work essentiality factors) or that long-term intent to turnover is present regardless of the nature of the tasks completed, therefore the type of work selected was not the strongest predictor of this intent.

In addition, it is important to consider that in the present effort, turnover intent spanned all HITs to reference intent to leave the eLance role. This more closely mirrors the ASA framework in a standard work context, but is also the only aspect of the model tested in this study that refers to the role collectively, which could explain the lack of demonstrated predictors of turnover intent. Alternatively, although turnover intention scores from the second survey were not found to be more range-restricted than those from the first survey, it is still possible that range restriction occurred. More specifically, as the mean turnover intention scores ranged from 2.84 to 2.85 on a 7-point scale across both survey efforts, it is evident that turnover intentions were collectively low for this sample. When considering the high level of experience with this sample, which had an average of over 36,000 completed HITs, it is not surprising that this sample had low intent to turnover, as they would likely have done so prior to gaining this level of experience. Taken together, there are a number of potential explanations for the lack of support for this segment of the model.

On this note, it is important to consider that perhaps unlike the manner in which turnover intent is conceptualized in a standard work context, high turnover intentions from the eLance work role may not always be considered a negative outcome. As the work environment has been considered by some to be exploitative and unjust (e.g., Gray & Suri, 2019; Pittman & Sheehan, 2016), not to mention low-paying and not requiring expertise in a particular area (Webster, 2016), individuals may view eLance work as a stepping stone to more skilled work or simply an avenue in which one can make money in a pinch. As such, feedback from the job predicting increased intent to turnover may not be problematic, as it could mean that eLancers are gaining experience needed to move on to more highly skilled and higher paying work. Stated differently, increased intent to turnover could actually be a positive outcome for eLancers.

The last unexpected effect was the manner in which calling moderated the relationship between attraction to and selection of task significance, finding that this relationship was weakened as the extent to which an individual viewed MTurk work as a calling increased. A potential explanation for this finding could be that at high levels of calling, attraction to all types of task characteristics is important to such individuals, as they view their work on MTurk to be extremely meaningful in general. However, for those with low levels of calling, they may need strong significance of tasks in order to experience attraction to a form of work. This could explain why individual with low levels of calling demonstrated the strongest relationship between attraction to and selection of task significance, rather than those that reported high levels of a calling perspective on work. It is important to note that given the number of interactions tested and the small number of significant interactions that emerged, it is possible that this was a spurious effect that occurred by chance rather than a meaningful effect.

Theoretical Implications

It is important to consider how the findings of this study align with each stage of the ASA process, as well as Schroeder et al.'s (2021) theoretical eLance work design framework. The present effort provided support for ASA's proposition that individuals select work environments that are congruent with their personalities. This is demonstrated by the strong links between specific personality traits and attraction to certain task characteristics. For instance, the finding that prosocial individuals have increased attraction to MTurk HITs that provide task significance aligns with ASA theory's expectation of homogeneity with one's work environment, such that individuals will choose work environments that align with their personal characteristics. In addition, this provides support for Schroeder et al.'s proposition that average levels of task characteristics present in work may be reflective of a worker's personal characteristics.

Furthermore, for all factors except feedback from the job, attraction to task characteristics was predictive of subsequent selection of those characteristics. This demonstrates partial support for the attraction to selection link of the ASA framework. However, there was little to no support provided for the selection to attrition aspect of the model. As mentioned previously, this aligns with Williams et al.'s (2021) conclusion that the attrition aspect of the framework is less relevant than the attraction and selection components within this specific segment of workers. As such, these findings suggest that it cannot be said that the ASA model is fully applicable to this unique work context.

Schroeder et al.'s (2021) model suggested both an indirect effect of personality on outcomes via work characteristics and proposed that work essentiality factors would be predictors of work characteristics. Although the order of mediators differs in the present effort to what was proposed in the original model, the evidence provided here does demonstrate that no indirect effects involving the outcome of turnover intentions were present. However, the findings do demonstrate that personality is predictive of the work characteristics present in one's work, as theorized by the work design model. Although modeled as predictors rather than moderators in the original model, career and calling perceptions of work were found to interact with attraction to some characteristics to predict the presence of specific task characteristics in one's work. As such, this effort provides support for and serves as the first empirical test of aspects of Schroeder et al.'s (2021) eLance work design model.

It is also important to note that these findings may also provide indirect support for P-J theory in an MTurk work context. Notably, Schulze et al. (2012) had posited that in regard to P-J fit's applicability to this work context, the fit between the worker and MTurk tasks may predict intention to select tasks (Schulze et al., 2012). Given the alignment between specific personality traits and task characteristics noted above (e.g., prosociality and task significance), this could demonstrate a form of fit between the individual and the task. Further, as select indirect effects were found among the personality, attraction, and selection links, this could indicate that the alignment between personality and attraction could, perhaps, jointly be predictive of selection. To reiterate, P-J theory was not directly being tested in this study, but these findings demonstrate interesting alignment with Schulze's propositions regarding how P-J fit may manifest in an MTurk work context.

Practical Implications

Taken together, these results shed valuable light on the work design considerations of eLancers. The findings of this study have important implications, as they provide information that MTurk requesters can use to benefit workers by designing their tasks in order to be enjoyable and beneficial to workers. To this point, several efforts have taken the stance that requesters on MTurk should be motivated, and perhaps even ethically obligated, to create the best work environment possible for workers, as well as design work to meet worker needs and specific skill sets (see, e.g., Parent-Rouchelau & Parker, 2021; Parker & Grote, 2020; Schroeder et al., 2021). As the eLance workforce houses individuals with innumerable skills, abilities, and digital experiences (Colbert et al., 2016), MTurk is a conduit for work enrichment, as workers can design their work to fit their desired specifications (Deng et al., 2016). However, workers cannot do such if they do not have tasks with these characteristics available to them, or if such HITs are available yet poorly described, thereby failing to highlight the presence of these task characteristics in the work.

eLancers being unaware of the task characteristics provided by a potential HIT appears to be a prevalent issue, as highlighted frequently by participants in the present effort when sharing information about factors that prevented them from selecting HITs with specific characteristics. This issue offers valuable insight into the link between attraction to and selection of tasks, as participants may be unable to intentionally select tasks. This was certainly exemplified in the present effort, as the strongest link between attraction to and selection of a given characteristic was with task identity, resulting in a coefficient of .34. As task characteristics are often the mechanisms through which eLancers design their own work (Bush & Balven, 2021; Connelly et al., 2021), this is a pressing issue that is perhaps resulting in poor worker-task fit, which would be detrimental to eLancers and requesters alike.

As such, MTurk requesters should ensure that they take all possible measures needed to allow eLancers to engage in job crafting behaviors. The benefits of job crafting in other work arrangements were detailed previously, including increased career commitment and resilience (Wong et al., 2021), greater perceptions of meaningfulness, and stronger identification with work (Tims & Bakker, 2010; Wrzesniewski & Dutton, 2001). Therefore, in the spirit of promoting well-being among eLancers, requesters should make an intentional effort to provide workers with information that enables them to job craft, thereby providing an avenue for these beneficial outcomes. Such behaviors requesters can take to do so include being extremely detailed in the HIT descriptions, specifically describing not only the task but also the work characteristics provided in it to provide workers with the information needed to make meaningful work decisions. Doing so would, in addition, decrease the risk of misalignment between workers and tasks highlighted by Bush and Balven (2021), and enable eLancers to select tasks that are well-aligned with their expertise and interests.

In addition, the findings of this study provide information that requesters can use to attract specific types of workers to their tasks that hold desirable characteristics (e.g., conscientiousness). ASA theory posits that recruitment activities are key to attracting candidates that align with the hiring organization (Schneider, 1987), therefore the methods by which requesters recruit eLancers (i.e., HIT descriptions) are key to which types of workers they attract.

This aligns with Dan et al.'s (2021) recommendation that strategies that can be taken to attract digital workers include providing information about specifically what can be expected in the role in regard to task specifications. As such, if a requester wanted to make an effort to attract conscientious workers, the results of this study suggest that they should not only post tasks with high levels of task clarity, but also advertise the HIT as one that is clearly defined in regard to expectations.

In order to aid researchers in thoughtfully designing their HITs and understanding the implications of their work design decisions, a guide is presented in Table 5 that provides a quick reference point to inform researchers about which task characteristics were demonstrated to attract specific types of worker personalities. This will not only aid in enactment of the recommendations above, but also can inform researchers about the types of workers that they may be unintentionally attracting when posting a specific type of HIT. This information can also make researchers aware of potential range restriction of participants in their work, as these findings show that some personality factors demonstrated decreased attraction to specific types of work. Taken together, the findings of this study have significant implications for practice in the manner that eLance work is designed, advertised, and selected.

Limitations and Future Directions

Despite the strengths of this study, there are limitations to note. Notably, causation should not be solely determined from models using observational data (see, e.g., Selig & Little, 2012); however, the present effort deployed a longitudinal design in an effort to strengthen the causal inferences that can be made from these findings. Nevertheless, future work should attempt a cross-lagged model with additional time points and perhaps with longer time periods elapsed between survey waves to provide stronger evidence for causation. It is also important to highlight that as the reverse causality model demonstrated similar fit statistics to the causality model, there may be additional ways to model the variables examined in the present effort, which is an area of exploration for future work. In addition, there is much to be done in future work in regard to examining additional moderation options. For instance, as the model with additional moderation paths included (Model 1d) was ultimately not retained, future work should examine not only moderators not included in this study, but also various placement of moderation paths to determine if there are meaningful interactions taking place.

In turn, the sample size of this study offers an additional limitation. Although the literature suggests having between 10 and 20 participants per model parameter estimated, this is not particularly feasible for an effort such as this, in which a large model with hundreds of parameters is estimated and resources are limited. As such, this may impact the reliability of parameter estimates (Suhr, 2008). Future work should evaluate this model with larger sample sizes to confirm the replicability of parameter estimates.

Further, a common concern when collecting data about eLancers via a survey-based HIT is that the HIT may oversample individuals who have an innate preference for survey work (Gray et al., 2016), therefore there is a potential for selection bias. To mitigate this concern, the HIT was posted on MTurk with tags for a wide array of work, which is a practice that has been used in similar efforts (Gray et al., 2016). Therefore, if a worker was searching MTurk only looking for image tagging work, for example, the HIT would still appear on their dashboard, thereby capturing a broader audience of workers. In addition, future research should examine the differential effects of types of feedback provided from HITs on eLancer outcomes, such as turnover intentions.

An additional consideration is that due to the nature of the study in which the full eLance population was of interest, the study HIT could not have stringent qualifications placed on participation, as is typical for most MTurk HITs. For example, a significant number of MTurk HITs are specified such that they are only available workers with a 99% approval rate, or those that have completed thousands of approved HITs. If that tactic were used in the posting of this study's HIT, the risk of range restriction would be extremely high, as participants would consist of only high-quality, experienced workers. As such, it is possible that careless respondents slipped through the numerous quality control precautions used to screen responses, potentially reducing the quality of the data. An additional limitation to note is that participants may have experienced survey fatigue due to the large number and repetitive nature of survey items, therefore responses provided towards the end of the survey may be of lower quality than those answered at an earlier point.

Another area of consideration for studies examining this unique population is that perhaps the levels of personality characteristics present in this sample differ from the broader U.S. population, given the unexpected direction of extraversion's effects on attraction to task characteristics and the range restriction of extraversion in comparison to other Big Five characteristics. As such, future MTurk research efforts should examine levels of personality traits (e.g., introversion and extraversion) among this sample to determine if representativeness differs in this environment.

Although this study represents an initial empirical examination of eLance work design practices, there is still much work to be done. Namely, some factors in Schroeder et al.'s (2021) theoretical model were excluded due to the lack of alignment with the ASA model, which was the guiding framework for the selection of variables to be included in this study. As such, future empirical efforts to examine additional variables in the conceptual eLance work design model are needed to further explore the concepts presented in the Schroeder et al. (2021) article. An additional avenue for work investigating the applicability of existing theory to eLance work should directly test P-J theory among MTurk workers, given the indirect evidence provided by these findings.

Conclusion

Taken together, this study offers novel insight into how eLancers are attracted to and select eLance work tasks. As eLancing is a nontraditional selection process in which individuals self-select into work tasks by way of job crafting practices, testing an existing eLance work design model while acknowledging additional considerations raised by the ASA theory is necessary to understand this unique work process and the mechanisms by which it takes place. Such investigation is particularly timely, as the number of individuals engaging in gig work is increasing as a result of job loss from the COVID-19 pandemic (Semuels, 2020) and as research is lacking on eLancer attitudes and behavior (Cascio & Boudreau, 2017). As such, it is becoming increasingly important to understand the process by which eLancers select work tasks.

The results of this study indicate that an eLancer's personality does, in many cases, predict which types of task characteristics they are attracted to and select. In addition, for the majority of task characteristics, attraction to task characteristic predicts increased selection of that characteristic. These findings provide some support for portions of the ASA model within an eLancing context and aspects of Schroeder et al.'s (2021) eLance work design model. Notably, increased knowledge on this topic is likely to have significant implications for eLancers and MTurk requesters alike. For instance, the findings of this study can not only help workers select tasks that are most closely aligned with their personal characteristics, but can also inform requesters about which characteristics should be present in work to attract a specific group of workers (e.g., workers with high levels of self-efficacy). Taken together, these findings have the potential to benefit many parties in the eLance work environment.

References

Aguinis, H., & Lawal, S. O. (2013). eLancing: A review and research agenda for bridging the science–practice gap. *Human Resource Management Review, 23*(1), 6–17. https://doi.org/10.1016/j.hrmr.2012.06.003

Allen, T. D., & O'Brien, K. E. (2006). Formal mentoring programs and organizational attraction. *Human Resource Development Quarterly*, *17*(1), 43-58. https://doi.org/10.1002/hrdq.1160

Amazon Mechanical Turk. (2018). *FAQs.* https://www.mturk.com/worker/help

Appelbaum, E., Kalleberg, A., and Rho, H.J. (2019). Nonstandard work arrangements and older Americans, 2005–2017. *Washington, DC: Center for Economic and Policy Research and Economic Policy Institute*. Retrieved from https://files.epi.org/pdf/162673.pdf

Arruda, W. (2020, July 12). *6 trends that will shape the gig economy in the 2020s.* Forbes. https://www.forbes.com/sites/williamarruda/2020/07/12/6-trends-that-will-shape-the-gig-economy-in-the-2020s/?sh=19a49ed71565

Ashford, S. J., Caza, B. B., & Reid, E. M. (2018). From surviving to thriving in the gig economy: A research agenda for individuals in the new world of work. *Research in Organizational Behavior, 38*, 23–41. https://doi.org/10.1016/j.riob.2018.11.001

Ashford, S. J., George, E., & Blatt, R. (2007). Old assumptions, new work: The opportunities and challenges of research on non-standard employment. *The Academy of Management Annals, 1*, 65-117. https://doi.org/10.1080/078559807

Asseburg, J., Hattke, J., Hensel, D., Homberg, F., & Vogel, R. (2020). The tacit dimension of public sector attraction in multi-incentive settings. *Journal of Public Administration Research and Theory*, *30*(1), 41-59. https://doi.org/10.1093/jopart/muz004

Bandalos, D. L., & Finney, S. J. (2001). Item parceling issues in structural equation modeling. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling: New developments and techniques.* Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Bandura, A. (1997). *Se!f-efficacy: The exercise of control.* New York, NY: Freeman.

Barbeau, K., Boileau, K., Sarr, F., & Smith, K. (2019). Path analysis in Mplus: A tutorial using a conceptual model of psychological and behavioral antecedents of bulimic symptoms in young adults. *The Quantitative Methods for Psychology*, *15*(1), 38-53. https://doi.org/10.20982/tqmp.15.1.p038

Barratt, T., Goods, C., & Veen, A. (2020). 'I'm my own boss…': Active intermediation and 'entrepreneurial' worker agency in the australian gig-economy. *Environment and Planning. A, 52*(8), 1643-1661. https://doi.org/10.1177/0308518X20914346

Barrick, M. R. & Mount, M. K. (1991). The Big Five personality dimensions and job performance: A meta-analysis. *Personnel Psychology, 44*, 1-26. https://doi.org/10.1111/j.1744-6570.1991.tb00688.x

Barrick, M. R., & Mount, M. K. (1993). Autonomy as a moderator of the relationships between the Big Five personality dimensions and job performance. *Journal of Applied Psychology*, *78*(1), 111-118. https://doi.org/10.1037/0021-9010.78.1.111

Bateman, T. S., & Crant, J. M. (1993). The proactive component of organizational behavior: A measure and correlates. *Journal of Organizational Behavior, 14*, 103–118. https://doi.org/10.1002/job.4030140202

Berg, J. (2016). Income security in the on-demand economy: Findings and policy lessons from a survey of crowdworkers. *Comparative Labor Law & Policy Journal, 37*(3), 543–576.

Bentler, P. M. (1990). Comparative fit indices in structural models. *Psychological Bulletin*, *107*, 238–246.

Bentler, P. M. (1995). *Eqs structural equations program manual*. Encino, CA: Multivariate Software.

Brawley, A. M. (2017). The big, gig picture: We can't assume the same constructs matter. *Industrial and Organizational Psychology*, *10*(4), 687-696. https://doi.org/10.1017/iop.2017.77

Brawley, A. M., & Pury, C. L. (2016). Work experiences on MTurk: Job satisfaction, turnover, and information sharing. *Computers in Human Behavior, 54*, 531–546. https://doi.org/10.1016/j.chb.2015.08.031

Brett, J. F., & VandeWalle, D. (1999). Goal orientation and goal content as predictors of performance in a training program. *Journal of Applied Psychology, 84,* 863–873. https://doi.org/10.1037/0021-9010.84.6.863

Bretz, R. D., Ash, R. A., & Dreher, G. F. (1989). Do people make the place? An examination of the Attraction-Selection-Attrition hypothesis. *Personnel Psychology, 42*(3), 561–581. https://doi.org/10.1111/j.1744-6570.1989.tb00669.x

Bricka, T. M., & Schroeder, A. N. (2019). What's the gig deal? examining contemporary work issues in the gig economy. *Industrial and Organizational Psychology, 12*(4), 491-494. https://doi.org/10.1017/iop.2019.116

Bricka, T. M., & Schroeder, A. N. (2021, April). Not my type: Creating a typology of paid employment. In A. N. Schroeder & T. M. Bricka, *Generalizing nonstandard work doesn't work: Examining nonstandard work heterogeneity.* Symposium presented at the 36th annual Society for Industrial and Organizational Psychology Conference, New Orleans, LA.

Brown, D. J., Cober, R. T., Kane, K., Levy, P. E., & Shalhoop, J. (2006). Proactive personality and the successful job search: A field investigation with college graduates. *Journal of Applied Psychology, 91*(3), 717-726. https://doi.org/10.1037/0021-9010.91.3.717

Browne, R. (2021, February 19). *Uber loses a major employment rights case as the UK's top court rules its drivers are workers.* CNBC. https://www.cnbc.com/2021/02/19/uk-supreme-court-rules-uber-drivers-are-workers-not-contractors.html

Buettner, R. (2015, January). A systematic literature review of crowdsourcing research from a human resource management perspective. In *2015 48th Hawaii International Conference on System Sciences* (pp. 4609-4618). IEEE.

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality data? *Perspectives on Psychological Science, 6*(1), 3-5. https://doi.org/10.1177/1745691610393980

Bush, J. T., & Balven, R. M. (2021;2018;). Catering to the crowd: An HRM perspective on crowd worker engagement. *Human Resource Management Review, 31*(1), 100670. https://doi.org/10.1016/j.hrmr.2018.10.003

Byrne, B. M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming.* New York, NY: Routledge.

Cai, W., Lysova, E. I., Bossink, B. A., Khapova, S. N., & Wang, W. (2019). Psychological capital and self-reported employee creativity: The moderating role of supervisor support and job characteristics. *Creativity and Innovation Management*, *28*(1), 30-41. https://doi.org/10.1111/caim.12277

Cain, M. K., Zhang, Z., & Bergeman, C. S. (2018). Time and other considerations in mediation design. *Educational and psychological measurement*, *78*(6), 952–972. https://doi.org/10.1177/0013164417743003

Cappelli, P., & Keller, J. (2013). Classifying work in the new economy. *Academy of Management Review, 38*(4), 575–596. https://doi.org/10.5465/amr.2011.0302

Carless, S. A. (2005). Person-job fit versus person-organization fit as predictors of organizational attraction and job acceptance intentions: A longitudinal study. *Journal of Occupational and Organizational Psychology, 78*(3), 411–429. https://doi.org/10.1348/096317905x25995

Cascio, W. F., & Boudreau, J. W. (2017). Talent management of nonstandard employees. In D. G. Collings, K. Mellahi, & W. F. Cascio (Eds.), *The Oxford handbook of talent management*. https://doi.org/10.1093/oxfordhb/9780198758273.013.3

Cassady, E. A., Fisher, S., & Olsen, S. E. (2018). Using eHRM to manage workers in the platform economy. In J. H. Dulebohn, & D. L. Stone (Eds.). *The brave new world of eHRM 2.0* (pp. 217–246). Charlotte, NC: Information Age Publishing.

Chen, G., Gully, S. M., & Eden, D. (2001). Validation of a new general self-efficacy scale. *Organizational Research Methods, 4*, 62–83. https://doi.org/10.1177/109442810141004

Chen, W. C., Suri, S., & Gray, M. L. (2019, July). More than money: Correlation among worker demographics, motivations, and participation in online labor market. In *Proceedings of the International AAAI Conference on Web and Social Media* (Vol. 13, pp. 134-145).

Chmielewski, M., & Kucker, S. C. (2020). An MTurk crisis? Shifts in data quality and the impact on study results. *Social Psychological and Personality Science*, *11*(4), 464-473. https://doi.org/10.1177/1948550619875149

Choi, Y., & Chung, I. H. (2017). Attraction-selection and socialization of work values: Evidence from longitudinal survey. *Public Personnel Management, 46*(1), 66-88. https://doi.org/10.1177/0091026017696397

Colbert, A., Yee, N., & George, G. (2016). The digital workforce and the workplace of the future. *Academy of Management Journal, 59*, 731–739. https://doi.org/10.5465/amj.2016.4003

Cole, D. A., & Maxwell, S. E. (2003). Testing mediational models with longitudinal data: Questions and tips in the use of structural equation modeling. *Journal of Abnormal Psychology, 112*, 558–577. https://doi.org/10.1037/0021-843x.112.4.558

Conger, K. (2020, November 4). *Uber and Lyft drivers in California will remain contractors.* The New York Times. https://www.nytimes.com/2020/11/04/technology/california-uber-lyft-prop-22.html

Conklin, A. (2019, December 19). *Why the gig economy is popular: Americans love a side hustle.* FOX Business. https://www.foxbusiness.com/markets/gig-economy-popular-america

Connelly, C. E., Fieseler, C., Černe, M., Giessner, S. R., & Wong, S. I. (2021). Working in the digitized economy: HRM theory & practice. *Human Resource Management Review, 31*(1), 100762. https://doi.org/10.1016/j.hrmr.2020.100762

Dan, S., Ivana, D., Zaharie, M., Metz, D., & Drăgan, M. (2021). Digital talent management strategies and practices. In *Digital talent management* (pp. 29-45). Palgrave Macmillan. https://doi.org/10.1007/978-3-030-76750-1_3

Deng, X., & Joshi, K. D. (2016). Why individuals participate in micro-task crowdsourcing work environment: Revealing crowdworkers' perceptions. *Journal of the*

Association for Information Systems, 17, 648–673. https://doi.org/10.17705/1jais.00441

Deng, X., Joshi, K. D., & Galliers, R. D. (2016). The duality of empowerment and marginalization in microtask crowdsourcing: Giving voice to the less powerful through value sensitive design. *MIS Quarterly, 40*, 279–302. https://doi.org/10.25300/misq/2016/40.2.01

de Vreede, T. (2016). *Let the ideas flow: Antecedents of engagement in community-based crowdsourcing* (Doctoral dissertation, University of Nebraska at Omaha).

Difallah, D. E., Catasta, M., Demartini, G., Ipeirotis, P. G., & Cudré-Mauroux, P. (2015). The dynamics of micro-task crowdsourcing: The case of Amazon MTurk. In *Proceedings of the 24th International Conference on World Wide Web, International World Wide Web Conferences Steering Committee,* pp 238-247.

Donnellan, M. B., Frederick, L. O., Brendan, M. B., & Richard E. L. (2006). The Mini-IPIP Scales: Tiny-yet-effective measures of the Big Five factors of personality. *American Psychological Association, 18,* 192-203. https://doi.org/10.1037//1040-3590.18.2.192

Durward, D., Blohm, I., & Leimeister, J. M. (2020). The nature of crowd work and its effects on individuals' work perception. *Journal of Management Information Systems, 37*(1), 66-95. https://doi.org/10.1080/07421222.2019.1705506

Ehrhart, K. H., & Ziegert, J. C. (2005). Why are individuals attracted to organizations? *Journal of Management*, *31*(6), 901-919. https://doi.org/10.1177/0149206305279759

Eidelson, J. (2021, February 17). *The gig economy is coming for millions of American jobs.* Bloomberg Businessweek. https://www.bloomberg.com/news/features/2021-02-17/gig-economy-coming-for-millions-of-u-s-jobs-after-california-s-uber-lyft-vote

Eisenberger, R., Jones, J. R., Stinglhamber, F., Shanock, L., & Randall, A. T. (2005). Flow experiences at work: For high need achievers alone? *Journal of Organizational Behavior, 26,* 755–775. https://doi.org/10.1002/job.337

Ellmer, M., & Reichel, A. (2018). Crowdwork from an HRM perspective–integrating organizational performance and employee welfare. *University of Salzburg: Working Paper, 1.*

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*, 1149-1160.

Ford, R. C., Richard, B., & Ciuchta, M. P. (2015). Crowdsourcing: A new way of employing non-employees? *Business Horizons, 58,* 377-388. https://doi.org/10.1016/j.bushor.2015.03.003

Goldsmith, K. A., Chalder, T., White, P. D., Sharpe, M., & Pickles, A. (2018b). Measurement error, time lag, unmeasured confounding: Considerations for longitudinal estimation of the effect of a mediator in randomised clinical trials. *Statistical Methods in Medical esearch*, *27*(6), 1615-1633.

Goldsmith, K. A., MacKinnon, D. P., Chalder, T., White, P. D., Sharpe, M., & Pickles, A. (2018a). Tutorial: The practical application of longitudinal structural equation mediation models in clinical trials. *Psychological Methods*, *23*(2), 191-221.

Grant, A. M. (2007). Relational job design and the motivation to make a prosocial difference. *Academy of Management Review*, *32*(2), 393-417. https://doi.org/10.5465/amr.2007.24351328

Grant, A. M. (2008a). Does intrinsic motivation fuel the prosocial fire? Motivational synergy in predicting persistence, performance, and productivity. *Journal of Applied Psychology*, *93*(1), 48-58. https://doi.org/10.1037/0021-9010.93.1.48

Grant, A. M. (2008b). Designing jobs to do good: Dimensions and psychological consequences of prosocial job characteristics. *The Journal of Positive Psychology, 3*(1), 19-39. https://doi.org/10.1080/17439760701751012

Gray, M. L., & Suri, S. (2019). *Ghost work: How to stop Silicon Valley from building a new global underclass*. Eamon Dolan Books.

Gray, M. L., Suri, S., Ali, S. S., & Kulkarni, D. (2016, February). The crowd is a collaborative network. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (pp. 134-147).

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational Behavior and Human Performance, 16*, 250–279. https://doi.org/10.1016/0030-5073(76)90016-7

Hakala, J. (2009). The future of the academic calling? Junior researchers in the entrepreneurial university. *Higher Education*, *57*(2), 173-190. https://doi.org/10.1007/s10734-008-9140-6

Hakanen, J. J., Schaufeli, W. B., & Ahola, K. (2008). The Job Demands-Resources model: A three-year cross-lagged study of burnout, depression, commitment, and work engagement. *Work & Stress*, *22*(3), 224-241.

Hair, J., Black, W. C., Babin, B. J. & Anderson, R. E. (2010). *Multivariate data analysis (7th ed.)*. New Jersey, NJ: Pearson Educational International.

Hayashi, K., Bentler, P. M., & Yuan, K. H. (2010). Structural equation modeling. In C. R. Rao, J. P. Miller, and D. C. Rao (Eds.), *Essential statistical methods for medical statistics* (pp. 202-234).

Haynes, M. (2020, February 13). *Top 10 workplace trends for 2020.* Society for Industrial and Organizational Psychology. https://www.siop.org/Research-Publications/Items-of-Interest/ArtMID/19366/ArticleID/3361/Top-10-Workplace-Trends-for-2020

Heidel, E. (2022). Logistic regression. Retrieved from https://www.scalestatistics.com/logistic-regression.html.

Holt, J. K. (2004, October). Item parceling in structural equation models for optimum solutions. In *Annual Meeting of the Mid-Western Educational Research Association* (pp. 2-7).

Hosmer, D. W., Taber, S., & Lemeshow, S. (1991). The importance of assessing the fit of logistic regression models: A case study. *American Journal of Public Health*, *81*(12), 1630-1635.

Howe, J. (2008). *Crowdsourcing: How the power of the crowd is driving the future of business*. Random House.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*, 1–55. https://doi.org/10.1080/10705519909540118

Iacurci, G. (2020, February 4). *The gig economy has ballooned by 6 million people since 2010. Financial worries may follow.* CNBC. https://www.cnbc.com/2020/02/04/gig-economy-grows-15percent-over-past-decade-adp-report.html

International Labour Organization. (2021). *Helping the gig economy work better for gig workers.* https://www.ilo.org/washington/WCMS_642303/lang--en/index.htm

Ipeirotis, P. G. (2010). Demographics of Mechanical Turk *(Tech. Rep. No. CeDER-10-01)*. New York: New York University. Retrieved from http://hdl.handle.net/2451/29585

Jackson, D. N. (1974). *Personality Research Form manual* (2nd ed). Port Huron, MI: Research Psychologists Press.

John, O. P., & Srivastava, S. (1999). The Big Five trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of Personality: Theory and Research* (2nd ed., pp. 102–138). New York, NY: Guilford Press.

Jones, D. A., Willness, C. R., & Madey, S. (2014). Why are job seekers attracted by corporate social performance? Experimental and field tests of three signal-based mechanisms. *Academy of Management Journal*, *57*(2), 383-404. https://doi.org/10.5465/amj.2011.0848

Jordan, M., Herriot, P., & Chalmers, C. (1991). Testing Schneider's ASA theory. *Applied Psychology*, *40*(1), 47-53. https://doi.org/10.1111/j.1464-0597.1991.tb01357.x

Jöreskog, K. G. (1970). Estimation and testing of simplex models. *British Journal of Mathematical and Statistical Psychology*, *23*, 121–145.

Jöreskog, K. (1979). Statistical estimation of structural models in longitudinal developmental investi- gations. In J. R. Nesselroade & P. B. Baltes (Eds.), *Longitudinal research in the study of behavior and development*. (pp. 129–169) New York, NY: Academic Press.

Judge, T. A., & Cable, D. M. (1997). Applicant personality, organizational culture, and organization attraction. *Personnel Psychology*, *50*(2), 359-394. https://doi.org/10.1111/j.1744-6570.1997.tb00912.x

Kalleberg, A. L. (2000). Nonstandard employment relations: Part-time, temporary and contract work. *Annual Review of Sociology, 26*, 341-365. https://doi.org/10.1146/annurev.soc.26.1.341

Kalleberg, A., Rasell, E., Cassirer, N., Reskin, B. F., Hudson, K., & Webster, D., Appelbaum, E., & Spalter-Roth, R. (1997). Nonstandard work, substandard jobs. Flexible work arrangements in the U.S. *Economic Policy Institute.*

Kalleberg, A. L., Reskin, B. F., & Hudson, K. (2000). Bad jobs in America: Standard and nonstandard employment relations and job quality in the United States. *American Sociological Review, 65(2),* 256-278. https://doi.org/10.2307/2657440

Kao, R.-H. (2017). Task-oriented work characteristics, self-efficacy, and service-oriented organizational citizenship behavior. *Personnel Review, 46*(4), 718–739. https://doi.org/10.1108/pr-08-2015-0234

Kearney, M. W. (2017). Cross lagged panel analysis. In M. R. Allen (Ed.), *The SAGE Encyclopedia of Communication Research Methods.* Thousand Oaks, CA: Sage.

Keith, M. G., Tay, L., & Harms, P. D. (2017). Systems perspective of Amazon Mechanical Turk for organizational research: Review and recommendations. *Frontiers in Psychology*, *8*(1359), 1-19. https://doi.org/10.3389/fpsyg.2017.01359

Keith, M. G., Harms, P., & Tay, L. (2019). Mechanical turk and the gig economy: Exploring differences between gig workers. *Journal of Managerial Psychology, 34*(4), 286-306. https://doi.org/10.1108/JMP-06-2018-0228

Kim, E. T. (2020, January 10). *The gig economy is coming for your job.* The New York Times. https://www.nytimes.com/2020/01/10/opinion/sunday/gig-economy-unemployment-automation.html

Kim, H. J., Shin, K. H., & Swanger, N. (2009). Burnout and engagement: A comparative analysis using the Big Five personality dimensions. *International Journal of Hospitality Management*, *28*(1), 96-104. https://doi.org/10.1016/j.ijhm.2008.06.001

Kim, H.-Y. (2013). Statistical notes for clinical researchers: Assessing normal distribution using skewness and kurtosis. *Restorative Dentistry and Endontics, 38,* 52– 54. https://doi.org/10.5395/rde.2013.38.1.52

Kittur, A., Nickerson, J. V., Bernstein, M., Gerber, E., Shaw, A., Zimmerman, J., ... & Horton, J. (2013, February). The future of crowd work. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work* (pp. 1301-1318).

Kline, R. B. (2005). *Principles and practice of structural equation modeling (2nd ed.).* New York, NY: Guilford.

Konze, A. K., Rivkin, W., & Schmidt, K. H. (2017). Is job control a double-edged sword? A cross-lagged panel study on the interplay of quantitative workload, emotional dissonance, and job control on emotional exhaustion. *International journal of environmental research and public health*, *14*(12), 1608-1630.

Kristof-Brown, A. L., Zimmerman, R. D., & Johnson, E. C. (2005). Consequences of individuals' fit at work: A meta-analysis of person–job, person–organization, person–group, and person–supervisor fit. *Personnel Psychology, 58*(2), 281-342. https://doi.org/10.1111/j.1744-6570.2005.00672.x

Kuhn, K. M., & Maleki, A. (2017). Micro-entrepreneurs, dependent contractors, and instaserfs: Understanding online labor platform workforces. *Academy of Management Perspectives, 31*(3), 183-200. https://doi.org/10.5465/amp.2015.0111

Lewin, K. (1935). *Dynamic theory of personality*. New York, NY: McGraw-Hill.

Lievens, F., Decaesteker, C., Coetsier, P., & Geirnaert, J. (2001). Organizational attractiveness for prospective applicants: A Person–Organisation fit perspective. *Applied Psychology, 50*(1), 30-51. https://doi.org/10.1111/1464-0597.00047

Selig, J. P., & Little, T. D. (2012). Autoregressive and cross-lagged panel analysis for longitudinal data. In B. Laursen, T. D. Little, & N. A. Card (Eds.), *Handbook of developmental research methods* (pp. 265–278). The Guilford Press.

Leys, C., Delacre, M., Mora, Y. L., Lakens, D., & Ley, C. (2019). How to classify, detect, and manage univariate and multivariate outliers, with emphasis on pre-registration. *International Review of Social Psychology*, *32*(1), 1-28.

Luthans, F., Avolio, B. J., Avey, J. B., & Norman, S. M. (2007). Positive psychological capital: Measurement and relationship with performance and satisfaction. *Personnel Psychology*, *60*, 541-572. https://doi.org/10.1111/j.1744-6570.2007.00083.x

Luthans, F., & Youssef, C. (2004). Human, social and now positive psychological capital management: Investing in people for competitive advantage. *Organizational Dynamics, 33*, 143–160. https://doi.org/10.1016/j.orgdyn.2004.01.003

Ma, X., Khansa, L., & Hou, J. (2016). Toward a contextual theory of turnover intention in online crowdworking. In *Proceedings of the 37th International Conference on Information Systems,* Dublin, Ireland.

Ma, X., Khansa, L., & Kim, S. S. (2018). Active community participation and crowdworking turnover: A longitudinal model and empirical test of three mechanisms. *Journal of Management Information Systems, 35*(4), 1154-1187. https://doi.org/10.1080/07421222.2018.1523587

Malik, N., & Dhar, R. L. (2017). Authentic leadership and its impact on extra role behavior of nurses. *Personnel Review, 46*, 277–296. https://doi.org/10.1108/PR-05- 2015-0140

MasterCard. (2019). The global gig economy: Capitalizing on a ~$500B opportunity. Retrieved from https://newsroom.mastercard.com/wp-content/uploads/2019/05/Gig-Economy-White-Paper-May-2019.pdf

Meijerink, J., & Keegan, A. (2019). Conceptualizing human resource management in the gig economy: Toward a platform ecosystem perspective. *Journal of Managerial Psychology, 34*(4), 214-232. https://doi.org/10.1108/JMP-07-2018-0277

Morgeson, F. P., & Campion, M. A. (2003). Work design. In W. Borman, D. Ilgen, & R. Klimoski (Eds.). *Handbook of psychology: Industrial and organizational psychology* (pp. 423–452). Hoboken, NJ: Wiley.

Morgeson, F. P., & Humphrey, S. E. (2006). The work design questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology, 91*, 1321–1339. https://doi.org/10.1037/0021-9010.91.6.1321

Muchinsky, P. M. (2000). *Psychology applied to work: An introduction to industrial and organizational psychology*. Wadsworth/Thomson Learning.

Murray, H. A. (1938). *Explorations in personality*. New York, NY: Oxford University Press.

Nissly, J. A., Barak, M. E. M., & Levin, A. (2005). Stress, social support, and workers' intentions to leave their jobs in public child welfare. *Administration in Social Work*, *29*, 79-100. https://doi.org/10.1300/j147v29n01_06

Ollier-Malaterre, A., Jacobs, J. A., & Rothbard, N. P. (2019). Technology, work, and family: Digital cultural capital and boundary management. *Annual Review of Sociology, 45*(1), 425-447. https://doi.org/10.1146/annurev-soc-073018-022433

O'Reilly, C. A., Chatman, J., & Caldwell, D. F. (1991). People and organizational culture: A profile comparison approach to assessing person-organization fit. *Academy of Management Journal, 34*(3), 487-516. https://doi.org/10.2307/256404

Parker, S. K., & Grote, G. (2020). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology: An International Review, 0*(0), 1-45. https://doi.org/10.1111/apps.12241

Pedulla, D. S. & Mueller-Gastell, K. (2019). Nonstandard work and the job search process: Application pools, search methods, and perceived job quality. *RSF: The Russell Sage Foundation Journal of the Social Sciences, 5*(4), 130-158. https://doi.org/10.7758/rsf.2019.5.4.05

Peterson, M. F., Smith, P. B., Akande, A., Ayestaran, S., Bochner, S., Callan, V., Cho, N. G., Jesuino, J. C., D'Amorim, M., Francois, P., Hofmann, K., Koopman, P. L., Leung, K., Lim, T. K., Mortazavi, S., Munene, J., Radford, M., Ropo, A., Savage, G., Setiadi, B., Sinha, T. N., Sorenson, R., & Viedge, C. (1995). Role conflict, ambiguity, and overload: A 21-nation study. *Academy of Management Journal, 38,* 429-452.

Pittman, M., & Sheehan, K. (2016). Amazon's Mechanical Turk a digital sweatshop? Transparency and accountability in crowdsourced online research. *Journal of Media Ethics*, *31*(4), 260-262.

Posner, B. Z. (1982). Person-organization values congruence: No support for individual differences as a moderating influence. *Human Relations, 45,* 351-361. https://doi.org/10.1177/001872679204500403

Posner, B. Z., Kouzes, J. M., & Schmidt, W. H. (1985). Shared values make a difference: An empirical test of corporate culture. *Human Resource Management, 24,* 293-309. https://doi.org/10.1002/hrm.3930240305

Prieto, L. C. (2010). The influence of proactive personality on social entrepreneurial intentions among African American and Hispanic undergraduate students: The moderating role of hope. (Doctoral dissertation, Louisiana State University).

Robyn, C. M., & Mitonga-Monga, J. (2017). Psychological capital and work engagement in relation to employee commitment in a South African manufacturing organisation. *Journal of Contemporary Management*, *14*(1), 702-730.

Roll, S., Kondratjeva, O., & Grinstein-Weiss, M. (2019, December 13). Financial well-being: Measuring financial perceptions and experiences in low- and moderate-income households. *Brookings.* Retrieved from https://www.brookings.edu/blog/up-front/2019/12/13/financial-well-being-measuring-financial-perceptions-and-experiences-in-low-and-moderate-income-households/

Rosenblat, A. (2018). *Uberland: How algorithms are rewriting the rules of work* (1st ed.). University of California Press. https://doi.org/10.1525/j.ctv5cgbm3

Rosopa, P. J., Schroeder, A. N., & Hulett, A. L. (2013). Helping yourself by helping others: Examining personality perceptions. *Journal of Managerial Psychology, 28*(2), 147-163. https://doi.org/10.1108/02683941311300676

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*, 1-36.

Rosseel, Y. (2022). The lavaan tutorial. Retrieved from https://lavaan.ugent.be/tutorial/tutorial.pdf

Rosso, B. D., Dekas, K. H., & Wrzesniewski, A. (2010). On the meaning of work: A theoretical integration and review. *Research in Organizational Behavior, 30*, 91–127. https://doi.org/10.1016/j.riob.2010.09.001

Ryan, A. M., & Wessel, J. L. (2015). Implications of a changing workforce and workplace for justice perceptions and expectations. *Human Resource Management Review, 25*(2)*,* 162–175. https://doi.org/10.1016/j.hrmr.2015.01.001

Schimmack, U. (2020). *Why most cross lagged models are false*. Retrieved from https://replicationindex.com/2020/08/22/cross-lagged/

Schneider, B. (1987). The people make the place. *Personnel Psychology, 40,* 437–453. https://doi.org/10.1111/j.1744-6570.1987.tb00609.x

Schneider, B., Goldstein, H. W., & Smith, D. B. (1995). The ASA framework: An update. *Personnel Psychology*, *48*(4), 747-773. https://doi.org/10.1111/j.1744-6570.1995.tb01780.x

Schneider, B., Smith, D. B., & Goldstein, H. W. (2000). *Attraction–selection–attrition: Toward a person–environment psychology of organizations.* In W. B. Walsh, K. H. Craik, & R. H. Price (Eds.), *Person–environment psychology: New directions and perspectives* (p. 61–85). Lawrence Erlbaum Associates Publishers.

Schneider, B., Smith, D. B., Taylor, S., & Fleenor, J. (1998). Personality and organizations: A test of the homogeneity of personality hypothesis. *Journal of Applied Psychology, 83*(3), 462–470. https://doi.org/10.1037/0021-9010.83.3.462

Schor, J. B., Attwood-Charles, W., Cansoy, M., Ladegaard, I., & Wengronowitz, R. (2020). Dependence and precarity in the platform economy. *Theory and Society, 49*(5-6), 833-861. https://doi.org/10.1007/s11186-020-09408-y

Schroeder, A. N., Bricka, T. M., & Whitaker, J. H. (2021). Work design in a digitized gig economy. *Human Resource Management Review*, *31*(1), 100692. https://doi.org/10.1016/j.hrmr.2019.100692

Schulze, T., Krug, S., & Schader, M. (2012). *Workers' task choice in crowdsourcing and human computation markets.* Paper presented at the 33rd International Conference on Information Systems, Orlando, FL.

Seegers, G., & Boekaerts, M. (1993). Task motivation and mathematics achievement in actual task situations. *Learning and Instruction*, *3*(2), 133-150. https://doi.org/10.1016/0959-4752(93)90012-o

Seibert, S. E., Kraimer, M. L., & Crant, J. M. (2001). What do proactive people do? A longitudinal model linking proactive personality and career success. *Personnel Psychology, 54*, 845-874. https://doi.org/10.1111/j.1744-6570.2001.tb00234.x

Selig, J. P., & Preacher, K. J. (2009). Mediation models for longitudinal data in developmental research. *Research in Human Development*, *6*(2-3), 144-164.

Semuels, A. (2020, May 15). *'It's a race to the bottom.' The coronavirus is cutting into gig worker incomes as the newly jobless flood apps.* TIME. https://time.com/5836868/gig-economy-coronavirus/

Shaw, J. D., & Gupta, N. (2001). Pay fairness and employee outcomes: Exacerbation and attenuation effects of financial need. *Journal of Occupational and Organizational Psychology, 74*, 299-320. https://doi.org/10.1348/096317901167370

Shin, Y. (2004). A person-environment fit model for virtual organizations. *Journal of Management, 30*(5), 725–743. https://doi.org/10.1016/j.jm.2004.03.002

Slaughter, J. E., & Greguras, G. J. (2009). Initial attraction to organizations: The influence of trait inferences. *International Journal of Selection and Assessment*, *17*(1), 1-18. https://doi.org/10.1111/j.1468-2389.2009.00447.x

Slaughter, J. E., Stanton, J. M., Mohr, D. C., & Schoel III, W. A. (2005). The interaction of attraction and selection: Implications for college recruitment and Schneider's ASA model. *Applied Psychology: An International Review*, *54*(4), 419-441. https://doi.org/10.1111/j.1464-0597.2005.00218.x

Slaughter, J. E., Zickar, M. J., Highhouse, S., & Mohr, D. C. (2004). Personality trait inferences about organizations: Development of a measure and assessment of construct validity. *Journal of Applied Psychology*, *89*(1), 85-103. https://doi.org/10.1037/0021-9010.89.1.85

Smith, R., and Leberstein, S. (2015). *Rights on demand: Ensuring workplace standards and worker security in the on-demand economy.* National Employment Law Project. https://www.nelp.org/wp-content/uploads/Rights-On-Demand-Report.pdf

Smith, S. M., Roster, C. A., Golden, L. L., & Albaum, G. S. (2016). A multi-group analysis of online survey respondent data quality: Comparing a regular USA consumer panel to MTurk samples. *Journal of Business Research*, *69*(8), 3139-3148. http://doi.org/10.1016/j.jbusres.2015.12.002

Stark, A. (2021, January 20). *Top 10 work trends for 2021.* Society for Industrial and Organizational Psychology. https://www.siop.org/Research-Publications/Items-of-Interest/ArtMID/19366/ArticleID/4914/Top-10-Work-Trends-for-2021

Steers, R. M. (1987). Murray's manifest needs theory. In R. Steers & L. Porter (Eds.), *Motivation and work behavior* (pp. 59-67). New York: McGraw-Hill.

Steers, R. M., & Spencer, D. G. (1977). The role of achievement motivation in job design. *Journal of Applied Psychology, 62*, 472–479. https://doi.org/10.1037/0021-9010.62.4.472

Steiger, J. H. (1990). Structural model evaluation and modification: An internal estimation approach. *Multivariate Behavioral Research*, *25*, 173–180.

Streiner, D. L. (2005). Finding our way: an introduction to path analysis. *The Canadian Journal of Psychiatry*, *50*(2), 115-122. https://doi.org/10.1177/070674370505000207

Stoica, P., & Marzetta, T. L. (2001). Parameter estimation problems with singular information matrices. *IEEE Transactions on Signal Processing, 49*(1), 87-90. https://doi.org/10.1109/78.890346

Suhr, D. (2008, November). Step your way through path analysis. In *Western Users of SAS Software Conference Proceedings*. Retrieved from https://www.lexjansen.com/wuss/2008/pos/pos04.pdf

Taylor, F. W. (1911). *Principles of scientific management*. New York, NY: Harper.

Thompson, J. A., & Christensen, R. K. (2018). Bridging the public service motivation and calling literatures. *Public Administration Review*, *78*(3), 444-456. https://doi.org/10.1111/puar.12913

Tikhonov, A. (2019). Applying of employer branding system in the IT-companies' human resource management. *ESPACIOS Magazine, 40*(38), 23-29.

Tims, M., & Bakker, A. B. (2010). Job crafting: Towards a new model of individual job redesign. *SA Journal of Industrial Psychology, 36*, 1–9. https://doi.org/10.4102/sajip.v36i2.841

Todd, S. Y., & Kent, A. (2006). Direct and indirect effects of task characteristics on organizational citizenship behavior. *North American Journal of Psychology*, *8*(2), 253-268.

Torpey, E., & Hogan, A. (2016). Working in a gig economy. *Bureau of Labor Statistics.* Retrieved from https://www.bls.gov/careeroutlook/2016/article/what-is-the-gig-economy.htm

Tornau, K., & Frese, M. (2013). Construct clean-up in proactivity research: A meta-analysis on the nomological net of work-related proactivity concepts and their incremental validities. *Applied Psychology, 62*, 44–96. https://doi.org/10.1111/j.1464-0597.2012.00514.x

Turban, D. B., & Keon, T. L. (1993). Organizational attractiveness: An interactionist perspective. *Journal of Applied Psychology, 78*(2), 184–193. https://doi.org/10.1037/0021-9010.78.2.184

United Kingdom Parliament. (2017, April 29). Self-employment and the gig economy. https://publications.parliament.uk/pa/cm201617/cmselect/cmworpen/847/84704.htm

VandeWalle, D., Cron, W. L., & Slocum, J. W. (2001). The role of goal orientation following performance feedback. *Journal of Applied Psychology, 86*, 629–640. https://doi.org/10.1037/0021-9010.86.4.629

Vohs, K. D., Mead, N. L., & Goode, M. R. (2006). The psychological consequences of money. *Science, 314*, 1154–1156. https://doi.org/10.1126/science.1132491

Waldkirch, M., Bucher, E., Schou, P. K., & Grünwald, E. (2021). Controlled by the algorithm, coached by the crowd–how HRM activities take shape on digital work platforms in the gig economy. *The International Journal of Human Resource Management,* 1-36.

Wang, L., Zhang, Z., & Estabrook, R. (2009). Longitudinal mediation analysis of training intervention effects. In *Statistical methods for modeling human dynamics: An interdisciplinary dialogue*. New Jersey, NJ: Lawrence Erlbaum Associates.

Webster, J. (2016). Microworkers of the gig economy: Separate and precarious. *New Labor Forum, 25,* 56-64. https://doi.org/10.1177/1095796016661511

Werner, C., & Schermelleh-Engel, K. (2010). Deciding between competing models: Chi-square difference tests. *Introduction to structural equation modeling with LISREL.* https://perma.cc/2RTR-8XPZ

Whitaker, B. G., & Levy, P. (2012). Linking feedback quality and goal orientation to feedback seeking and job performance. *Human Performance*, *25*(2), 159-178. https://doi.org/10.1080/08959285.2012.658927

Williams, A. C., Mark, G., Milland, K., Lank, E., & Law, E. (2019). The perpetual work life of crowdworkers: How tooling practices increase fragmentation in crowdwork. *Proceedings of the ACM on Human-Computer Interaction*, *3*, 1-28.

Williams, P., McDonald, P., & Mayes, R. (2021). Recruitment in the gig economy: Attraction and selection on digital platforms. *The International Journal of Human Resource Management*, 1-27. https://doi.org/10.1080/09585192.2020.1867613

Wilson, C. (2016). Who wants to be a manager? Applying the attraction-selection-attrition framework to public relations education, *Journal of Public Relations Education* 2(1), 47-55.

Wong, S. I., Kost, D., & Fieseler, C. (2021). From crafting what you do to building resilience for career commitment in the gig economy. *Human Resource Management Journal, 31*(4), 918-935. https://doi.org/10.1111/1748-8583.12342

Wood, R., & Bandura, A. (1989). Impact of conceptions of ability on self-regulatory mechanisms and complex decision making. *Journal of Personality and Social Psychology, 56*(3), 407-415. https://doi.org/10.1037/0022-3514.56.3.407

Wright, B. E., & Christensen, R. K. (2007, October). Public service motivation: A longitudinal analysis of the job Attraction-Selection-Attrition model. In *9th Public Management Research Conference, Tucson, AZ.*

Wrzesniewski, A., & Dutton, J. E. (2001). Crafting a job: Revisioning employees as active crafters of their work. *Academy of Management Review, 26*, 179–201. https://doi.org/10.5465/amr.2001.4378011

Wrzesniewski, A., McCauley, C., Rozin, P., & Schwartz, B. (1997). Jobs, careers, and callings: People's relations to their work. *Journal of Research in Personality*, *31*, 21-33.

Zacher, H., & de Lange, A. H. (2011). Relations between chronic regulatory focus and future time perspective: Results of a cross-lagged structural equation model. *Personality and Individual Differences, 50*(8), 1255-1260.

Zhang, W., Jex, S. M., Peng, Y., & Wang, D. (2017). Exploring the effects of job autonomy on engagement and creativity: The moderating role of performance pressure and learning goal orientation. *Journal of Business and Psychology*, *32*(3), 235-251. https://doi.org/10.1007/s10869-016-9453-x

Zhang, Y., Crant, J. M., & Weng, Q. (2019). Role stressors and counterproductive work behavior: The role of negative affect and proactive personality. *International Journal of Selection and Assessment*, *27*(3), 267-279. https://doi.org/10.1111/ijsa.12255

Appendices

Appendix A – Quality Control Assessments

1. What factors do you consider when selecting HITs on MTurk?
    a. Response format is open ended
2. For quality control purposes, please select the response that is second from the left.
    a. Response format is on a seven-point Likert scale
3. Please skip this question and move on to the next question. Do not click on any of the responses. This is just to screen out random clicking.
    a. Response format is on a seven-point Likert scale
4. Which of the following words rhymes with "shoe"?
    a. Sky
    b. Hand
    c. Blue
    d. Phone

Appendix B – Personality Measures

Proactive Personality

1. I am constantly on the lookout for new ways to improve my life.
2. Wherever I have been, I have been a powerful force for constructive change.
3. Nothing is more exciting than seeing my ideas turn into reality.
4. If I see something I don't like, I fix it.
5. No matter what the odds, if I believe in something I will make it happen.
6. I love being a champion for my ideas, even against others' opposition.
7. I excel at identifying opportunities.
8. I am always looking for better ways to do things.
9. If I believe in an idea, no obstacle will prevent me from making it happen.
10. I can spot a good opportunity long before others can.

Learning Goal Orientation

1. I am willing to select a challenging work assignment that I can learn a lot from.
2. I often look for new opportunities to develop new skills and knowledge.
3. I enjoy challenging and difficult tasks at work where I'll learn new skills.
4. For me, development of my work ability is important enough to take risks.
5. I prefer to work in situations that require a high level of ability and talent.

Need for Achievement

1. I am pleased when I can take on added job responsibilities.
2. I am always looking for opportunities to improve my skills on the job.
3. I like to set challenging goals for myself on the job.

4. I enjoy situations at work where I am personally responsible for finding solutions to problems.
5. I try very hard to improve on my past performance at work.
6. I get the most satisfaction when completing job assignments that are fairly difficult.
7. I want frequent feedback on how I am doing on the job.
8. I do my best work when my job assignments are fairly difficult.

Self-Efficacy

1. I will be able to achieve most of the goals that I have set for myself.
2. When facing difficult tasks, I am certain that I will accomplish them.
3. In general, I think that I can obtain outcomes that are important to me.
4. I believe I can succeed at most any endeavor to which I set my mind.
5. I will be able to successfully overcome many challenges.
6. I am confident that I can perform effectively on many different tasks.
7. Compared to other people, I can do most tasks very well.
8. Even when things are tough, I can perform quite well.

Psychological Capital

1. I feel confident analyzing a long-term problem to find a solution.
2. I feel confident in representing my work area in meetings with management.
3. I feel confident contributing to discussions about the company's strategy.
4. I feel confident helping to set targets/goals in my work area.
5. I feel confident contacting people outside the company (e.g., suppliers, customers) to discuss problems.
6. I feel confident presenting information to a group of colleagues.

7. If I should find myself in a jam at work, I could think of many ways to get out of it.
8. At the present time, I am energetically pursuing my work goals.
9. There are lots of ways around any problem.
10. Right now I see myself as being pretty successful at work.
11. I can think of many ways to reach my current work goals.
12. At this time, I am meeting the work goals that I have set for myself.
13. When I have a setback at work, I have trouble recovering from it, moving on. (R)
14. I usually manage difficulties one way or another at work.
15. I can be “on my own,” so to speak, at work if I have to.
16. I usually take stressful things at work in stride.
17. I can get through difficult times at work because I’ve experienced difficulty before.
18. I feel I can handle many things at a time in my job.
19. When things are uncertain for me at work, I usually expect the best.
20. If something can go wrong for me work-wise, it will. (R)
21. I always look on the bright side of things regarding my job.
22. I’m optimistic about what will happen to me in the future as it pertains to work.
23. In my job, things never work out the way I want them to (R).
24. I approach my job as if “every cloud has a silver lining.”

(R) indicates a reverse coded item

The Big Five Traits

1. I am the life of the party.
2. I sympathize with others’ feelings.
3. I get chores done right away.

4. I have frequent mood swings.
5. I have a vivid imagination.
6. I don’t talk a lot.
7. I am not interested in other people’s problems.
8. I often forget to put things back in their proper place.
9. I am relaxed most of the time.
10. I am not interested in abstract ideas.
11. I talk to a lot of different people at parties.
12. I feel others’ emotions.
13. I like order.
14. I get upset easily.
15. I have difficulty understanding abstract ideas.
16. I keep in the background.
17. I am not really interested in others.
18. I make a mess of things.
19. I seldom feel blue.
20. I do not have a good imagination.

Prosociality

1. It is important to me to make a real difference in people’s lives through my work.
2. At work, I care about improving the welfare of other people.
3. One of my objectives at work is to make a positive difference in others’ lives.

Appendix C - Work Essentiality Measures

Financial Need Self-Report

When answering the following questions, consider essential expenses to be bills such as utilities or rent/mortgage and nonessential expenses to be voluntary expenditures such as concert tickets.

Without the income provided by your work on MTurk, how would you classify your financial need?

I would be able to pay for...

1. All essential expenses
2. Most essential expenses
3. Some essential expenses
4. No essential expenses

I would be able to pay for...

1. All nonessential expenses
2. Most nonessential expenses
3. Some nonessential expenses
4. No nonessential expenses

Perceptions of Work

1. Job – Person A works primarily to earn enough money to support their life outside of their job. If they were financially secure, they would no longer continue with their current line of work, but would really rather do something else instead. Person A's job is basically a necessity of life, a lot like breathing or sleeping. They often wish the time would pass more quickly at work. They greatly anticipate weekends and vacations. If Person A lived their life over again, they probably would not go into the

same line of work. They would not encourage their friends and children to enter their line of work. Person A is very eager to retire.

2. Career – Person B basically enjoys their work, but does not expect to be in their current job five years from now. Instead, they plan to move on to a better, higher level job. They have several goals for their future pertaining to the positions they would eventually like to hold. Sometimes their work seems a waste of time, but they know that they must do sufficiently well in their current position in order to move on. Person B can't wait to get a promotion. For them, a promotion means recognition of their good work, and is a sign of their success in competition with their coworkers.
3. Calling – Person C's work is one of the most important parts of their life. They are very pleased that they are in this line of work. Because what they do for a living is a vital part of who they are, it is one of the first things they tells people about themself. They tend to take their work home with them and on vacations, too. The majority of their friends are from their place of employment, and they belong to several organizations and clubs relating to their work. Person C feels good about their work because they love it, and because they think it makes the world a better place. They would encourage their friends and children to enter their line of work. Person C would be pretty upset if they were forced to stop working, and they are not particularly looking forward to retirement.

Appendix D – Task Characteristic Items

Work Scheduling Autonomy

1. HITs that allow me to make my own decisions about how to schedule my work.
2. HITs that allow me to decide on the order in which things are done on the job.
3. HITs that allow me to plan how I do my work.

Decision-Making Autonomy

1. HITs that give me a chance to use my personal initiative or judgment in carrying out the work.
2. HITs that allow me to make a lot of decisions on my own.
3. HITs that provide me with significant autonomy in making decisions.

Work Methods Autonomy

1. HITs that allow me to make decisions about what methods I use to complete my work.
2. HITs that give me considerable opportunity for independence and freedom in how I do the work.
3. HITs that allow me to decide on my own how to go about doing my work.

Task Variety

1. HITs that involve a great deal of task variety.
2. HITs that involve doing a number of different things.
3. HITs that require the performance of a wide range of tasks.
4. HITs that involve performing a variety of tasks.

Task Significance

1. HITs in which the results are likely to significantly affect the lives of other people.

2. HITs in which the HIT itself is very significant and important in the broader scheme of things.
3. HITs that have a large impact on people outside the organization/requester.
4. HITs in which the work performed has a significant impact on people outside the organization/requester.

Task Identity

1. HITs that involve completing a piece of work that has an obvious beginning and end.
2. HITs that are arranged so that I can do an entire piece of work from beginning to end.
3. HITs that provide me the chance to completely finish the pieces of work I begin.
4. HITs that allow me to complete work I start.

Feedback from the Job

1. HITs in which the HIT itself provides direct and clear information about the effectiveness (e.g., quality and quantity) of my performance.
2. HITs in which the HIT itself provides feedback on my performance.
3. HITs in which the HIT itself provides me with information about my performance.

Task Clarity

1. HITs in which there are clear planned goals and objectives.
2. HITs in which I know exactly what is expected of me.
3. HITs in which I know what my responsibilities are.
4. HITs in which I feel certain about how much responsibility I have.
5. HITs in which my responsibilities are clearly defined.

Included in second survey only following the selection of task characteristic items: If desired, use the space below to share any factors that may have prevented you from participating in HITs with the above characteristics (e.g., no HITs that allowed for decision-making were available in the past 14 days).

Appendix E - Turnover Intentions

1. In the next few months I intend to stop working through MTurk.
2. In the next few years I intend to stop working through MTurk.
3. I occasionally think about stopping my work through MTurk.
4. I'd like to continue completing work through MTurk until I reach retirement age (R).

Appendix F - Demographics

1. Please report your age in years.

   Text response: _________

2. Please select which best describes you:

   Male

   Female

   Non-binary

   Prefer to self-describe: _______________

   Prefer not to say

3. Please select all of the following that apply to you:

   White

   Black or African American

   Hispanic or Latino

   Asian

   American Indian and Alaska Native

   Native Hawaiian and Other Pacific Islander

   Other (please specify): _______________

4. Please identify your highest level of education.

   Some high school

   High school degree/GED

   Some college, no degree

   Associate's degree

   Bachelor's degree

Master's degree

Doctoral degree

Professional degree

5. What is your marital status?

Single, never married

Married or domestic partnership

Widowed

Divorced

Separated

6. How many children under the age of 18 reside in your household?

Text response: _________

7. How many individuals in your household work at least 20 hours per week?

Text response: _________

8. How many hours per week do you typically work on MTurk?

Text response: _________

9. How many hours per week do you typically work in jobs outside of MTurk?

Text response: _________

10. Aside from working on MTurk, how many other sources of work-related income do you have?

Text response: ______

11. How many approved HITs have you completed on MTurk?

Text response: ______

12. What types of HITs do you typically complete on MTurk (e.g., image tagging, surveys, audio transcription HITs)?
13. How many approved HITs have you completed on MTurk in the last 14 days? (question included in second survey only)

    Text response: ______

Tables

Table 1
Descriptive Statistics and Scale Reliabilities for all Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. Proactive personality	5.18	0.98	--	--	--	--	--	--	--	--
2. Learning goal orientation	5.42	1.10	.70**	--	--	--	--	--	--	--
3. Need for achievement	5.30	1.02	.73**	.87**	--	--	--	--	--	--
4. Learning goal orientation/Need for achievement parcel	5.36	1.02	.74**	.97**	.96**	--	--	--	--	--
5. Self-efficacy	5.50	0.95	.72**	.63**	.61**	.64**	--	--	--	--
6. Psychological capital	5.26	0.88	.70**	.69**	.68**	.71**	.82**	--	--	--
7. Extraversion	3.75	1.43	.38**	.39**	.35**	.38**	.38**	.43**	--	--
8. Agreeableness	5.24	1.19	.26**	.29**	.35**	.33**	.29**	.38**	.25**	--
9. Conscientiousness	5.18	1.17	.23**	.12*	.15**	.14*	.36**	.40**	.06	.33**
10. Neuroticism	3.30	1.44	-.24**	-.22**	-.19**	-.21**	-.44**	-.54**	-.21**	-.18**
11. Openness	5.06	1.34	.22**	.28**	.25**	.27**	.23**	.29**	.23**	.46**
12. Prosociality	5.40	1.28	.59**	.59**	.61**	.62**	.45**	.48**	.36**	.46**
13. Financial need index	-0.14 (T1) -0.16 (T2)	1.23 1.19	.08	.07	.06	.07	.10	.02	.09	-.17**
14. Financial need self-report	2.34 (T1) 2.36 (T2)	0.85 0.85	-.19**	-.26**	-.26**	-.27**	-.28**	-.36**	-.07	-.12*
15. Perceptions of work – job	3.82 (T1) 3.88 (T2)	1.78 1.90	-.21**	-.27**	-.22**	-.25**	-.31**	-.42**	-.17**	-.20**
16. Perceptions of work – career	4.10 (T1) 4.13 (T2)	1.74 1.75	.22**	.18**	.21**	.20**	.11*	.03	.25**	-.03
17. Perceptions of work – calling	3.81 (T1) 3.81 (T2)	1.87 1.91	.35**	.38**	.36**	.38**	.32**	.30**	.23**	-.01
18. Attraction – autonomy	5.73 (T1) 5.63 (T2)	0.87 0.85	.43**	.42**	.46**	.46**	.37**	.38**	.23**	.31**
19. Attraction – task variety	5.29 (T1) 5.18 (T2)	1.27 1.25	.47**	.54**	.56**	.57**	.48**	.46**	.32**	.32**

Table 1 (continued)

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
20. Attraction – task significance	5.28 (T1) 5.32 (T2)	1.16 1.21	.44**	.46**	.48**	.48**	.34**	.37**	.27**	.41**
21. Attraction – task identity	5.89 (T1) 5.84 (T2)	0.89 0.91	.27**	.34**	.38**	.38**	.30**	.32**	.04	.35**
22. Attraction – feedback	5.69 (T1) 5.69 (T2)	1.07 1.03	.29**	.34**	.37**	.37**	.30**	.24**	.06	.22**
23. Attraction - task clarity	5.99 (T1) 6.01 (T2)	0.88 0.83	.24**	.25**	.27**	.27**	.27**	.27**	-.01	.34**
24. Selection – autonomy	4.86 (T1) 4.77 (T2)	1.29 1.27	.43**	.35**	.39**	.39**	.38**	.31**	.25**	.04
25. Selection – task variety	4.84 (T1) 4.70 (T2)	1.26 1.31	.43**	.41**	.45**	.44**	.41**	.33**	.27**	.10
26. Selection – task significance	4.51 (T1) 4.36 (T2)	1.45 1.46	.41**	.31**	.39**	.36**	.29**	.24**	.21**	.09
27. Selection – task identity	5.57 (T1) 5.55 (T2)	1.01 1.04	.30**	.32**	.33**	.33**	.30**	.32**	.16**	.14*
28. Selection – feedback	4.68 (T1) 4.54 (T2)	1.37 1.39	.37**	.32**	.37**	.36**	.36**	.29**	.23**	-.04
29. Selection – task clarity	5.50 (T1) 5.49 (T2)	0.92 0.93	.33**	.34**	.33**	.35**	.39**	.34**	.20**	.21**
30. Turnover intentions	2.84 (T1) 2.85 (T2)	1.35 1.41	-.15**	-.15**	-.21**	-.20**	-.24**	-.28**	-.02	-.20**
31. Number of HITs completed in the last 14 days (transformed)	2.27	0.58	.06	.06	.10	.08	.02	.04	-.06	.02

Table 1 (continued)

Variable	9	10	11	12	13	14	15	16	17	18
1. Proactive personality	--	--	--	--	.09	-.18**	-.22**	.28**	.31**	.38**
2. Learning goal orientation	--	--	--	--	.09	-.19**	-.25**	.26**	.33**	.39**
3. Need for achievement	--	--	--	--	.07	-.20**	-.24**	.25**	.31**	.37**
4. Learning goal orientation/Need for achievement parcel	--	--	--	--	.08	-.21**	-.25**	.26**	.33**	.39**
5. Self-efficacy	--	--	--	--	.10	-.26**	-.30**	.17**	.25**	.35**
6. Psychological capital	--	--	--	--	.05	-.27**	-.37**	.09	.27**	.31**
7. Extraversion	--	--	--	--	.08	-.14**	-.11	.22**	.23**	.26**
8. Agreeableness	--	--	--	--	-.10	-.13*	-.27**	-.01	.05	.20**
9. Conscientiousness	--	--	--	--	-.16**	-.18**	-.20**	-.17**	-.05	.06
10. Neuroticism	-.42**	--	--	--	.07	.26**	.28**	.11*	-.18**	-.08
11. Openness	.25**	-.22**	--	--	-.17**	-.08	-.19**	-.02	-.01	.18**
12. Prosociality	.10	-.07	.21**	--	.12*	-.18**	-.18**	.19**	.32**	.36**
13. Financial need index	-.17**	.07	-.22**	.08	**.84****	.03	-.02	.14**	.08	.12**
14. Financial need self-report	-.17**	.25**	-.07	-.07	.06	**.61****	.20**	-.03	-.15**	-.13*
15. Perceptions of work – job	-.24**	.37**	-.20**	-.16**	-.03	.20**	**.59****	-.05	-.34**	-.06
16. Perceptions of work – career	-.14**	.10	.02	.11*	.10	.09	.12*	**.46****	.11	.08
17. Perceptions of work – calling	-.06	-.09	-.10	.40**	.17**	-.06	-.28**	.09	**.57****	.20**
18. Attraction – autonomy	.15**	-.13*	.30**	.40**	-.01	-.11*	-.10	.07	.16**	**.63****
19. Attraction – task variety	.13*	-.17**	.15**	.48**	.07	-.18**	-.11	.17**	.29**	.49**
20. Attraction – task significance	.09	-.04	.24**	.61**	-.04	-.13*	-.12*	.08	.26**	.44**
21. Attraction – task identity	.20**	-.06	.21**	.36**	-.08	-.15*	-.07	.02	.12*	.61**
22. Attraction – feedback	.14*	.02	.12*	.32**	.05	-.11*	-.05	.05	.17**	.48**
23. Attraction - task clarity	.24**	-.09	.24**	.22**	-.15**	-15**	-.10	-.04	-.02	.55**
24. Selection – autonomy	-.03	-.04	.05	.37**	.12*	-.05	-.10	.18**	.26**	.49**
25. Selection – task variety	-.01	-.07	.05	.44**	.13*	-.02	-.12*	.20**	.37**	.40**
26. Selection – task significance	-.05	.04	.03	.41**	.07	.00	-.07	.16**	.25**	.40**

Table 1 (continued)

Variable	9	10	11	12	13	14	15	16	17	18
27. Selection – task identity	.11	-.17**	.16**	.25**	.01	-.06	-.13*	.05	.14*	.47**
28. Selection – feedback	-.09	-.04	-.03	.31**	.15**	-.06	-.11*	.23**	.30**	.31**
29. Selection – task clarity	.12*	-.11	.15**	.30**	.03	-.11	-.14*	.11*	.16**	.51**
30. Turnover intentions	-.28**	.19**	-.16**	-.09	-.03	.16**	.24**	.05	-.06	-.20**
31. Number of HITs completed in the last 14 days (transformed)	.01	.04	-.02	.00	-.03	.08	-.01	-.01	-.05	.10

Table 1 (continued)

Variable	19	20	21	22	23	24	25	26	27	28
1. Proactive personality	.34**	.36**	.20**	.26**	.21**	.36**	.41**	.43**	.25**	.38**
2. Learning goal orientation	.39**	.38**	.20**	.27**	.18**	.31**	.37**	.29**	.24**	.30**
3. Need for achievement	.42**	.40**	.23**	.34**	.24**	.32**	.42**	.36**	.23**	.34**
4. Learning goal orientation/Need for achievement parcel	.42**	.40**	.22**	.31**	.22**	.33**	.40**	.33**	.24**	.33**
5. Self-efficacy	.32**	.25**	.24**	.19**	.25**	.33**	.34**	.27**	.25**	.25**
6. Psychological capital	.25**	.23**	.20**	.15**	.22**	.23**	.26**	.21**	.24**	.18**
7. Extraversion	.19**	.19**	.08	.00	-.05	.20**	.20**	.20**	.10	.21**
8. Agreeableness	.15**	.25**	.19**	.11	.27**	.02	.05	.00	.12*	-.04
9. Conscientiousness	-.05	-.04	.07	.08	.17**	-.08	-.02	-.08	.12*	-.07
10. Neuroticism	-.08	.06	-.06	.03	-.10	-.01	-.01	.06	-.12*	.10
11. Openness	.03	.14*	.08	.08	.20**	.03	.00	-.02	.13*	.03
12. Prosociality	.35**	.44**	.22**	.23**	.23**	.33**	.42**	.32**	.20**	.32**
13. Financial need index	.12*	.06	.01	.04	.00	.16**	.17**	.12**	.07	.19**
14. Financial need self-report	-.09	-.10	-.11*	-.09	-.06	-.06	.01	.02	-.05	-.02
15. Perceptions of work – job	-.06	-.12*	-.04	-.03	-.05	-.02	-.02	-.03	.01	.09
16. Perceptions of work – career	.21**	.17**	.02	.16**	.03	.28**	.32**	.32**	.04	.33**
17. Perceptions of work – calling	.29**	.26**	.10	.08	.02	.27**	.26**	.31**	.08	.16**
18. Attraction – autonomy	.44**	.51**	.54**	.39**	.46**	.51**	.32**	.37**	.41**	.30**
19. Attraction – task variety	**.59****	.46**	.28**	.33**	.15**	.40**	.62**	.39**	.25**	.35**
20. Attraction – task significance	.50**	**.63****	.40**	.37**	.33**	.39**	.37**	.52**	.32**	.32**
21. Attraction – task identity	.43**	.38**	**.53****	.46**	.64**	.28**	.16**	.15**	.54**	.14*
22. Attraction – feedback	.38**	.37**	.58**	**.51****	.47**	.29**	.26**	.30**	.41**	.36**
23. Attraction - task clarity	.25**	.29**	.70**	.60**	**.64****	.19**	.12*	.12*	.45**	.10
24. Selection – autonomy	.35**	.29**	.25**	.29**	.18**	**.67****	.66**	.69**	.44**	.70**
25. Selection – task variety	.59**	.40**	.30**	.34**	.19**	.71**	**.71****	.65**	.32**	.65**
26. Selection – task significance	.39**	.50**	.21**	.30**	.17**	.63**	.65**	**.70****	.36**	.67**

Table 1 (continued)

Variable	19	20	21	22	23	24	25	26	27	28
27. Selection – task identity	.26**	.25**	.46**	.32**	.42**	.49**	.41**	.38**	**.56****	.41**
28. Selection – feedback	.37**	.27**	.13*	.31**	.08	.70**	.70**	.67**	.42**	**.63****
29. Selection – task clarity	.34**	.32**	.40**	.31**	.47**	.56**	.46**	.45**	.61**	.36**
30. Turnover intentions	-.22**	-.14**	-.28**	-.29**	-.29**	-.07	-.11*	-.06	-.15**	-.06
31. Number of HITs completed in the last 14 days (transformed)	.04	.02	.10	.14*	.17**	.04	.10	.09	-.08	.04

Table 1 (continued)

Variable	29	30
1. Proactive personality	.34**	-.19**
2. Learning goal orientation	.30**	-.23**
3. Need for achievement	.29**	-.21**
4. Learning goal orientation/need for achievement parcel	.30**	-.22**
5. Self-efficacy	.36**	-.29**
6. Psychological capital	.30**	-.33**
7. Extraversion	.22**	-.05
8. Agreeableness	-.04	-.24**
9. Conscientiousness	.14*	-.30**
10. Neuroticism	-.09	.26**
11. Openness	.16**	-.16**
12. Prosociality	.24**	-.11
13. Financial need index	.07	-.04
14. Financial need self-report	-.10	.11*
15. Perceptions of work – job	-.01	.30**
16. Perceptions of work – career	.12*	.08
17. Perceptions of work – calling	.08	-.01
18. Attraction – autonomy	.39**	-.18**
19. Attraction – task variety	.27**	-.08
20. Attraction – task significance	.32**	-.12*
21. Attraction – task identity	.39**	-.18*
22. Attraction – feedback	.29**	-.10
23. Attraction - task clarity	.39**	-.19**
24. Selection – autonomy	.52**	-.06
25. Selection – task variety	.36**	-.03
26. Selection – task significance	.42**	-.02
27. Selection – task identity	.69**	-.19**
28. Selection – feedback	.49**	.06
29. Selection – task clarity	**.57****	-.14**
30. Turnover intentions	-.15**	**.78****
31. Number of HITs completed in the last 14 days (transformed)	.00	-.09

Note. $N = 325$ for all study variables. M and *SD* are used to represent mean and standard deviation, respectively. Time 1 scores are reported below the diagonal, Time 2 scores are reported above the diagonal for applicable measures. Relationships between Time 1 and Time 2 measures are reported in the diagonal, when applicable, and are bolded for visibility. * $p < .05$. ** $p < .01$.

Table 2
Summary of models tested and comparison statistics

Model Number	Model	χ^2	*df*	CFI	TLI	SRMR	RMSEA	Model Comparison	$\Delta\chi^2$	Δdf
1a	Original model with no moderators	80.95	46	.99	.95	.03	.05	--	--	--
1b	**Original model with moderators**	**544.01**	**340**	**.97**	**.94**	**.05**	**.04**	**--**	**--**	**--**
1c	Original model with variables that had no significant paths fixed to zero	1074.71	368	.88	.80	.09	.08	1b to 1c	530.71*	28
1d	Original model with moderators added on personality -> attraction paths	1434.97	890	.95	.91	.08	.04	--	--	--
2a	Stability model	429.77	156	.92	.88	.11	.07	--	--	--
2b	Causal model	1260.61	374	.89	.80	.20	.09	--	--	--
2c	Reverse causality model	1263.04	374	.89	.80	.20	.09	2b to 2c	2.43	0
2d	Reciprocal model	1250.12	362	.89	.80	.20	.09	2b to 2d 2c to 2d	10.49 12.92	12 12
3a	Combination of Models 1b and 2b	1813.04	824	.89	.85	.16	.06	--	--	--

Note. * indicates a significant difference at the $p < .05$ level. The bolded text indicates the model that was ultimately was retained for hypothesis testing.

Table 3
Parameter estimates for Model 1b

Predictor	Attraction to Autonomy		Attraction to Task Variety		Attraction to Task Significance		Attraction to Task Identity		Attraction to Feedback from the Job		Attraction to Task Clarity	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*
Proactive personality	.10	.08	-.07	.10	.08	.09	-.12†	.07	-.05	.09	.00	.08
Learning goal orientation/Need for achievement	.18*	.09	.46**	.10	.15	.11	.19*	.08	.32**	.11	.11	.09
Self-efficacy	.06	.09	.30*	.13	.03	.12	.12	.09	.29*	.13	.12	.10
Psychological capital	-.05	.11	-.15	.15	-.02	.16	.10	.14	-.19	.17	.04	.16
Extraversion	-.01	.03	.06	.04	.01	.04	-.11**	.04	-.09†	.04	-.12**	.04
Agreeableness	.07	.05	.13*	.06	.14*	.06	.13**	.05	.07	.06	.16**	.05
Conscientiousness	.02	.04	.00	.06	-.02	.06	.07†	.04	.09†	.05	.09*	.04
Neuroticism	.00	.04	.00	.06	.06	.06	.07†	.04	.10*	.05	.06	.04
Openness	.09*	.04	-.05	.06	.04	.05	.02	.04	.01	.05	.06	.04
Prosociality	.10†	.06	.14*	.07	.35**	.07	.12*	.05	.10	.07	.01	.05

Table 3 (continued)

Predictor	Selection of Autonomy		Selection of Task Variety		Selection of Task Significance		Selection of Task Identity	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*
Proactive personality	.13	.10	.20	.13	.58**	.13	.10	.10
Learning goal orientation/Need for achievement	.02	.12	.07	.11	.01	.13	.08	.10
Self-efficacy	.42**	.13	.21	.15	.15	.17	.09	.12
Psychological capital	-.20	.16	-.21	.18	-.16	.19	-.02	.14
Extraversion	.04	.05	.01	.05	.07	.06	.01	.05
Agreeableness	-.14*	.07	-.19*	.07	-.16†	.08	-.06	.06
Conscientiousness	-.15*	.06	-.03	.07	-.11	.08	.01	.06
Neuroticism	.03	.06	.05	.06	.09	.07	-.03	.05
Openness	-.02	.06	-.04	.05	-.08	.07	.03	.05
Prosociality	.19*	.08	.24**	.07	.00	.09	.02	.06
Attraction to autonomy	.24**	.07	--	--	--	--	--	--
Calling x Attraction to autonomy	-.06	.06	--	--	--	--	--	--
Financial need x Attraction to autonomy	-.03	.06	--	--	--	--	--	--
Attraction to task variety	--	--	.29**	.06	--	--	--	--
Calling x Attraction to task variety	--	--	-.10	.07	--	--	--	--
Financial need x Attraction to task variety	--	--	.02	.06	--	--	--	--
Attraction to task significance	--	--	--	--	.27**	.06	--	--
Calling x Attraction to task significance	--	--	--	--	-.16*	.06	--	--
Financial need x Attraction to task significance	--	--	--	--	-.06	.06	--	--
Attraction to task identity	--	--	--	--	--	--	.34**	.07
Calling x Attraction to task identity	--	--	--	--	--	--	-.02	.06
Financial need x Attraction to task identity	--	--	--	--	--	--	-.02	.06
Number of HITs completed in last 14 days	.15	.11	.20	.13	.18	.14	-.04	.11

Table 3 (continued)

Predictor	Selection of Feedback from the Job		Selection of Task Clarity		Turnover Intentions	
	β	*SE*	β	*SE*	β	*SE*
Proactive personality	.36**	.12	.13	.08	.05	.14
Learning goal orientation/Need for achievement	.10	.12	.03	.09	-.09	.13
Self-efficacy	.15	.15	.24**	.09	-.04	.15
Psychological capital	-.15	.17	-.11	.12	-.25	.19
Extraversion	.11†	.06	.07	.04	.06	.06
Agreeableness	-.25**	.08	.05	.06	-.10	.09
Conscientiousness	-.04	.08	.01	.05	-.17*	.08
Neuroticism	.15*	.06	.04	.04	.06	.06
Openness	.03	.06	.01	.04	-.01	.07
Prosociality	.20*	.08	-.02	.06	.10	.10
Attraction to autonomy	--	--	--	--	.12	.12
Attraction to task variety	--	--	--	--	-.10	.09
Attraction to task significance	--	--	--	--	.01	.09
Attraction to task identity	--	--	--	--	-.01	.14
Attraction to feedback from the job	.05	.05	--	--	-.19*	.09
Attraction to task clarity	--	--	.19**	.06	-.07	.13
Selection of autonomy	--	--	--	--	-.15	.09
Selection of task variety	--	--	--	--	.05	.10
Selection of task significance	--	--	--	--	-.02	.09
Selection of task identity	--	--	--	--	-.14	.10
Selection of feedback from the job	--	--	--	--	.19*	.08
Selection of task clarity	--	--	--	--	.03	.12
Calling x Attraction to feedback from the job	-.04	.06	--	--	--	--
Financial need x Attraction to feedback from the job	-.04	.05	--	--	--	--
Calling x Attraction to task clarity	--	--	.00	.06	--	--
Financial need x Attraction to task clarity	--	--	-.07	.05	--	--
Number of HITs completed in last 14 days	.12	.15	-.02	.08	-.01	.12

Note. ** denotes significance at the $p < .01$ level, * denotes significance at the $p < .05$ level, and † denotes marginal significance at the $p < .10$ level.

Table 4
Indirect effects tested for the mediation model

Indirect effect	β	SE	CI (lower, upper)
Learning goal orientation/Need for achievement → Attraction to autonomy → Selection of autonomy → Turnover intentions	-.01	.01	-.02, .00
Learning goal orientation/Need for achievement → Attraction to task variety → Selection of task variety → Turnover intentions	.01	.02	-.02, .04
Learning goal orientation/Need for achievement → Attraction to task identity → Selection of task identity → Turnover intentions	-.01	.01	-.03, .00
Learning goal orientation/Need for achievement → Attraction to feedback from the job → Selection of feedback from the job → Turnover intentions	.00	.00	.00, .01
Self-efficacy → Attraction to task variety → Selection of task variety → Turnover intentions	.01	.01	-.01, .03
Self-efficacy → Attraction to feedback from the job → Selection of feedback from the job → Turnover intentions	.00	.00	.00, .01
Extraversion → Attraction to task variety → Selection of task variety → Turnover intentions	.01	.01	.00, .02
Extraversion → Attraction to feedback from the job → Selection of feedback from the job → Turnover intentions	.00	.00	-.01, .00
Extraversion → Attraction to task clarity → Selection of task clarity → Turnover intentions	.00	.00	-.01, .01
Agreeableness → Attraction to task variety → Selection of task variety → Turnover intentions	.00	.00	-.01, .01
Agreeableness → Attraction to task significance → Selection of task significance → Turnover intentions	.00	.00	-.01, .01
Agreeableness → Attraction to task identity → Selection of task identity → Turnover intentions	-.01	.01	-.02, .00
Agreeableness → Attraction to task clarity → Selection of task clarity → Turnover intentions	.00	.00	-01, .01
Conscientiousness → Attraction to task clarity → Selection of task clarity → Turnover intentions	.00	.00	.01, .00
Neuroticism → Attraction to feedback from the job → Selection of feedback from the job → Turnover intentions	.00	.00	.00, .01
Openness → Attraction to autonomy → Selection of autonomy → Turnover intentions	.00	.00	-.01, .00
Prosociality → Attraction to task variety → Selection of task variety → Turnover intentions	.00	.01	-.01, .02

Table 4 (continued)

Indirect effect	β	SE	CI (lower, upper)
Prosociality → Attraction to task significance → Selection of task significance → Turnover intentions	.00	.01	-.02, .02
Prosociality → Attraction to task identity → Selection of task identity → Turnover intentions	-.01	.01	-.02, 00
Learning goal orientation/Need for achievement → Attraction to autonomy → Selection of autonomy	.04	.02	.00, .11
Learning goal orientation/Need for achievement → Attraction to task variety → Selection of task variety	.13**	.04	.06, .23
Learning goal orientation/Need for achievement → Attraction to task identity → Selection of task identity	.06*	.03	.01, .14
Learning goal orientation/Need for achievement → Attraction to feedback from the job → Selection of feedback from the job	.02	.02	-.02, .05
Self-efficacy → Attraction to task variety → Selection of task variety	.09*	.04	.01, .17
Self-efficacy → Attraction to feedback from the job → Selection of feedback from the job	.02	.02	-.01, .06
Extraversion → Attraction to task variety → Selection of task variety	-.04*	.02	-.07, -.01
Extraversion → Attraction to feedback from the job → Selection of feedback from the job	-.01	.01	-.02, .00
Extraversion → Attraction to task clarity → Selection of task clarity	-.02*	.01	-.04, -.01
Agreeableness → Attraction to task variety → Selection of task variety	.04	.02	.00, .08
Agreeableness → Attraction to task significance → Selection of task significance	.04	.02	.00, .09
Agreeableness → Attraction to task identity → Selection of task identity	.05*	.02	.02, .09
Agreeableness → Attraction to task clarity → Selection of task clarity	.03*	.01	.01, .06
Conscientiousness → Attraction to task clarity → Selection of task clarity	.02	.01	.00, .04
Neuroticism → Attraction to feedback from the job → Selection of feedback from the job	.01	.01	.00, .02
Openness → Attraction to autonomy → Selection of autonomy	.02	.01	.00, .05
Prosociality → Attraction to task variety → Selection of task variety	.04	.03	.00, .10
Prosociality → Attraction to task significance → Selection of task significance	.10**	.03	.05, .15
Prosociality → Attraction to task identity → Selection of task identity	.04*	.02	.01, .09

Note. Indirect effects were only examined for significant regression paths in the path analysis. * denotes significance at the $p < .05$ level and ** denotes significance at the $p < .01$ level.

Table 5
Researcher guide to designing MTurk HITs, summarizing which task characteristics were demonstrated to attract specific types of worker personalities

Attraction characteristic	Personality factor	Relationship
Autonomy	Learning goal orientation/Need for achievement composite	Positive
	Openness	Positive
Task variety	Learning goal orientation/Need for achievement composite	Positive
	Self-efficacy	Positive
	Agreeableness	Positive
	Prosociality	Positive
Task significance	Agreeableness	Positive
	Prosociality	Positive
Task identity	Learning goal orientation/Need for achievement composite	Positive
	Extraversion	Negative
	Agreeableness	Positive
	Prosociality	Positive
Feedback from the job	Learning goal orientation/Need for achievement composite	Positive
	Self-efficacy	Positive
	Neuroticism	Positive
Task clarity	Extraversion	Negative
	Agreeableness	Positive
	Conscientiousness	Positive

Figures

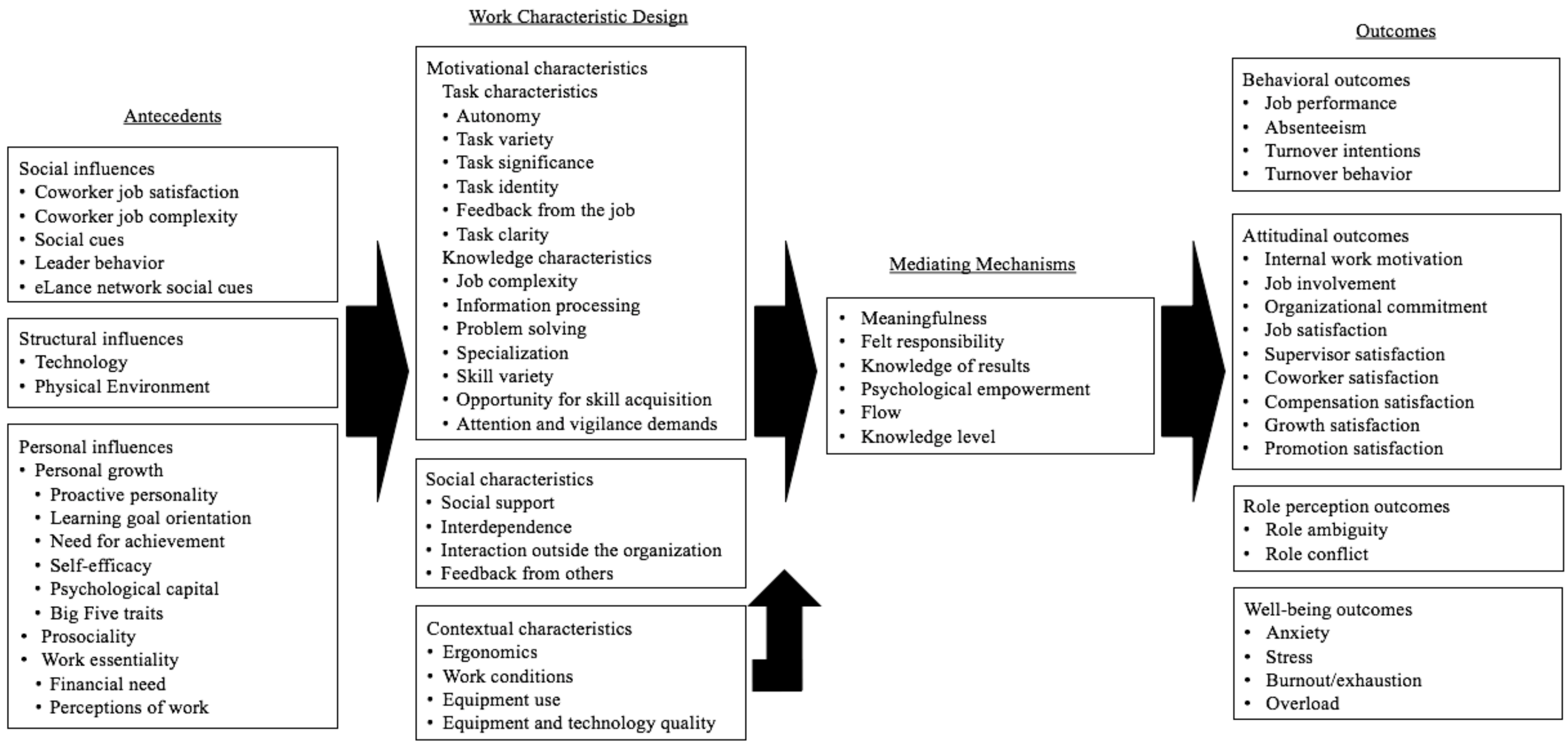

Figure 1. An eLance work design framework proposed by Schroeder, Bricka, & Whitaker (2021).

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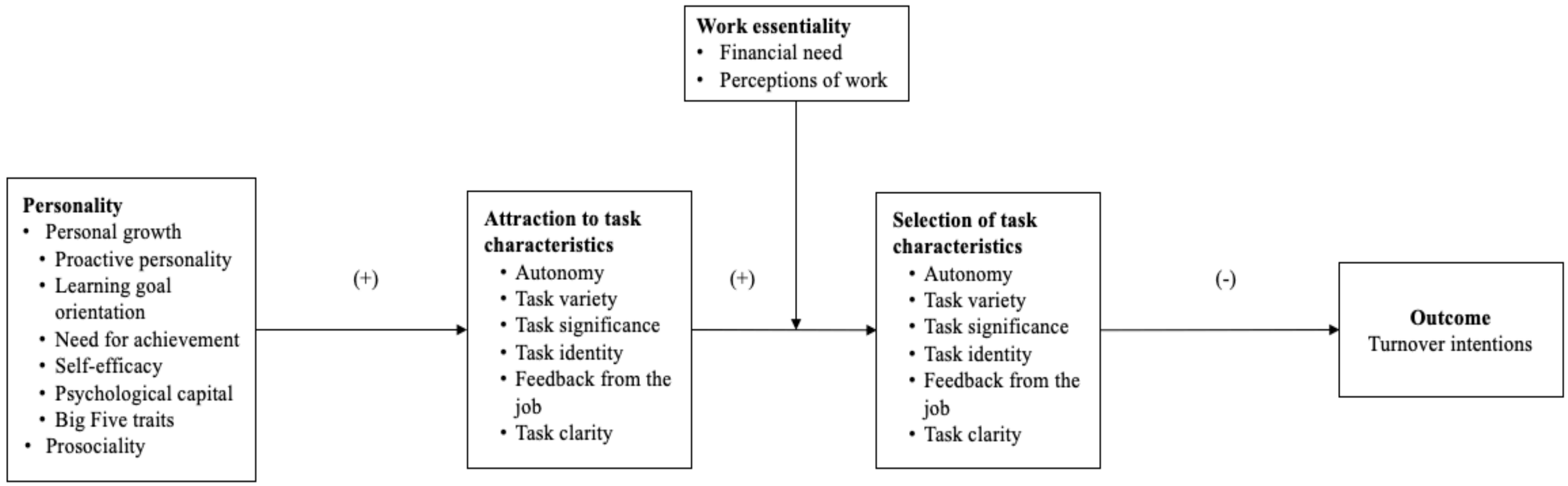

Figure 2. The proposed eLance work design model which incorporates ASA theory tenets into aspects of Schroeder et al.'s (2021) model.

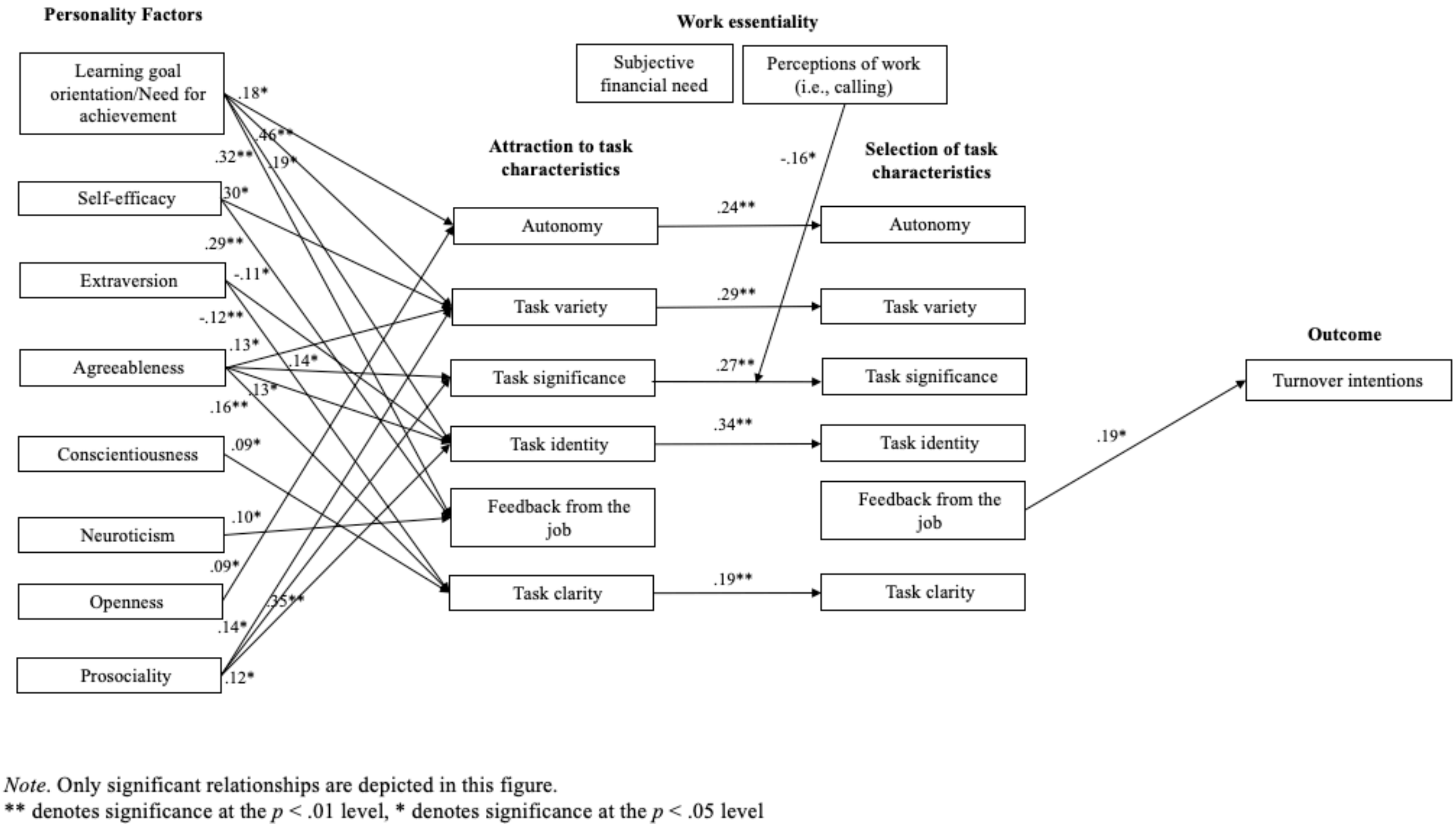

Figure 3. The results of Model 1b, with only significant paths depicted in the figure.

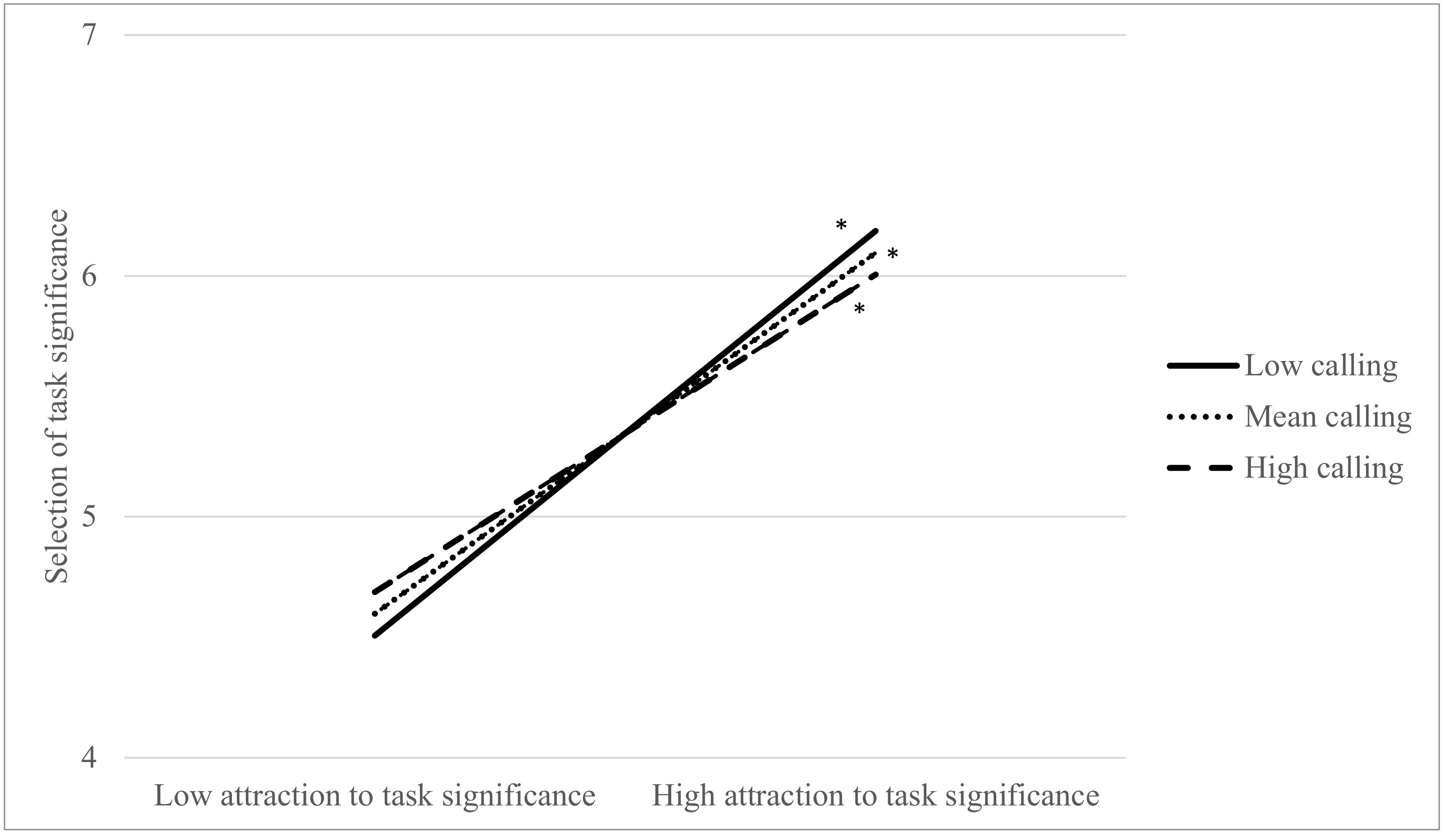

Figure 4. Interactive effects of holding a calling perception of work and attraction to task significance on selection of task significance.

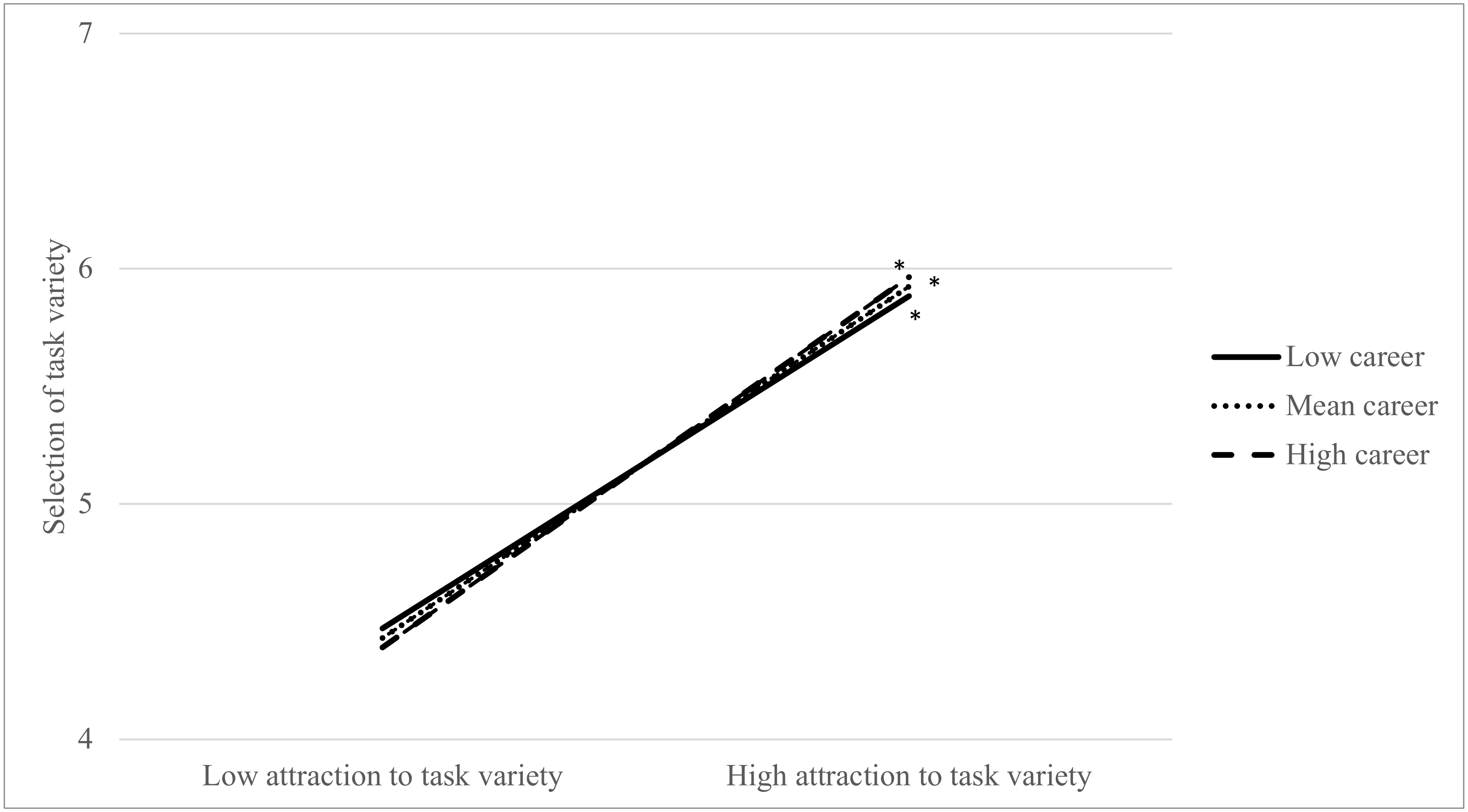

Figure 5. Interactive effects of holding a career perception of work and attraction to task variety on selection of task variety.