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WHEN CONSCIENTIOUS EMPLOYEES MEET INTELLIGENT MACHINES: AN INTEGRATIVE APPROACH INSPIRED BY COMPLEMENTARITY THEORY AND ROLE THEORY

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Over the past century, conscientiousness has become seen as the preeminent trait for predicting performance. This consensus is due in part to these employees' ability to work with traditional 20th-century technology. Such pairings balance the systematic nature of conscientious employees with the technology's need for user input and direction to perform tasks—resulting in a complementary match. However, the 21st century has seen the incorporation of intelligent machines (e.g., artificial intelligence, robots, and algorithms) into employees' jobs. Unlike traditional technology, these new machines are equipped with the capability to make decisions autonomously. Thus, their nature overlaps with the orderliness subdimension of conscientious employees—resulting in a non-complementary mismatch. This calls into question whether the consensus about conscientious employees' effectiveness with 20th-century technology applies to 21st-century jobs. Integrating complementarity and role theory, we refine this consensus. Across three studies using distinct samples (an experience sampling study, a field experiment, and an online experiment from working adults in Malaysia, Taiwan, and the United States), each focused on a different type of intelligent machine, we show not only that using intelligent machines has benefits and consequences, but, importantly, that conscientious (i.e., orderly) employees are less likely to benefit from working with them.

One of the most enduring findings in organizational and social science research is that conscientiousness "may be the most important" personality trait when it comes to performance at work (Barrick,

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Mount, & Strauss, 1993: 721; Wells, 1919). This consensus stems from an array of empirical studies, reviews, and meta-analyses, each concluding that conscientiousness is "the most valid personality predictor" of important work behavior across jobs and work settings (e.g., Dudley, Orvis, Lebiecki, & Cortina, 2006: 40; Li, Barrick, Zimmerman, & Chiaburu, 2014; Mount & Barrick, 1995). As a result, the preeminence of this trait has become accepted doctrine within academic scholarship (e.g., Hill & Jackson, 2016; Hogan & Ones, 1997; Jensen-Campbell & Malcolm, 2007), organizational practice (e.g., Behling, 1998; Chamorro-Premuzic, Garrad, & Elzinga, 2018; Indeed Editorial Team, 2020), and pedagogy (e.g., Jackson & Roberts, 2017; Noe, Hollenbeck, Gerhart, & Wright, 2020).

The effectiveness of conscientious employees is due in part to their ability to work with the "traditional technology"[1] associated with the Third Industrial Revolution (20th-century systems and machines that require clear and explicit operational commands from employees; Cascio & Montealegre, 2016: 367). As conscientious employees tend to be orderly and systematic (Cianci, Klein, & Seijts, 2010), scholars view them as particularly effective at operating traditional technology (Banham, 1980; Luk'yanenko, 1975). Young and Menter (1973: 345) spoke directly to this in their remark that, when it comes to managing and directing traditional machines, "a special kind of [person] is required, with qualities including absolute conscientiousness." This highlights the complementary nature of conscientiousness and traditional technology that balances the orderly and systematic nature of these employees with the "non-intelligent" machines of the prior century that require user input and direction to carry out work tasks (Troxler, 2013). Pairing conscientious employees with these technologies thus begets a structured, employee-directed workflow that facilitates their ability to perform their work role (e.g., Kahn & Quinn, 1970; Naylor, Pritchard, & Ilgen, 1980).

In contrast to the traditional technologies of the Third Industrial Revolution, the intelligent technologies of the Fourth Industrial Revolution (21st-century "artificial intelligence, algorithms, and robotics"; Brougham & Haar, 2018; Gerrish, 2018; Kelly & Hamm, 2013; Oosthuizen, 2019; Santana & Cobo, 2020) are equipped with automated reasoning, machine learning, and the capability to (semi)autonomously make decisions (Brynjolfsson & McAfee, 2014; Brynjolfsson, Mitchell, & Rock, 2018). This "new generation of technology" processes work tasks in a systematic and orderly manner on its own, meaning workflows may be directed by the intelligent machines with less employee guidance or direction (Agrawal, Gans, & Goldfarb, 2017; Finlay, 2017; Glikson & Woolley, 2020: 627). Put differently, 21st-century machines have characteristics that duplicate the orderly nature of conscientious employees, which results in the opposite of a complementary balance (what we will refer to as "non-complementary" [Kiesler, 1983: 200]).[2] This calls into question whether the established 20th-century consensus about the effectiveness of conscientious employees and traditional technology may apply to 21st-century work. This changing nature of work may challenge the notion that conscientious employees consistently perform best in work roles involving technology.

To investigate this question, we integrate complementarity theory (Carson, 1969; Heider, 1982; Kiesler, 1983) and role theory (Kahn, Wolfe, Quinn, Snoek, & Rosenthal, 1964). The central premise of complementarity theory is that people often prefer complementary matches that maintain balance between their own attributes and the attributes of other work entities (e.g., extraverted leaders prefer working with less extraverted employees [Grant, Gino, & Hofmann, 2011]). This creates a problem for conscientious employees, as modern intelligent machines are similarly "orderly," "organized," and "systematic" (Fernandez, Gutierrez, Ruiz, Perez, & Gil, 2012: 54; Lwowski, Benavidez, Prevost, & Jamshidi, 2017: 48; Mahadevaiah, Rv, Bermejo, Jaffray, Dekker, & Wee, 2020: 228). Thus, these

[1] Traditional 20th-century technology is typically seen as programmable machines and equipment such as computers, data-filing and retrieval systems, and industrial equipment (Cooper & Kaplinsky, 2005). For example, Cascio and Montealegre (2016: 367) specifically noted that "traditional technology is characterized by interactions based on keyboards, computer mice, joysticks, monitors, and devices." These machines typically operate based on a "fixed set of preprogrammed instructions" (Chalmers, MacKenzie, & Carter, 2021: 1030). This is in contrast to modern, 21st-century technology that consists of intelligent machines that "have the capacity to learn, and can therefore improve and adapt based on experience" (Chalmers et al., 2021: 1030).

[2] Note that Hu and Judge (2017) used the term "anti-complementary" instead of "non-complementary." Conceptually, these authors and we are referring to the same phenomenon (i.e., the opposite of complementary balance). However, we prefer the broader term "non-complementary," as it is a more inclusive label for the nature of interactions that are, in some fashion, out of balance (Kiesler, 1983). We thank an anonymous reviewer for highlighting this point.

employees may not experience balance when working with intelligent machines—rather, they may see such work pairings as less beneficial. The non-complementarity that results can be viewed through the lens of role theory—a theory through which the intersection of work and technology has often been viewed (Cascio & Montealegre, 2016). Role theory posits that employees have a "set of expectations" attached to their work roles (Naylor et al., 1980; Van Sell, Brief, & Schuler, 1981: 43). Integrating these theories, we expect conscientious employees may find working with intelligent machines to be less beneficial for their understanding of, and ability to exceed, role expectations. These employees should thus experience reduced "role breadth self-efficacy" (a capability to "carry out a broad" range of work tasks; Parker, 1998: 835) and increased "role ambiguity" (a lack of clarity about the expectations of work tasks [Rizzo, House, & Lirtzman, 1970]) when working with intelligent machines—both of which should differently affect work performance.

We test our model in three studies—each involving a different type of intelligent machine ("artificial intelligence, algorithms, and robotics"; Brougham & Haar, 2018: 239). First, we conducted an experience sampling method (ESM) field study in Malaysia with analysts who work with *artificial intelligence* (Study 1). We then conducted a pre-registered field experiment with service employees in a Taiwanese hotel that uses *robots* into service delivery (Study 2). Finally, we conducted a pre-registered online experiment employing an *algorithm* for a business consultancy task with working adults from a variety of jobs and industries in United States (Study 3). In so doing, we make several contributions to scholarship on conscientiousness, the use of new technologies at work, and the theories from which we draw.

First, we seek to shift the established consensus about conscientiousness in the literature.[3] The arrival of 21st-century intelligent machines reveals that the consensus on conscientiousness—based on the success of these employees in working with 20th-century technology (Roberts, Jackson, Fayard, Edmonds, & Meints, 2009)—may need to be revised. Indeed, our findings call into question whether these employees are best situated to benefit from working with these intelligent machines, as their performance may suffer relative to less conscientious employees (e.g., Brynjolfsson & McAfee, 2017; Davenport & Kirby, 2016). Our second contribution follows directly from this. The current state of technology research in the organizational sciences is one in which both the performance benefits (e.g., Davenport & Ronanki, 2018; Raisch & Krakowski, 2021; Wilson & Daugherty, 2018) and the psychological drawbacks of working with intelligent machines have been acknowledged (e.g., Dietvorst, Simmons, & Massey, 2015; Efendić, Van de Calseyde, & Evans, 2020; Lawless, Mittu, Sofge, Moskowitz, & Russell, 2019). Yet, an unanswered question is *for whom* these positive or negative effects will accrue. Our identification of conscientiousness (specifically, orderliness) as a moderator answers this important question.

Third, our integrative approach contributes to the theories from which we draw. Scholars have specifically noted that using technology can impact employee role perceptions (e.g., Barley, 1990, 1996; Rizzo et al., 1970). Yet, studies of the role-relevant implications of modern technology remain scarce, despite advocacy such as that from Cascio and Montealegre (2016: 368) that "role theory may be especially useful" to understanding how these technologies impact employees. Thus, we return role theory to the forefront of such conversations as we explicate how modern intelligent machines affect role perceptions. Meanwhile, complementarity theory is typically applied to the study of human-to-human interactions (e.g., Grant et al., 2011; Grijalva & Harms, 2014). Thus, we extend its range with our focus on the interactions with intelligent machines. Our work has practical implications as well, as we highlight important ways in which the incorporation of intelligent machines to the workplace may impact human resource practice (Vrontis, Christofi, Pereira, Tarba, Makrides, & Trichina, 2021).

[3] Personality theorists have subdivided each Big Five personality construct into two subdimensions (DeYoung, Quilty, & Peterson, 2007). While we frame our manuscript around conscientiousness to establish our footing in the ongoing conversation about this trait, our theorizing (and formal hypotheses) will focus specifically on the "orderliness" subdimension (a tendency to maintain structure, order, and organization). This is because we view the characteristics of intelligent machines as being particularly similar to characteristics captured by this subdimension (e.g., as noted above, "orderly" and "systematic"), compared to those captured by the "industriousness" subdimension (a tendency to work efficiently and persistently). In the pages to follow, we mostly refer to conscientiousness (particularly when discussing theory and prior findings related to this construct). However, when developing our specific hypotheses and measurement for this manuscript, we will increase our precision by also referring to orderliness as necessary.

THEORETICAL DEVELOPMENT AND HYPOTHESES

Conscientiousness and the Technology of the Third Industrial Revolution

Over the past century, scholars from multiple disciplines (e.g., medicine, psychology, organizational management, and political science) have highlighted the benefits of conscientiousness (e.g., Bogg & Roberts, 2013; Digman, 1990; Gerber, Huber, Doherty, & Dowling, 2011; Reiss, Eccles, & Nielsen, 2014). Particularly in the work domain, conscientious employees are directive, purposeful, and disciplined (Roberts et al., 2009; Stewart, Carson, & Cardy, 1996). It is thus no surprise that conscientiousness has often been found to be a key predictor of performance (Barrick & Mount, 2000; Li et al., 2014).

Conscientious employees are driven to create order in fulfilling work role expectations (Witt, Burke, Barrick, & Mount, 2002). In so doing, these employees tend to "autonomously" develop structure and routine in their role (Mount, Barrick, & Strauss, 1999: 710), take a "hands-on approach" to tasks, and possess "a strong desire to take charge of" goal accomplishment (Hu & Judge, 2017: 939). These characteristics have been advantageous when operating traditional workplace technology—*passive* machines and systems that require instruction and guidance to function (Cascio & Montealegre, 2016; Cooper & Kaplinsky, 2005; Greenwood, 1997). Such technologies operate in a unidirectional manner: users provide an input, to which the machine responds in a pre-programmed fashion (Chalmers et al., 2021). Such technologies have relatively low "richness" (i.e., capacity to process information and provide personalized feedback; Daft & Lengel, 1986; Lengel & Daft, 1984), as they can only respond to user direction based on predetermined programming (Cable & Yu, 2007; Cooper & Kaplinsky, 2005; Daft & Lengel, 1984). As such, these technologies may be preferred by conscientious employees, as they can enact their orderly and systematic tendencies in the pursuit of work goals (e.g., Young & Menter, 1973).

Conscientiousness and the Technology of the Fourth Industrial Revolution

Yet, two decades into the 21st century, the workplace is changing (Schwab & Davis, 2018). Indeed, Salas, Kozlowski, and Chen (2017: 595) recently noted intelligent machines are altering "the nature of work in many industries, and have the potential to profoundly change work." Unlike the passive machines of the last century (Cooper & Kaplinsky, 2005), employees now collaborate with intelligent machines that not only "learn" (e.g., Jago, 2019: 39) but also have the capability to take what they have learned and use it to autonomously make decisions, synthesize information, and structure workflows and other processes (Brougham & Haar, 2018).

This distinction is critical to differentiating intelligent machines from their 20th century counterparts (Murray, 2015). While intelligent machines have idiosyncratic differences based on specific technical design aspects or intended tasks, these modern machines share a common ability to learn by analyzing prior decisions made by employees (Brynjolfsson & McAfee, 2015; Dunjko & Briegel, 2018; Wisskirchen et al., 2017). Thus, relative to traditional technologies, interactions with intelligent machines are much richer (e.g., Daft & Lengel, 1984, 1986; Suen, Chen, & Lu, 2019), in that, while they *accept* directive user input, their autonomous capabilities allow them to both *provide* suggestions and directive input to a user, as well as make decisions that are not otherwise directed by the user (Brynjolfsson & Mitchell, 2017). As such, these machines can "reduce the burden of repetitive tasks" (Ackerman & Kanfer, 2020: 448) and provide useful and timely information to employees (Lee, Kusbit, Metsky, & Dabbish, 2015).

While this paints an idyllic picture of how intelligent machines can augment employee effectiveness (Daugherty & Wilson, 2018; Gregory, Henfridsson, Kaganer, & Kyriakou, 2020), a problem arises at the intersection of this emergent trend and a separate trend that has existed for decades—the prioritization of conscientiousness in selection and recruitment (Barrick & Mount, 2000; Behling, 1998). While highly conscientious employees are seen as effective at working with technology in fulfilling their work role (e.g., Tumin, 1955; Young & Menter, 1973), these conclusions are based on 20th-century technology. Our thesis is that the intelligent machines of the 21st century may upend this consensus because of the non-complementarity between these machines and conscientious employees. To this end, we draw from complementarity theory to explain why organized and systematic (i.e., orderly) employees who work with technology that is also organized and systematic (Brynjolfsson & McAfee, 2015; Dwivedi et al., 2019) may find it difficult to fulfill work role expectations (e.g., Carson, 1969; Organ & Greene, 1974).

Complementarity Theory

Complementarity theory helps to explain the nature of interactions between people (Kiesler, 1983). This theory captures the spontaneous (and, typically, "unconscious" [Tiedens, Chow, & Unzueta, 2007: 412; Tiedens & Fragale, 2003]) responses of individuals regarding the degree to which their interactions with another entit(ies) are balanced or otherwise considered to "fit together" (Ansell, Kurtz, & Markey, 2008: 502; Leary, 1957/2004; Sadler, Ethier, & Woody, 2011). In organizational scholarship, this theory has typically been applied to person-to-person interactions, with a focus on the match between one individual's dominant characteristics and another's submissive characteristics (e.g., Grant et al., 2011; Hu & Judge, 2017; Piasentin & Chapman, 2007; Sadler et al., 2011). In the modern workplace, however, intelligent machines are increasingly seen as "coworkers" of human employees (Smids, Nyholm, & Berkers, 2020; see also De Cremer, 2020; Kozlowski, Grand, Baard, & Pearce, 2015)—that is, both independent and codependent interaction partners at work (e.g., De Cremer, 2020; Dwivedi et al., 2019; Murray, Rhymer, & Sirmon, 2021). Thus, complementarity theory can arguably provide useful insights on the consequences of interactions between employees and modern intelligent machines.

Complementarity theory's central tenet is people prefer *balance*, or *complementarity*, regarding the attributes of interaction partners (Carson, 1969; Leary, 1957/2004). Viewed through a complementarity theory lens, it follows that employees with higher orderliness—those who are inclined to create order and direct work activities while fulfilling role responsibilities (e.g., Digman, 1990; Goldberg, 1990; McCrae & Costa, 1987)—should prefer interactions with *less* orderly entities (the user-directed technology of the 20th century). Such pairings maintain balance and complementarity in the relationship, thus constituting a "match" (Grant et al., 2011: 531). In contrast, these employees may see intelligent, 21st-century technologies as non-complementary. That is, because these machines autonomously create order and direct work activities without user input, more orderly employees may struggle to find the balance between their tendency to structure workflows and the machines' tendency to do the same (e.g., Kiesler, 1983). This resulting *mis*match may make employees less effective at fulfilling their role responsibilities. To unpack the consequences that may occur from pairing orderly employees and intelligent technology, we turn now to our integration of complementarity theory and role theory.

The Role Implications of (Non)Complementarity between Employees and Intelligent Machines

While critical to complementarity theory, interactional balance is likewise critical to role theory; indeed, role theory highlights how interaction partners help employees make sense of their work role (e.g., "behavioral expectations attached to a position"; Sluss, Van Dick, & Thompson, 2011: 506). In fact, role theorists have long been interested in how incorporating technology into work influences perceptions of work roles (Barley, 1990; Coovert & Thompson, 2014). Thus, role theory is well suited to our examination of complementarity theory and the pairing of orderly employees with intelligent machines (Biddle, 1986; Kahn & Quinn, 1970).

Role theory was first introduced as a way of understanding how and why employees' perceptions of work roles are related to organizational outcomes (e.g., Gross, Mason, & McEachern, 1958; Neiman & Hughes, 1951; Parsons, 1951). Role theorists posited that employees are "continually exposed to a variety of expectations from the work environment that may affect the perceptions of their organizational roles" (Szilagyi, 1977: 376). In the years since, scholars have identified role perceptions that impact employee performance positively and negatively. We focus specifically on role breadth self-efficacy and role ambiguity.[4]

Role breadth self-efficacy. "Role breadth self-efficacy" reflects a feeling of confidence in an employee's ability to "take on broader duties" in the workplace (Parker, 1998: 835). Notably, this confidence to perform in an *expanded* role within the organization goes beyond confidence to perform the basic requirements of one's prescribed role (Parker, 1998). This distinction is important as, while scholars argue that working with intelligent machines augments employee abilities regarding their primary role (Gregory et al., 2020; Huang, Rust, & Maksimovic, 2019; Metcalf, Askay, & Rosenberg, 2019), working with these machines may increase employee confidence to expand their role by providing them with the slack resources and valuable information needed to take on an expanded set of responsibilities.

[4] Role theorists often consider a third role perception termed "role conflict" (Tubre & Collins, 2000). We do not hypothesize effects for role conflict, but we do control for this mechanism in our analyses. To explain, role ambiguity arises when employees feel confusion with regard to the responsibilities and expectations associated with their role (Rizzo et al., 1970). Role conflict, in contrast, occurs when an organizational actor sends a request that is external to, and thus otherwise incompatible with, an employee's current role (e.g., Naylor et al., 1980; Tracy & Johnson, 1981). This is unlikely to occur with intelligent machines, as these machines are designed and intended to serve an augmentation function that lies within the scope of the employee's current role.

An important feature of intelligent machines is their ability to handle repetitive and cognitively demanding tasks (Davenport & Kirby, 2016). These machines alleviate burden by autonomously taking on routine tasks associated with the employee's role (Ackerman & Kanfer, 2020). This helps employees by providing them with slack resources (Davenport, Brynjolfsson, McAfee, & Wilson, 2019), which they can use to exercise discretion and flexibility—both of which are important for role breadth self-efficacy (Axtell & Parker, 2003; Sonnentag & Spychala, 2012). Meanwhile, a feature of intelligent machines is their ability to continuously "capture and mine large quantities of data," and use machine learning to understand and interpret these data without the employee having to provide guidance or direction (Jordan & Mitchell, 2015: 257; McAfee & Brynjolfsson, 2017). This enables them to draw connections—often without employee input—between disparate pieces of information the employee may not have noticed.

Prior work on media richness (Cable & Yu, 2007; Daft & Lengel, 1984) suggests that the user experience described above should lead to intelligent machines being seen as a credible work partner, which should increase the likelihood that employees will value the resources and information provided, and be more likely to rely on the machines (Daft & Lengel, 1986; Suen et al., 2019). In this way, the novel insights from intelligent machines may make employees feel confident in proactively taking on other tasks (Castro & New, 2016; Raisch & Krakowski, 2021). Armed with timely and relevant information—for instance, about customer preferences and patterns—employees may be more willing to help customers or other stakeholders, or provide recommendations to colleagues or managers in ways that go beyond in-role responsibilities (e.g., Parker, 2000; Parker, Bindl, & Strauss, 2010; Wilson & Daugherty, 2018).

However, complementarity theory suggests these benefits may be less salient to some employees. That is, when working with the "dumb" (Wilson & Daugherty, 2018: 7) machines of the 20th century, those employees with higher levels of orderliness have been able to set their own goals and dictate how work was done. Thus, the collision of the autonomous and systematic features of 21st-century intelligent machines with the similar characteristics of orderly employees generates a non-complementary mismatch (Horowitz, Wilson, Turan, Zolotsev, Constantino, & Henderson, 2006). Indeed, orderly employees may not appreciate the richness of these machines; rather, they are more likely to prefer the more unidirectional, user-directed nature of traditional technology (Costantini & Perugini, 2016; Jackson, Wood, Bogg, Walton, Harms, & Roberts, 2010). Thus, the nature of these modern technologies may go against the "strong desire to take charge" of work procedures possessed by these employees (Hu & Judge, 2017: 939).

Following from the above, employees with higher levels of orderliness may not see the information or suggestions provided by intelligent machines as credible. Put differently, instead of being guided by an intelligent machine, orderly employees are likely to want to develop novel insights and methods of approaching tasks on their own (e.g., Barrick et al., 1993; Cianci et al., 2010). As a result, these employees may glean fewer slack resources from interacting with these machines. Unfortunately, this detracts from the benefits of this technology by limiting the discretion and flexibility to expand their role responsibilities offered by these machines.

In contrast, employees with lower levels of orderliness should be more receptive to the autonomous capabilities of intelligent machines and regard them as a good match at work. These employees have less "built-in desire" to control their work processes (Cianci et al., 2010: 620), and should thus be more likely to see the intelligent machines as credible and accept the information and insights these machines provide (e.g., Cable & Yu, 2007). This is important, as employees with lower levels of orderliness should be well positioned to take advantage of the benefits that these machines can provide. In contrast to their higher-orderliness counterparts, these employees should be more willing to see the information provided by intelligent machines as valuable, and, as such, take greater advantage of the slack resources that come from interacting with these machines. Accordingly, using intelligent machines should make these employees more willing to take on expanded role responsibilities. Taken together, we hypothesize:

> *Hypothesis 1. Conscientiousness (orderliness) moderates the positive relationship between the usage of intelligent machines at work and role breadth self-efficacy, such that this positive relationship is stronger at lower levels of conscientiousness (orderliness) and weaker at higher levels.*

Role ambiguity. Beyond role breadth self-efficacy, role theorists acknowledge another role perception: role ambiguity (House & Rizzo, 1972; Rizzo et al., 1970). "Role ambiguity" reflects "perceptions of uncertainty concerning various aspects" of the job (Breaugh & Colihan, 1994: 191), and occurs when work factors negatively affect employees' understanding of what is expected at work and how to adequately fulfill role responsibilities (e.g., Breaugh & Colihan, 1994). Although working with intelligent machines may carry the benefits discussed above, this may come at a cost of inducing a sense of role ambiguity (e.g., Cascio & Montealegre, 2016).

The capabilities of intelligent machines allow them to think, process information, and autonomously perform tasks (Brynjolfsson & McAfee, 2015, 2017; Davenport & Ronanki, 2018; Hupfer, 2020). This is typically the province of employees, which can cause confusion as to whom is responsible for the job and its outcomes (i.e., the employee or the machine; McCorduck, 2004; Sun & Medaglia, 2019). That is, these machines more rapidly synthesize information, which they use to learn and adapt (Raisch & Krakowski, 2021). This can result in the unexpected introduction of new data, or modifications to how role responsibilities are enacted (e.g., Barley, 1990; Carter & Nielsen, 2017; Davenport, 2018; Rizzo et al., 1970), for which the employee was not prepared. While such alterations might be useful, the richness afforded by these machines can be disrupting and confusing (Bauer & Simmons, 2000; Schuler, 1977; Suen et al., 2019). Indeed, intelligent machines may create confusion as employees question what "comprises their role set" (Cascio & Montealegre, 2016: 368).

Bridging back to complementarity theory, more orderly employees in particular should feel as if their preferred working style is incompatible with these intelligent machines. These employees approach work in a directive and systematic fashion, and are accustomed to "controlling activities" (Hu & Judge, 2017: 939). As such, they may be unsettled with the ways that intelligent machines autonomously adjust work processes, and feel unclear and uneasy about the decisions made by the intelligent machines, the process that led to those decisions, or the effectiveness of those changes (Brynjolfsson & Mitchell, 2017; Rahwan et al., 2019). Thus, these employees may feel ambiguity about who is ultimately in control of assigned role responsibilities and be unsure of how to go about fulfilling the expectations of their role (e.g., Rizzo et al., 1970).

In contrast, employees with lower levels of orderliness are less driven to maintain control over their tasks (Digman, 1990; McCrae & Costa, 1987), which may make them more open to the intelligent machines' advanced capabilities, and willing to allow these technologies to control and define the scope of the employee's role responsibilities (Brynjolfsson & McAfee, 2017; Davenport & Ronanki, 2018). As these employees are less concerned about maintaining control over work processes, they are more likely to see intelligent machines as credible, and thus are more willing to accept changes and decisions these machines make (e.g., Cable & Yu, 2007). Consequently, working with intelligent machines should be complementary for these employees, and not create ambiguity with regard to role responsibilities. Together, we therefore hypothesize:

> *Hypothesis 2. Conscientiousness (orderliness) moderates the positive relationship between the usage of intelligent machines at work and role ambiguity, such that this positive relationship is stronger at higher levels of conscientiousness (orderliness) and weaker at lower levels.*

From Role Perceptions to Task Performance

By integrating complementarity theory (Carson, 1969; Kiesler, 1983) with role theory (Kahn & Quinn, 1970; Kahn et al., 1964), we have thus far elucidated the (non-)complementarity between (more) less conscientious employees in the era of intelligent machines (Brougham & Haar, 2018). Drawing further on role theory, we close the loop on this process by explaining the differential effects of role breadth self-efficacy and ambiguity on employee task performance.

Role breadth self-efficacy reflects a state in which employees feel that they can take on a broader set of duties beyond their primary role (Morgeson, Delaney-Klinger, & Hemingway, 2005; Parker, 1998, 2000). Alongside a willingness to expand one's role should be higher levels of performance; indeed, role breadth self-efficacy is associated with proactively accomplishing work tasks (Beltrán-Martín, Bou-Llusar, Roca-Puig, & Escrig-Tena, 2017; Parker, 2000; Strauss, Griffin, & Rafferty, 2009). While this confidence may lead employees to take on extra-role tasks (e.g., making proactive contributions to improve the company's strategy, or collaborating with people across different departments and teams to provide suggestions; Parker, 1998), they may also be more effective at anticipating and performing in-role tasks. Indeed, role breadth self-efficacy makes employees willing to "carry out a range of proactive [and] integrative" tasks (Parker, 2000: 452), which may also reflect a dedication to in-role responsibilities.

Thus, combined with confidence to perform these tasks, role breadth self-efficacy should create a solid foundation for the performance of one's work role (e.g., Griffin, Neal, & Parker, 2007). And, to this point, direct and indirect empirical evidence supports the aforementioned claims. For example, Parker (1998) found positive associations between role breadth self-efficacy and performance indicators such as job enrichment. Hao, He, and Long (2018) similarly observed a positive association between role breadth self-efficacy and job performance. Combining our arguments from Hypothesis 1 with the above, we hypothesize:

Hypothesis 3. The indirect effect of usage of intelligent machines on task performance via role breadth self-efficacy is moderated by conscientiousness (orderliness), such that the indirect effect will be stronger when conscientiousness (orderliness) is lower compared to higher.

Because role ambiguity reflects employees' uncertainty about the expectations and responsibilities associated with their role (Breaugh & Colihan, 1994; Hamner & Tosi, 1974), role ambiguity should detract from work performance (e.g., Rizzo et al., 1970). Indeed, employees in this situation lack "clarity about [the] behavioral expectations" involved in their work role (e.g., Van Sell et al., 1981: 50), and may thus they may end up "working at the wrong things" (Organ & Greene, 1974; Van Sell et al., 1981: 51). This should reduce the effort they devote toward work goals (Beehr, Walsh, & Taber, 1976; Brief & Aldag, 1976; Yoon et al., 2021).

Indeed, empirical evidence from previous role studies provides direct support to this relationship. For example, Szilagyi (1977) found a negative relationship between employee role ambiguity and their task performance, whereas Jackson and Schuler (1985) found in their meta-analysis that role ambiguity is detrimental to employee performance. More recently, Yun, Takeuchi, and Liu's (2007) findings demonstrated that role ambiguity and task performance are negatively related. Combining our arguments from Hypothesis 2 with the above, we hypothesize:

Hypothesis 4. The indirect effect of usage of intelligent machines on task performance via role ambiguity is moderated by conscientiousness (orderliness), such that the indirect effect will be stronger when conscientiousness (orderliness) is lower compared to higher.

OVERVIEW OF STUDIES

We conducted three studies that (a) involve the three different types of intelligent machines mentioned earlier (artificial intelligence, algorithms, and robotics), (b) employ different research methodologies (i.e., an ESM field study, a field experiment, and an online experiment), and (c) recruit participants from various national cultures (i.e., overall, 681 from Malaysia, Taiwan, and the United States). In so doing, our research comports with what Chatman and Flynn (2005: 434) termed a "full cycle" research approach—examining the phenomenon in a field setting, and following up with a series of experimental studies to address limitations and enhance internal and external validity (see also Hekman, Johnson, Foo, & Yang, 2017). Study 1 reports an ESM study that offers a preliminary examination of our model in a technology service company headquartered in Malaysia—an under-sampled country in social sciences—where employees use artificial intelligence software on a daily basis. Study 2 enhances these findings by testing our model in a pre-registered field experiment in a Taiwanese hotel where employees work with robots to serve customers. Finally, Study 3 tests our model in a pre-registered online experiment wherein we manipulated whether participants performed a task on their own or alongside what they thought was a smart algorithm powered by Amazon Polly. Figure 1 illustrates our theoretical model.

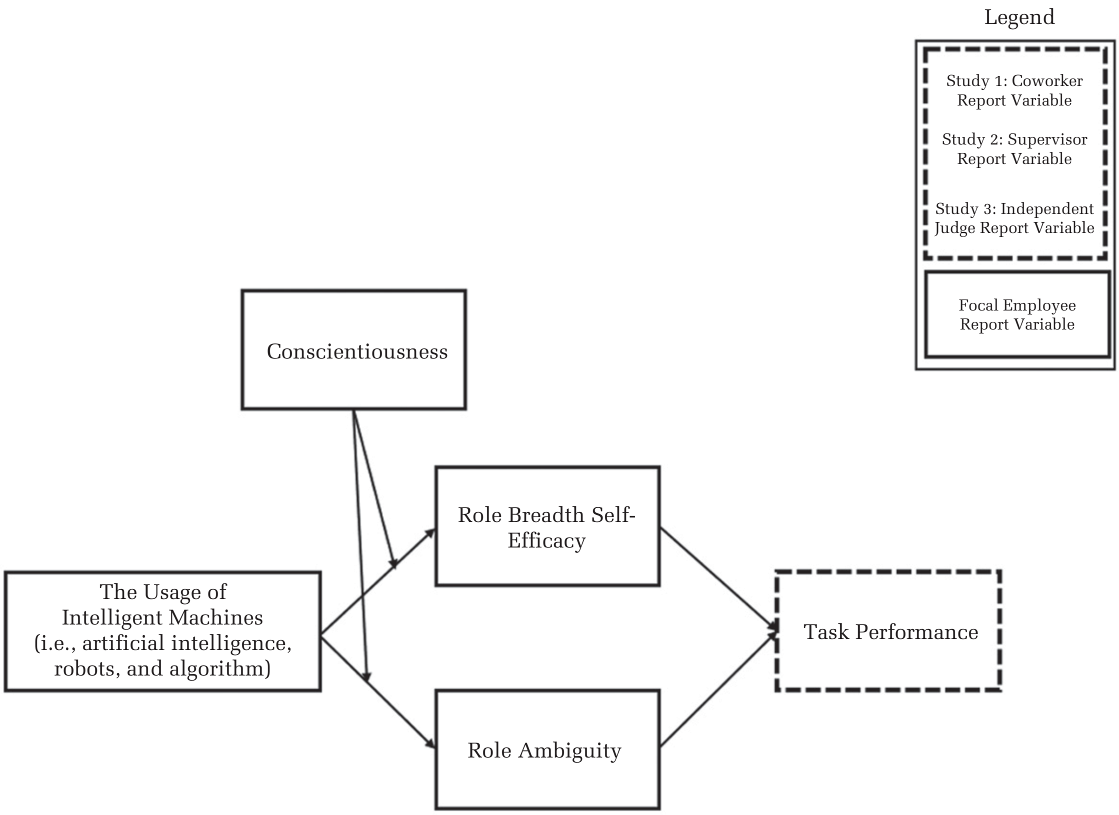
STUDY 1: METHOD

Sample and Procedure

Syntax, data, and appendices for all study materials can be found at https://osf.io/nszmx. In Study 1, we examine artificial intelligence as the specific form of intelligent machine with which participants work (Brougham & Haar, 2018). Artificial intelligence is being increasingly incorporated into a number of employees' jobs—especially in the professional services sector (e.g., Agrawal et al., 2017; Qasim & Kharbat, 2020; Tambe, Cappelli, & Yakubovich, 2019; Vogl, Seidelin, Ganesh, & Bright, 2020; Wilson & Daugherty, 2018). We recruited employees from a technology company in Malaysia that provides screening and regulatory compliance monitoring services for governmental authorities. Our sample consisted of analysts whose primary responsibilities involve working with artificial intelligence to evaluate employee compliance with regulations and policies (see online Appendix A, available at https://osf.io/vyk72, for a sample photo).

An announcement was emailed to 122 analysts, which contained study details, and an opt-in survey link (measuring demographics and our moderator). One week later, we began sending three surveys per day (two to employees and one to a coworker for 10 workdays; no focal employee acted as a coworker for another employee, and coworkers rated only a single employee). We assigned coworkers based on physical proximity to, and opportunity to observe, the focal employee, to ensure that they could provide accurate ratings (Rodell, 2013; Trougakos, Beal,

FIGURE 1
Theoretical Model



Cheng, Hideg, & Zweig, 2015). Focal employees received surveys at the middle and end of their workday (i.e., between 1 and 2 p.m. and between 5 and 6 p.m.), and coworkers received their survey at the end of the workday (between 5 and 6 p.m.). Midday surveys contained a measure of daily artificial intelligence usage at work, while end-of-work survey had measures of daily role breadth self-efficacy and role ambiguity. The coworker's end-of-work survey contained a measure of the focal employee's task performance. From the initial 122 analysts, 114 participated and provided 776 day-level observations (68% response rate). Employees mostly identified as female (74.6%), and on average were 35.84 years old (*SD* = 8.47), had worked for the company for 3.32 years (*SD* = 2.67), and had 2.18 years (*SD* = 0.83) experience using intelligent machines.

Measures for Hypothesized Variables

In line with previous ESM studies (e.g., Mitchell, Greenbaum, Vogel, Mawritz, & Keating, 2019), and best practices (Beal, 2015; Gabriel et al., 2019a), we shortened some scales (based on conversations with company directors) and used the same anchors (1 = *strongly disagree*, 7 = *strongly agree*) to minimize participant burden. Online Appendix B reports all items used in this study (see https://osf.io/vyk72). To evaluate the convergence of the short measures with the longer versions, we followed an approach used by Rosen, Simon, Gajendran, Johnson, Lee, and Lin (2019). In a sample of 178 individuals from Prolific (an online source for recruiting participants we discuss further in Study 3), we administered our shortened scales, as well as full-length scales, and examined their correlations. Results showed all short-form scales had strong correlations with the long-form counterparts (*r*s ranging from .78 to .92), which suggests our use of shortened scales is not likely a threat to the validity of our findings.

Conscientiousness. We measured conscientiousness in the sign-up survey with four items from Saucier (1994). Although this scale largely samples from orderliness content, Saucier (1994) and other research using these items label the scale as pertaining to conscientiousness and thus we do as well. Participants rated their agreement about whether the adjectives accurately described themselves. A sample item was the adjective "organized." The coefficient alpha was .74.

Daily artificial intelligence usage. To measure daily artificial intelligence usage, we adapted three items from Medcof (1996): "I used artificial intelligence to carry out most of my job functions," "I spent most of the time working with artificial intelligence," and "I worked with artificial intelligence in making major work decisions." Participants indicated their agreement with these items for the first half of their workday. Average daily alpha was .92 (range = .83 to .96).

To evaluate the validity of this measure, and to differentiate using artificial intelligence from using traditional 20th-century workplace technology (personal computers; word processing or spreadsheet software, such as Microsoft Word or Excel; the Internet), we followed procedures articulated by Colquitt, Sabey, Rodell, and Hill (2019) and used in recent studies (Baer et al., 2018a; Baer, Van Der Werff, Colquitt, Rodell, Zipay, & Buckley, 2018b). We recruited 130 U.S. employees from Prolific and showed them a definition of artificial intelligence usage:

> The extent to which an employee uses and spends time with artificial intelligence (a specific type of modern software equipped with autonomous learning, reasoning, problem-solving, and decision-making capability) in the pursuit of work goals.

Participants then rated the definitional correspondence of our items, as well as adapted versions for the alternatives mentioned above (1 = *item is an extremely bad match to the definition*, 7 = *item is an extremely good match to the definition*). Mean definitional correspondence for our items was 6.20, which was greater than the three alternatives (2.68, 2.51, and 2.56, respectively). We used this to calculate *htc* and *htd* statistics (Colquitt et al., 2019). Using benchmarks from these authors, results suggest our items have strong definitional correspondence (.89) and distinctiveness from the alternatives (.60).

Daily role breadth self-efficacy. We adapted three items from Parker (1998); a similarly adapted three-item shortened version of this scale was used in recent ESM study from Ouyang, Cheng, Lam, and Parker (2019). In the end-of-day survey, participants rated their agreement with how confident they felt about the listed tasks since the last survey. A sample item is "Helping to set targets/goals at work." Average daily alpha was .81 (range = .71 to .85).

Daily role ambiguity. We adapted six items from Rizzo et al. (1970). In the end-of-day survey, participants rated their agreement with each statement since the last survey. A sample item is "I do not know exactly what is expected of me." Average daily alpha was .90 (range = .86 to .92).

Daily task performance. A coworker rated the focal employee's task performance at the end of the day with four items from Turnley, Bolino, Lester, and Bloodgood (2003). A sample item is "[name of focal employee] fulfilled all the responsibilities specified in his/her job description." Average daily alpha was .91 (range = .87 to .96).

Measures for Control Variables

Daily role conflict. As discussed previously, role conflict is an important role perception identified by role theorists. Although we do not expect role conflict to transmit the effects of daily artificial intelligence usage to performance, it could represent an alternative explanation for our proposed effects; as such, we measured and controlled for it for robustness purposes. We adapted three items from Rizzo et al. (1970). In the end-of-day survey, participants rated their agreement with each statement since the last survey. A sample item is "I received incompatible requests from the artificial intelligence." Average daily alpha was .77 (range = .72 to .82).

Analytic Strategy

To further isolate our proposed effects, and to account for potential contaminants, we controlled for a number of theoretically and empirically relevant factors (though, our results and conclusions are unchanged with all controls removed; see online Appendix C). First, as previously mentioned, we modeled a path through daily role conflict. Second, to account for potential cyclicality and other temporal factors, we followed recent recommendations (e.g., Gabriel et al., 2019a) and controlled for the day of the week as well as the sine and cosine of that day,[5] along with the day of the study and lagged,

[5] ESM scholars have noted that daily (temporal) data is often associated with cyclical components (Gabriel et al., 2019a). That is, such data "are particularly likely to have associated weekly" cycles (West & Hepworth, 1991: 618). For example, it is possible that employees may feel particular states on a given day that wax or wane over the course of a week, thus creating predictable pattern that could serve as an alternative explanation for our findings. For this reason, Beal and Weiss (2003: 456) explicitly advised

prior-day versions of all endogenous study variables. Finally, as the length of time employees have worked with intelligent machines may give them insight into their operation, potentially dampening their effects on role perceptions (Dokko, Wilk, & Rothbard, 2009), we also controlled for tenure of working with this technology.

We used multilevel path analysis with Mplus 7.4 (Muthén & Muthén, 2015) to test our model. Specifically, we modeled relationships among hypothesized within-person variables and alternate mechanisms with random slopes (e.g., Gabriel et al., 2019a), and modeled within-person controls with fixed slopes to reduce model complexity (e.g., Gabriel, Volpone, MacGowan, Butts, & Moran, 2019b; Koopman, Lin, Lennard, Matta, & Johnson, 2020). Conscientiousness was modeled at Level 2. Exogenous within-person variables were group-mean centered, and the moderator was grand-mean centered to facilitate interpretability. To test conditional indirect effects, we followed suggestions from Preacher, Zyphur, and Zhang (2010) to calculate the value of each conditional path at high (+1 *SD*) and low (−1 *SD*) levels of conscientiousness (Aiken & West, 1991). We constructed 95% bias-corrected confidence intervals (CIs) around each conditional indirect effect using a Monte Carlo simulation with 20,000 replications. Moderation is supported when the CI for the difference between indirect effects at high and low levels of the moderator excludes zero.

We examined the proportion of variance at the within-person level for daily study variables (ranging from 86 to 99%, which falls within the range of "11% to 99%" found in Podsakoff, Spoelma, Chawla, & Gabriel's (2019: 732) review). Thus, study variables showed sufficient within-person variation. Next, we conducted a multilevel confirmatory factor analysis (CFA). Our hypothesized model contains five within-person variables (daily AI work usage, role breadth self-efficacy, role ambiguity, role conflict, and performance) and one between-person variable (i.e., conscientiousness). This six-factor model demonstrated acceptable fit to the data, $\chi^2(144) = 406.98$ (RMSEA = .05, CFI = .96, $\text{SRMR}_{\text{Within}} = .04$, $\text{SRMR}_{\text{Between}} = .03$), and fit better than a series of alternative models (available upon request).

scholars to control for "sine/cosine functions of time" in ESM analyses so as to account for the potential presence of such artifactual influences (see also Beal & Ghandour, 2011).

STUDY 1: RESULTS

Table 1 presents descriptive statistics and correlations; Table 2 contains path analysis results. Hypothesis 1 predicted that the positive relationship between the usage of intelligent machines (i.e., daily artificial intelligence usage in this study) on role breadth self-efficacy would be stronger at lower levels of conscientiousness than at higher levels of conscientiousness. First, on days in which artificial intelligence usage was higher, employees reported higher levels of role breadth self-efficacy ($\gamma = .29$, $SE = 0.03$, $p < .01$). Failing to support Hypothesis 1, however, conscientiousness did not significantly moderate this relationship ($\gamma = .05$, $SE = 0.04$, $p = .20$).

Hypothesis 2 predicted that the positive relationship between intelligent machine usage on role ambiguity would be stronger at higher levels of conscientiousness than at lower levels of conscientiousness. First, artificial intelligence usage was positively associated with role ambiguity ($\gamma = .14$, $SE = 0.03$, $p < .01$). Supporting Hypothesis 2, the moderating effect of conscientiousness on this relationship was significant ($\gamma = .07$, $SE = 0.03$, $p = .04$). As expected (Figure 2), the effect of artificial intelligence usage was more positive for employees with higher levels of conscientiousness ($\gamma = .19$, $p < .01$) than for those with lower levels ($\gamma = .09$, $p = .01$).

Hypothesis 3 predicted that the positive, indirect effect of the usage of intelligent machines at work at work on daily task performance, through role breadth self-efficacy, would be stronger at lower levels of conscientiousness than at higher levels. First, the effect of role breadth self-efficacy on task performance was significant ($\gamma = .40$, $SE = 0.04$, $p < .01$). However, because conscientiousness did not moderate the relationship between artificial intelligence usage and role breadth self-efficacy, Hypothesis 3 was not supported. That is, while the conditional indirect effect was significant at both higher (conditional indirect effect = .129, 95% CI [.091, .177]) and lower (indirect effect = .103, 95% CI [.067, .146]) conscientiousness, the difference between the two was not significant (95% CI [−.014, .071]).

Hypothesis 4 posited that the negative, indirect effect of the usage of intelligent machines at work on task performance, through role ambiguity, would be stronger at higher, compared to lower, levels of conscientiousness. First, the effect of role ambiguity on task performance was significant ($\gamma = -.29$, $SE = 0.04$, $p < .01$). The negative indirect relationship between artificial intelligence usage and task performance through role ambiguity was significant at

TABLE 1
Study 1: Descriptive Statistics and Correlations among Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7
Level 1									
1. Daily artificial intelligence work usage	3.48	1.86	(.92)						
2. Daily role breadth self-efficacy	4.37	1.35	.41*	(.81)					
3. Daily role ambiguity	2.87	1.29	.18*	.08*	(.90)				
4. Daily role conflict	3.75	1.15	−.05	−.02	.08*	(.77)			
5. Daily task performance	4.57	1.38	.08*	.39*	−.26*	−.08*	(.91)		
Level 2									
6. Conscientiousness (between-person)	5.94	0.72	.71*	.48*	.13	.20*	−.23*	(.74)	
7. Tenure with intelligent machines (in years)	2.18	0.83	−.11	−.52*	−.12	.11	−.12	−.02	—

Notes: Level 1, $n = 776$; Level 2, $n = 114$. Average scale reliabilities, across study days, are reported in parentheses along the diagonal.
* $p < .05$

higher (conditional indirect effect = −.053, 95% CI [−.078, −.033]) and lower levels of conscientiousness (conditional indirect effect = −.026, 95% CI [−.049, −.007]). Further, the difference between these indirect effects was significant (95% CI [−.058, −.002]). As such, Hypothesis 4 was supported.

STUDY 1: DISCUSSION

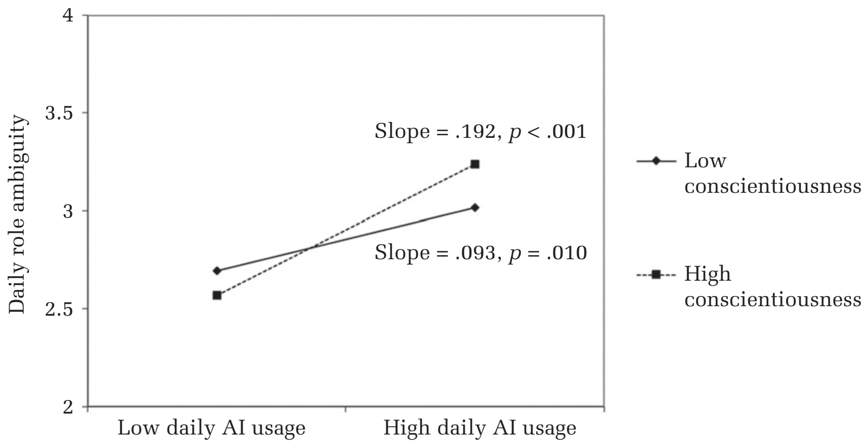
Study 1 provides initial evidence for our hypotheses on the effects of using artificial intelligence software (i.e., intelligent machines) at work for conscientious employees. Employees felt more role ambiguity on days when they more frequently worked with artificial intelligence, and this effect was stronger for employees

TABLE 2
Study 1: Daily Path Analytic Results

	Daily mechanisms						Daily outcome	
	Role breadth self-efficacy		Role ambiguity		Role conflict		Task performance	
Variables	γ	*SE*	γ	*SE*	γ	*SE*	γ	*SE*
Controls								
Study day	.00	(0.02)	−.04*	(0.01)	.01	(0.01)	.02	(0.01)
Week day	−.02	(0.05)	.08	(0.07)	.05	(0.05)	−.01	(0.06)
Week day (sine)	−.07	(0.09)	.08	(0.12)	.13	(0.09)	−.02	(0.10)
Week day (cosine)	.15	(0.08)	−.02	(0.08)	−.04	(0.08)	.01	(0.09)
Tenure with intelligent machines	−.08	(0.05)	−.02	(0.05)	.06	(0.06)	.00	(0.05)
Lagged role breadth self-efficacy	−.15*	(0.05)						
Lagged role ambiguity			−.20*	(0.05)				
Lagged role conflict					−.18*	(0.06)		
Lagged task performance							−.09	(0.06)
Predictors								
Daily artificial intelligence work usage	.29*	(0.03)	.14*	(0.03)	−.02	(0.02)	−.02	(0.03)
Conscientiousness (between-person)	.08	(0.06)	.04	(0.06)	.15	(0.08)		
Daily artificial intelligence work usage × Conscientiousness	.05	(0.04)	.07*	(0.03)	.00	(0.03)		
Daily role breadth self-efficacy							.40*	(0.04)
Daily role ambiguity							−.29*	(0.04)
Daily role conflict							−.09	(0.05)
Intercept	4.47*	(0.17)	2.86*	(0.22)	3.56*	(0.17)	3.91*	(0.35)
ΔR^2 (controls)	2%		3%		3%		2%	
ΔR^2 (main effects)	19%		4%		1%		16% ǀ 8% ǀ 0%	
ΔR^2 (interaction)	1%		3%		0%			

Notes: Level 1, $n = 776$; Level 2, $n = 114$. Unstandardized coefficients are reported.
* $p < .05$

FIGURE 2
Study 1: Moderating Effect of Conscientiousness on the Relationship between Daily Artificial Intelligence (AI) Usage and Daily Role Ambiguity



with higher levels (compared to lower levels) of conscientiousness. In contrast, while working with artificial intelligence was also associated with increased role breadth self-efficacy, this relationship was not moderated by conscientiousness.

Despite this study's strengths, it has several limitations that hinder our ability to draw firm conclusions. While the design of Study 1 is useful for establishing external validity, it is limited in its ability to establish internal validity—this is better accomplished via experimental designs. Plus, despite controlling for role conflict as an alternative mechanism for the link between artificial intelligence usage and performance, there are other variables (notably, job autonomy and job demands) that are potential confounds to the relationship between the use of intelligent machines and our focal role mediators that should be controlled for as well.

Further limitations pertain to measurement. As is the norm in ESM research, we used shortened measures (Mitchell et al., 2019; Ouyang et al., 2019; Zhang, Mayer, & Hwang, 2018). However, a more robust approach would be to use full scales. Questions also remain in relation to the use of coworkers to report on employee performance, as it is not clear they are qualified to evaluate this. Plus, employees knew coworkers were completing a survey about their daily behavior, which could influence their performance. More importantly, the scale we used for our moderator is a notable limitation. Although this scale largely samples from the orderliness subdimension, it would be more robust to use a measure designed to capture that specific content space of the broader conscientiousness construct (DeYoung et al., 2007). Finally, although our study variables all exhibited considerable daily variance, there is nothing explicitly within-individual about this phenomenon or the theoretical arguments we develop. To this point, Voelkle, Brose, Schmiedek, and Lindenberger (2014) argued that researchers should conduct studies at both levels of analysis (i.e., within- and between-person) to provide a comprehensive view of the phenomena of interest. To address these limitations, we now report results of a pre-registered field experiment conducted with employees who work in conjunction with robots.

STUDY 2: METHOD

Sample and Procedure

Syntax, data, and appendices for all study materials can be found at https://osf.io/nszmx. In Study 2, we examine robots as a specific form of intelligent machines (Brougham & Haar, 2018). Indeed, organizations are increasingly adopting intelligent robots into their business operations (i.e., as indicated by an increase of 61% in the sale of these machines; International Federation of Robotics, 2019). We conducted a pre-registered[6] field experiment with service employees in a contemporary Taiwanese hotel who use robots to perform their primary responsibility of providing customer service. Indeed, service

[6] Pre-registration material: https://aspredicted.org/blind.php?x=pv38vs

employees represent one of the fasting-growing workforce segments whose jobs are being augmented with robots (e.g., Choi, Choi, Oh, & Kim, 2020; Fortune Business Insights, 2020; Naumov, 2019; Yu, 2020).

One author and four research assistants conducted a face-to-face briefing session with all 168[7] service employees at the hotel. We described the nature of and compensation for the study (i.e., a market coupon for approximately 60 USD) with potential participants. The next day, we began the study with the 162 employees who agreed to participate. Employees completed a baseline (Phase One) survey that measured orderliness, role breadth self-efficacy, role ambiguity, two controls (job demands and job autonomy), and demographics. Each participant's supervisor also provided a baseline rating on that person's service performance (as a control).

Participants were then randomly assigned to two conditions (i.e., robotic and control). Following prior field experiments, we randomly assigned conditions by service sections (clubhouse, reception, concierge, and lounge), instead of by individuals, to avoid contamination within condition (Dvir, Eden, Avolio, & Shamir, 2002; Langer & Rodin, 1976; Lee, Forlizzi, Kiesler, Rybski, Antanitis, & Savetsila, 2012). For three consecutive days, employees were instructed to either work and collaborate with intelligent service robots to serve customers as much as possible (robotic condition) or not to use service robots at all when serving customers (control condition). A research assistant (blind to the study hypotheses) was assigned to each section to ensure participants followed instructions (e.g., Becker, 1978). Online Appendix D (available at https://osf.io/vyk72) provides a sample photo that illustrates an instance of the robotic condition.

After the three workdays (i.e., Dvir et al., 2002), participants reported their role breadth self-efficacy, role ambiguity, and role conflict over the last three days (Phase Two), and also completed manipulation check items. Each participant's immediate supervisor rated their service performance over the last three days (Madjar, Oldham, & Pratt, 2002; Tepper, Moss, & Duffy, 2011). All 162 service employees (55.6% female) completed the study. On average, participants were 32.13 years old (SD = 6.82), and had worked for the organization for 2.56 years (SD = 1.16). On average, they had 1.73 years (SD = 0.83) experience in using intelligent machines.

[7] We used the effect size of the interaction effect from Study 1 (f^2 = .053) to determine the sample size needed. An a priori power analysis suggests that approximately 211 total observations are required to achieve 80% power at an alpha of .05 (Cohen, 1992a, 1992b). However, this number exceeded the total number of service employees (168) of the organization. A post-hoc power analysis based on the actual effect size of the interaction effect between the robot condition and orderliness from this study (f^2 = .153) yielded a power of .99 at an alpha of .05, making this sample sufficient for hypothesis testing.

Measures for Hypothesized Variables

We translated measures from English to Taiwanese via the back-translation procedure (Brislin, 1980), and used the same anchors as Study 1. Online Appendix E reports all items (see https://osf.io/vyk72).

Conscientiousness (orderliness). We measured conscientiousness in the baseline (i.e., Phase One) survey using the orderliness subscale from DeYoung et al. (2007). Participants were asked to what extent they agreed that each statement accurately described themselves. Sample items include "like order" and "want everything to be 'just right.'" Coefficient alpha was .92.

Role breadth self-efficacy. We measured role breadth self-efficacy in the baseline Phase One survey (as a control) and also post-manipulation (i.e., over the past three days; Phase Two) using the 10-item scale developed by Parker (1998), with slight adaptations to the service context based on informal conversations with the line managers of the hotel. Participants rated their agreement with how confident they felt about the listed tasks at work. A sample item is "Contributing to discussions about your company's strategy." Coefficients alphas were .97 and .99, respectively.

Role ambiguity. We measured role ambiguity in the baseline Phase One survey (as a control) and also post-manipulation (i.e., over the past three days; Phase Two) using the six-item scale from Rizzo et al. (1970), with similar adaptations as role breadth self-efficacy. Participants rated their agreement with each statement. A sample item is "I do not know exactly what is expected of me to provide services to customers." Coefficients alphas were .92 and .97, respectively.

Service performance. We asked the immediate supervisor for each employee to rate their baseline Phase One service performance (as a control), as well as post-manipulation (i.e., over the past three days; Phase Two) using the three-item scale from Salanova, Agut, and Peiró (2005). Supervisors rated their agreement with each statement. A sample item is "[name of employee] satisfied customers with his/her excellent service." Coefficient alphas were .83 and .97, respectively.

Measures for Control Variables and Manipulation Check

Role conflict. In line with our rationale in Study 1, we controlled for role conflict. We measured role conflict in the baseline Phase One survey (as a control) and post-manipulation (i.e., over the past three days; Phase Two) with eight items from Rizzo et al. (1970), adapted similar to role breadth self-efficacy and role ambiguity scales. Participants rated their agreement with each statement. A sample item is "I have received incompatible requests while working to provide services to customers." Coefficient alphas were .89 and .94, respectively.

Conscientiousness (industriousness). While our theoretical model primarily focuses on the orderliness subdimension of conscientiousness, for robustness purposes, we also controlled for the industriousness subdimension, which we measured in the baseline survey (DeYoung et al., 2007). Participants rated their agreement that the statements accurately described themselves. Sample items include "Finish what I start" and "Get things done quickly." Coefficient alpha was .88.

Job autonomy. Job autonomy is a potential confound for the effects of working with intelligent machines predicting role breadth self-efficacy (Axtell & Parker, 2003; Parker, Wall, & Jackson, 1997; Sonnentag & Spychala, 2012), as greater autonomy may also motivate employees to obtain skills and integrate more tasks into their role. We measured job autonomy in the baseline Phase One survey with the three-item scale from Morgeson et al. (2005). Participants rated their agreement with how accurately the statements describe their job. A sample item is "I have significant autonomy in determining how I do my job." Coefficient alpha was .89.

Job demands. Job demands are also a potential confound for the effects of working with intelligent machines predicting both role perceptions, as job demands can both hinder the ability to feel greater role breadth self-efficacy and introduce more ambiguity into the role (e.g., Lobban, Husted, & Farewell, 1998). Thus, working with intelligent machines could be a job demand, and not something with unique effects on role perceptions (e.g., Dwivedi et al., 2019). We measured job demands in the baseline Phase One survey with seven items from Karasek (1979). Participants rated their agreement with how accurately the statements described their job. A sample item is "My job requires a great deal of work to be done." Coefficient alpha was .87.

Manipulation check items. We used the three items from Study 1 (adapted to robots) to assess the effectiveness of our manipulation by asking participants whether they had primarily fulfilled their job responsibilities by working in conjunction with robots *over the last three days*. A sample item is "I worked with robot(s) in making work decisions." Coefficient alpha was .98.

Analytic Strategy

Our primary model mirrored Study 1 (modeling role conflict as an alternative mechanism, controlling tenure working with intelligent machines; Dokko et al., 2009). We further controlled for baseline assessments of endogenous variables following prior multi-wave field experiments (Buller & Bell, 1986; Lawler & Hackman, 1969). In online Appendix F, we retain those control variables, and add the additional controls discussed above (industriousness, job autonomy, and job demands)—note that results and conclusions are unchanged. As these latter variables reflect potential confounds, and not theoretically relevant alternative explanations (i.e., role conflict), we did not retain them in our primary model (Becker, 2005; Becker, Atinc, Breaugh, Carlson, Edwards, & Spector, 2016; Bernerth & Aguinis, 2016). As with Study 1, we also report a model with no control variables in online Appendix G (all online appendices are available at https://osf.io/vyk72).

We conducted a CFA on our primary study variables (conscientiousness [orderliness], role breadth self-efficacy, role ambiguity, role conflict, and service performance). This model fit the data adequately, $\chi^2(619) = 1219.96$ (CFI = .92, TLI = .91, RMSEA = .08, SRMR = .06). Next, a one-way analysis of variance (ANOVA) supported our manipulation—manipulation check responses differed significantly between the robotic condition ($M = 4.88$, $SD = 0.96$) and control condition ($M = 1.58$, $SD = 1.12$), $t(160) = 20.12$, $p < .001$, $d = 3.16$. We again used path analysis to test our hypotheses. Of note is that the supervisor report of performance creates a level of non-independence in our data, as supervisors rated multiple employees. To account for this, we used the COMPLEX modeling command in Mplus, which uses a sandwich estimator (Muthén & Satorra, 1995) to calculate robust standard errors (see Frieder, Wang, & Oh, 2018). Tests for mediation and moderated mediation were identical to those in Study 1.

STUDY 2: RESULTS

Descriptive statistics and correlations are presented in Table 3, while Table 4 provides the results of the path analysis. First, employees in the robotic work condition had higher role breadth self-efficacy compared to those in the control condition (B = 2.05, SE = 0.24, $p < .01$). In support of Hypothesis 1, the moderating effect of orderliness on the relationship between robotic work and role breadth self-efficacy was significant ($B = -0.66$, $SE = 0.18$, $p < .01$). As Figure 3 shows, the effect of the robotic condition was stronger for employees with lower levels of orderliness ($B = 2.80$, $p < .01$) compared to those with higher levels ($B = 1.31$, $p < .01$).

Meanwhile, employees in the robotic work condition reported higher role ambiguity than those in the control condition ($B = 0.79$, $SE = 0.27$, $p < .01$). Supporting Hypothesis 2, the moderating effect of orderliness on this relationship was significant ($B = 0.67$, $SE = 0.26$, $p < .01$). As Figure 4 shows, the effect of robotic work was stronger at higher levels of orderliness ($B = 1.55$, $p < .01$) than at lower levels ($B = 0.03$, $p = .90$).

Next, we examined the effect of role breadth self-efficacy on employees' performance, and found that this was not significant ($B = 0.13$, $SE = 0.08$, p = .12). As such, the indirect effect of robotic work on service performance, through role breadth self-efficacy, was not significant at higher (conditional indirect effect = .170, 95% CI [−.051, .478]) or lower (conditional indirect effect = .363, 95% CI [−.133, .859]) levels of conscientiousness. The difference between these two effects was also not significant (95% CI [−.224, .025]), failing to support Hypothesis 3.

Finally, the effect of role ambiguity on employees' service performance was significant ($B = -0.34$, SE = 0.08, $p < .01$). Robotic work was negatively and significantly associated with service performance, through role ambiguity, at higher levels of conscientiousness (conditional indirect effect = −.522, 95% CI [−.904, −.193]), but not at lower levels (conditional indirect effect = −.011, 95% CI [−.163, .145]). Further, the difference between these two conditional indirect effects was significant (95% CI [−.412, −.094]). As such, Hypothesis 4 was supported.

STUDY 2: DISCUSSION

Findings from Study 2 again mostly support our hypotheses, and constructively replicate Study 1. We again found that working with intelligent machines (specifically, service robots) was associated with greater role ambiguity, and that this relationship was stronger for employees with higher levels of orderliness. Similarly, working with service robots was associated with greater role breadth self-efficacy, and, unlike in Study 1, this effect was (as hypothesized) attenuated for employees with higher levels of orderliness. Meanwhile, role ambiguity was again related to performance (negatively), but role breadth self-efficacy did not predict performance. More importantly, unlike in Study 1, we did not shorten the scales we used for study variables.

Overall, Study 2 builds upon Study 1 by extending the scope of our arguments (i.e., to a new type of intelligent machine—robots; Brougham & Haar, 2018), and addressing limitations from Study 1. First, by conducting a pre-registered experiment, our study design offers strong evidence for the internal validity of our findings, while maintaining evidence for external validity through the field setting. Plus, we enhanced the measurement of our dependent variable by using a supervisor rating of the employee's service performance. Finally, by showing similar results between our within-individual Study 1 and between-individual Study 2, we provide evidence for the convergence of our theory across levels of analysis (e.g., Voelkle et al., 2014).

Yet, this study is not without limitations. Despite the different nationalities of participants in Studies 1 and 2, both were from Eastern cultures, which could affect the generalizability of our findings (Chen, Chen, & Meindl, 1998). While the samples for Studies 1 and 2 come from different industries (i.e., technology consultancy and service industries), each used participants from a single organization, which can limit generalizability. Extending from this, although we control for tenure working with intelligent machines, employees in both studies may have known such interactions would be frequent upon being hired—implicitly creating a potential boundary around our findings. Yet, we think our findings generalize beyond this, and are important for managers who may wish to introduce intelligent machines into their employees' work. Thus, we turn to Study 3, wherein we mimic the introduction of intelligent machines. We used participants in a Western context from a broad spectrum of jobs and industries to increase generalizability.

STUDY 3: METHOD

Sample and Procedure

Syntax, data, and appendices for all study materials can be found at https://osf.io/nszmx. We conducted a

TABLE 3
Study 2: Descriptive Statistics and Correlations among Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Primary study variables																
1 Robotic work condition	0.49	0.50	—													
2 Role breadth self-efficacy (Phase Two)	3.92	1.74	.62*	(.99)												
3 Role ambiguity (Phase Two)	2.82	1.53	.21*	.01	(.97)											
4 Role conflict (Phase Two)	3.90	1.44	−.06	−.00	−.06	(.94)										
5 Service performance (Phase Two)	4.87	1.68	.53*	.44*	−.18*	.01	(.97)									
6 Conscientiousness (Orderliness; Phase One)	5.32	1.14	.04	.26*	−.20*	.01	.14	(.92)								
Control																
7 Role breadth self-efficacy (Phase One)	4.00	1.60	−.06	−.07	−.24*	.03	−.01	−.00	(.97)							
8 Role ambiguity (Phase One)	2.51	1.29	−.06	−.08	.28*	.32*	−.16*	−.08	−.15	(.92)						
9 Role conflict (Phase One)	4.02	1.32	−.05	−.05	−.02	.68*	−.06	−.04	.17*	.48*	(.89)					
10 Service performance (Phase One)	5.66	.80	−.07	.06	−.09	.01	.01	.10	.08	−.09	−.12	(.83)				
11 Job autonomy (Phase One)	5.42	1.20	−.02	.06	−.37*	.06	.07	.25*	.25*	−.17*	.08	.01	(.89)			
12 Job demand (Phase One)	4.85	1.16	.13	−.03	−.10	.19*	.10	.16*	.28*	.17*	.42*	.02	.15	(.87)		
13 Tenure with intelligent machines (in years; Phase One)	1.73	0.83	.29*	.26*	−.06	.01	.07	−.01	−.05	−.07	−.02	.05	.09	.19*	—	
14 Conscientiousness (Industriousness; Phase One)	4.92	1.03	−.06	.05	−.34*	−.20*	.05	.29*	.28*	−.42*	−.26*	.14	.29*	.05	.13	(.88)

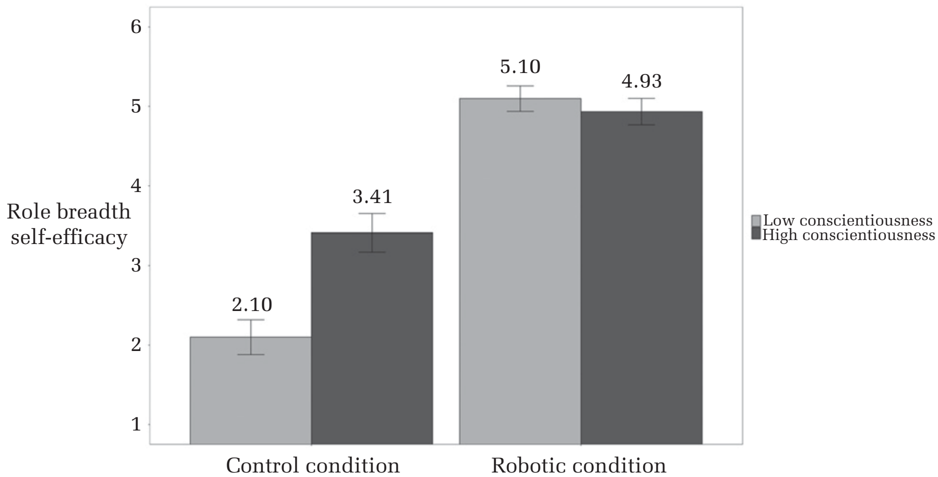
Notes: $N = 162$. Scale reliabilities are reported in parentheses along the diagonal.
* $p < .05$

TABLE 4
Study 2: Path Analytic Results

	Mechanisms						Outcome	
	Role breadth self-efficacy		Role ambiguity		Role conflict		Service performance	
Variables	***B***	***SE***	***B***	***SE***	***B***	***SE***	***B***	***SE***
Controls								
Tenure with intelligent machines	0.16	(0.11)	−0.16	(0.13)	0.04	(0.11)	−0.29*	(0.11)
Baseline role breadth self-efficacy	−0.02	(0.05)						
Baseline role ambiguity			0.37*	(0.09)				
Baseline role conflict					0.73*	(0.07)		
Baseline service performance							0.04	(0.12)
Predictors								
Robotic work condition	2.05*	(0.24)	0.79*	(0.27)	−0.09	(0.20)	1.84*	(0.42)
Conscientiousness (orderliness)	0.62*	(0.12)	−0.52*	(0.13)	0.11	(0.09)		
Robotic work condition × Conscientiousness (orderliness)	−0.66*	(0.18)	0.67*	(0.26)	−0.16	(0.13)		
Role breadth self-efficacy							0.13	(0.08)
Role ambiguity							−0.34*	(0.08)
Role conflict							0.03	(0.08)
Intercept	2.73*	(0.27)	1.78*	(0.28)	0.93*	(0.37)	4.56*	(0.87)
ΔR^2 (controls)	7%		6%		46%		31%	
ΔR^2 (main effects)	30%		8%		0%		1% | 8% | 0%	
ΔR^2 (interaction)	10%		15%		1%			

Notes: $N = 162$. Unstandardized coefficients are reported.
* $p < .05$

FIGURE 3
Study 2: Moderating Effect of Conscientiousness on the Relationship of Robotic Work and Role Breadth Self-Efficacy



Notes: Error bars show +/− 1 standard error. Low/high conscientiousness mean 1 standard deviation below/above the mean.

pre-registered[8] study with participants from the United States through Prolific—a crowd-sourcing website through which individuals complete research projects for compensation. Prior research has shown Prolific participants to be more diverse and attentive compared to those on platforms such as MTurk, as well as more naive to social science research, lessening potential demand effects (Palan & Schitter, 2018; Peer, Brandimarte, Samat, & Acquisti, 2017).

Based on an a priori power analysis, we aimed to recruit a minimum of 186 participants per condition.[9] As some responses may be excluded due to failing an attention check, previously having seen this same task, or not understanding questions, we predetermined to recruit 200 participants per condition. Overall, 415 full-time employees in the United States completed the study; Prolific automatically expanded the available spots when 15 participants "timed out" (i.e., finished the study in more time than allotted).[10] Participants received $6 for their participation.

After excluding 10 participants (i.e., three who failed an attention check question, five who indicated that they had previously participated in studies using a similar task, and two who indicated that they could not understand the survey questions), our final sample consisted of 405 participants (82.0%, Caucasian; 58.3%, female; average age = 33.33 years, SD = 6.84) who work in various industries and roles, as shown in online Appendix H. On average, participants had 11.62 years (SD = 7.93) of full-time work experience and 1.31 years (SD = 3.69) of working with intelligent machines (e.g., robots and/or artificial intelligence). Participants held job titles such as accountant, computer engineer, financial advisor, pharmacist, and teacher. We randomly assigned participants to either an algorithm condition (199), where they worked with what they believed to be a "smart" algorithm, or to the control condition (206), where they worked alone.

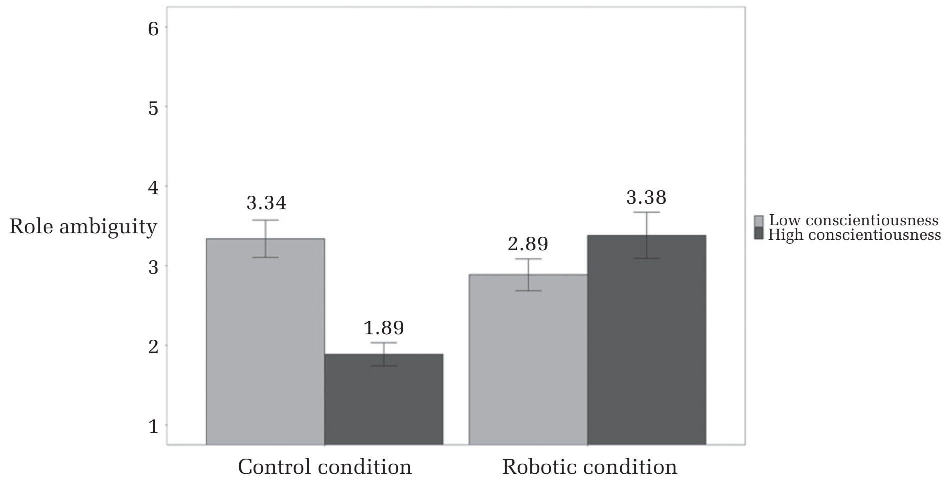
Participants completed a measure of orderliness, and were then told that they would be taking part in a business consulting simulation in which they would provide consulting services for clients operating a lemonade stand business. We adapted this scenario from Ederer and Manso (2013), which has been used in other studies (e.g., Manson, 2017; Sommer, Bendoly, & Kavadias, 2020). The simulation had four rounds in total. In rounds *one*, *two*, and *three*,

[8] Pre-registration material: https://aspredicted.org/blind.php?x=u69c7t

[9] We again used the effect size of the interaction from Study 1 (f^2 = .053) to determine the sample size needed. A power analysis suggests that approximately 186 cases per cell are required to achieve 90% power at an alpha of .01 (Cohen, 1992a, 1992b). We used more stringent criteria for both type I and II errors because using Prolific allows us to assess more participants than a field setting.

[10] We chose to retain the 15 timed-out participants in the final sample because they completed the entire experiment. Removing them from the analysis does not affect our findings.

FIGURE 4
Study 2: Moderating Effect of Conscientiousness on the Relationship between Robotic Work and Role Ambiguity



Notes: Error bars show +/− 1 standard error. Low/high conscientiousness mean 1 standard deviation below/above the mean.

participants made recommendations to a client about how to run a lemonade stand (i.e., choosing location, sugar and lemon content, color, and price). Participants had three choices for location, two for color, 10 each for sugar and lemon content, and 100 for price ($.10 increments from $0 to $10), yielding 75,000 possible combinations. At the end of each round (rounds one to three), participants learned how much profit their client had earned based on their recommendations (using the calculations from Ederer & Manso, 2013). Specifically, based on the original profit-calculation scheme developed by those authors, the most profitable strategy was to set the lemonade stand business in the school district and to make lemonades with pink color, high sugar content, low lemon content, and low price. While this particular combination is arbitrary, that differing combinations of options led to differing levels of profit simulates complex, real-world business problems (i.e., that achieving higher profits requires not just random trials but deliberate exploration [for examples, see Gabaix, Laibson, Moloche, & Weinberg, 2006; Meloso, Copic, & Bossaerts, 2009]).

In both conditions, task and recommendation options were identical. The manipulation involved whether participants made recommendations on their own (control), or with a "smart" algorithm that participants were told would work alongside them and provide additional, timely information to help their decision (detailed slides can be seen at https://osf.io/nszmx). In both conditions, participants completed the first three rounds wherein they made recommendations to their client regarding the lemonade stand. At the end of the third round, all participants reported role perceptions (i.e., role breadth self-efficacy, role ambiguity, and role conflict), other perceived aspects of the job (job demands and autonomy), and manipulation check items. We used the fourth (final) round to measure participant performance (described in detail below).

Working with "smart" algorithms manipulation. In the "smart" algorithm condition, participants worked with a digital assistant named "Ai." To increase psychological realism, Ai interacted with participants conversationally, which was conducted via embedded video in the survey that combined sophisticated-looking animation and a robotic-sounding voice created by an artificial intelligence-based text-to-voice service, Amazon Polly (this can be seen in the slides referred to above). To mimic the machine-learning and information-searching functions of "smart" algorithms (Jones, Mosca, & Hansen, 1998; von Krogh, 2018), Ai assisted with the task by autonomously offering participants additional information upon which they could base their decisions. For example, Ai would provide participants with information about different aspects of the lemonade (e.g., the implications of different sugar levels and lemon content, etc.).

Once all decisions had been made, Ai ostensibly combined its own knowledge of the lemonade business with the participants' choices to develop a joint recommendation to provide to the client. For example, participants in the algorithm condition were asked to estimate the highest price ($0 to $12.5) that could be accepted by customers in the location that they selected. Ai's recommended price was proportional to the participants' estimate (i.e., a random number between 0.7 and 0.8; based on Ederer & Manso, 2013). After Ai provided its recommendation, participants could choose to submit the business plan to the client or to revise it. On average, 78.6% of participants in the algorithm condition chose to submit Ai's recommendation without changes (round 1 = 79.9%; round 2 = 74.4%; round 3 = 81.4%). In the control condition, participants completed the task without the assistance of Ai and made selections on their own.

Measures for Hypothesized Variables

Following Studies 1 and 2, we used the same scale anchors (1 = *strongly disagree*, 7 = *strongly agree*) across different measurements. Online Appendix I reports all items (see https://osf.io/vyk72).

Conscientiousness (orderliness). Similar to Study 2, we measured conscientiousness using the orderliness subscale from DeYoung et al. (2007) before the experiment ($\alpha = .89$).

Role breadth self-efficacy and role ambiguity. We used the same scales as in Study 2 to measure role breadth self-efficacy ($\alpha = .99$) and role ambiguity ($\alpha = .94$). At the end of the third round, we asked participants to indicate their agreement with each item at that moment.

Performance. To obtain an independent measure of performance and further increase the psychological realism of the experiment, we had participants perform a final task that mirrors the work of a business consultant. Participants were approached by a new client, Lloyd's Lemonade, which had experienced a downturn due to factors such as product substitutes, competition, and the COVID-19 pandemic. Participants received Lloyd's Lemonade's current business plan and were told, based on their knowledge of the lemonade industry from having completed the prior tasks, to develop a business plan that evaluates Lloyd's Lemonade's strengths and weaknesses, and makes recommendations about their target customers, potential differentiation strategies, and both short-term and long-term plans. Participants were told their business plan would be evaluated by external judges who are experts in this domain, and that the quality would affect whether they would get a bonus of $3 (given to those who ranked in the top 5% of submitted plans).

We used the consensual assessment technique (Amabile, 1982) to evaluate business proposal quality. Sixteen independent judges were recruited via the authors' personal networks in the United States: eight beverage business owners, and eight business graduate students in operation management, finance, and marketing. Following Berg (2019)'s approach, to help calculate interrater reliability, the 405 business proposals were randomly divided into four groups (three groups of 101 and one group of 102). Each proposal group was evaluated by two business owners and two graduate students on five dimensions. We selected each dimension based on prior research on the most important criteria for evaluating business plans. To begin, Fredrickson and Mitchell (1984) suggested "comprehensiveness" (degree to which the business plan is exhaustive in analyzing the problems and generating solutions) as a critical criterion to evaluate the quality of business strategies. Berg (2019) indicated that "concreteness" (degree to which the business plan provides enough details about how to help the business overcome current challenges and grow) is another key feature for demonstrating how people effectively forecast the potential of a business idea. Mueller, Melwani, Loewenstein, and Deal (2018) identified "likely to be profitable" (degree to which the business plan makes business sense and would help to increase profitability) as something managers should consider when evaluating the economic impacts of a business plan. Lastly, Loewenstein and Mueller (2016) found both "novelty" (degree to which the ideas in the business plan are unique from existing ideas) as well as "feasibility" (degree to which the business plan is feasible in practice) to be important criteria that customers across different cultures use while evaluating business products. We therefore asked the independent judges to rate the business plans on these five dimensions, from 1 ("*extremely low*") to 7 ("*extremely high*") (average $\alpha = .86$).

Ratings from both groups met standard cutoffs for interrater reliability (owners: ICC(A, 8) = .95; students: ICC(A, 8) = .88) (LeBreton & Senter, 2008; McGraw & Wong, 1996). Ratings from the two groups were highly correlated ($r = .62$, $p < .001$), so we averaged them to create a single performance measure (see online Appendix J for details of the rating process).

Measures for Control Variables, Manipulation Check, and Psychological Realism Check

Role conflict. We used the same scale as in Study 2 to measure role conflict ($\alpha = .92$). At the end of the third round, participants indicated their agreement with each item *at that moment*.

Conscientiousness (industriousness). We measured the industriousness subscale (α = .98) from DeYoung et al. (2007) before the experiment.

Job autonomy and job demands. We measured job autonomy and job demands with the same scales as in Study 2. At the end of the third round, we asked participants to indicate their agreement with each item as it pertained to the task they just completed. We could not measure these before the experiment, as participants would have had no basis on which to evaluate these characteristics of the business consultancy task (see Derfler-Rozin, Baker, & Gino, 2018; Fuchs, Sting, Schlickel, & Alexy, 2019, for a similar approach). Coefficients alphas were .88 and .91.

Manipulation check items. We used the three-item scale adapted from Study 2 to assess the effectiveness of our manipulation by asking participants whether the participants worked jointly with the algorithm throughout the experiment. A sample item is "worked with an algorithm software in making decisions." Coefficient alpha was .93.

Psychological realism check. Algorithm condition participants evaluated psychological realism with items adapted from Farh, Lanaj, and Ilies (2017). Approximately 71% at least somewhat agreed (i.e., rating 5, 6, or 7; 1 = *strongly disagree*, 7 = *strongly agree*) with the item "It is realistic that I might work with technologies like Ai in the exercise" (M = 4.96, SD = 1.66), 68% at least somewhat agreed with the item "It is realistic that I might experience similar interactions with technologies like I just experienced in the exercise" (M = 4.88, SD = 1.62), and 59% at least somewhat agreed with the item "At some point during my career, I will probably encounter a situation like I just experienced in the exercise" (M = 4.64, SD = 1.71).

Analytic Strategy

As with the prior two studies, we included role conflict as an alternative mechanism for the effects of working with an algorithm, and controlled for tenure working with intelligent machines. We did not control for baseline variables (e.g., baseline role perceptions) because, unlike in Study 2, participants had no prior knowledge of the scenario for this study (as we created it for this experiment). We again provide results from a model that includes all other control variables in online Appendix K—note that results and conclusions remain unchanged. We also present a model with no control variables in online Appendix L (available at https://osf.io/vyk72). We conducted a CFA on our primary study variables (conscientiousness [orderliness], role breadth self-efficacy, role ambiguity, and role conflict—note that performance was excluded, as it is not a Likert-scale measure). This model fit the data adequately, $\chi^2(521)$ = 1597.42 (CFI = .93, TLI = .92, RMSEA = .07, SRMR = .05). Next, we conducted a one-way ANOVA; supporting our manipulation, responses to the manipulation check items differed significantly between the algorithm condition (M = 5.77, SD = 1.22) and control condition (M = 3.81, SD = 1.81), $t(403)$ = 12.71, $p <$ .001, d = 1.27. Then, we proceeded to perform path analysis using Mplus as in Study 2, including following the same procedures for testing mediation and moderated mediation.

STUDY 3: RESULTS

Descriptive statistics and correlations are presented in Table 5, while Table 6 provides path analysis results. First, employees in the algorithmic manipulation reported higher role breadth self-efficacy than the control condition (B = 2.21, SE = 0.16, $p <$ .01). In support of Hypothesis 1, orderliness significantly moderated this effect (B = −0.50, SE = 0.15, $p <$ .01). As Figure 5 shows, the effect of the algorithmic manipulation was stronger for employees at lower levels of orderliness (B = 2.75, $p <$ .01), compared to those at higher levels (B = 1.67, $p <$ .01).

Next, employees in the algorithmic manipulation had higher role ambiguity compared to those in the control condition (B = 0.62, SE = 0.12, $p <$ .01). Supporting Hypothesis 2, orderliness significantly moderated this relationship (B = 0.80, SE = 0.12, $p <$ .01). Figure 6 shows the effect of the algorithmic manipulation was stronger for employees at higher levels of orderliness (B = 1.47, $p <$ .01), compared to those at lower levels (B = −0.26, p = .147).

We next examined the effect of role breadth self-efficacy on performance, and found that this was significant (B = 0.06, SE = 0.02, $p <$ .01). The algorithmic condition was positively and significantly associated with performance, through role breadth self-efficacy, at higher levels of orderliness (conditional indirect effect = .107, 95% CI [.030, .198]), but not at lower levels (conditional indirect effect = .176, 95% CI [.045, .306]). Further, the difference between these two indirect effects was significant (95% CI [−.069, −.007]), supporting Hypothesis 3.

TABLE 5
Study 3: Descriptive Statistics and Correlations among Study Variables

	Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
	Primary study variables												
1	Algorithm condition	0.49	0.50	—									
2	Role breadth self-efficacy	4.42	1.98	.57*	(.99)								
3	Role ambiguity	3.12	1.35	.21*	−.07	(.94)							
4	Role conflict	2.75	1.35	.05	−.04	.24*	(.92)						
5	Task performance (Independent judge rating)	3.10	0.83	.18*	.27*	−.29*	−.21*	—					
6	Conscientiousness (Orderliness)	5.07	1.08	.08	.22*	−.16*	−.04	.14*	(.89)				
	Control												
7	Job autonomy	5.34	1.25	−.10*	.01	−.28*	−.31*	.09	.15*	(.88)			
8	Job demand	2.93	1.32	−.16*	−.15*	.04	.43*	−.22*	.04	−.15*	(.91)		
9	Tenure with intelligent machines (in years)	1.31	3.69	.05	.09	−.09	.02	−.01	.04	.07	.05	—	
10	Conscientiousness (Industriousness)	5.43	1.14	.03	.12*	−.22*	−.08	.10*	.31*	.15*	.05	.15*	(.98)

Notes: $N = 405$. Scale reliabilities are reported in parentheses along the diagonal.
* $p < .05$

Finally, role ambiguity was significantly associated with performance ($B = -0.18$, $SE = 0.03$, $p < .01$). Meanwhile, the algorithmic condition was negatively and significantly associated with performance, through role ambiguity, at higher levels of orderliness (conditional indirect effect = −.267, 95% CI [−.372, −.161]), but not at lower levels (conditional indirect effect = .046, 95% CI [−.012, .115]). The difference between these two conditional indirect effects was significant (95% CI [−.209, −.084]). Thus, Hypothesis 4 was supported.

STUDY 3: DISCUSSION

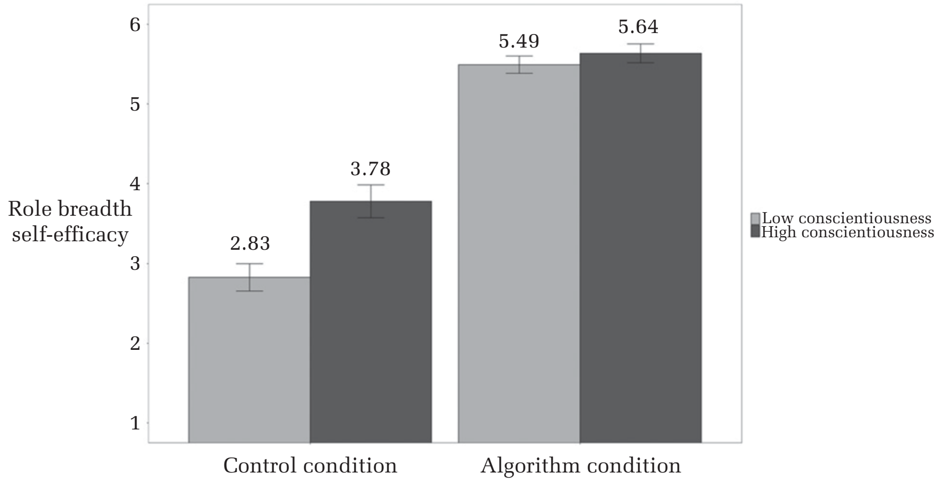
Study 3 supported all hypotheses, constructively replicated both Studies 1 and 2 with a third type of intelligent machine (algorithms) in a more controlled experimental environment with a Western

TABLE 6
Study 3: Path Analytic Results

	Mechanisms						Outcome	
	Role breadth self-efficacy		Role ambiguity		Role conflict		Task performance	
Variables	***B***	***SE***	***B***	***SE***	***B***	***SE***	***B***	***SE***
Control								
Tenure with intelligent machines	0.04	(0.02)	−0.04*	(0.02)	0.01	(0.02)	−0.01	(0.01)
Predictors								
Algorithm condition	2.21*	(0.16)	0.62*	(0.12)	0.14	(0.13)	0.27*	(0.10)
Conscientiousness (orderliness)	0.53*	(0.10)	−0.57*	(0.07)	−0.03	(0.08)		
Algorithm condition × Conscientiousness (orderliness)	−0.50*	(0.15)	0.82*	(0.11)	−0.05	(0.13)		
Role breadth self-efficacy							0.06*	(0.02)
Role ambiguity							−0.18*	(0.03)
Role conflict							−0.09*	(0.03)
Intercept	3.31*	(0.11)	2.84*	(0.09)	2.67*	(0.10)	3.49*	(0.15)
ΔR^2 (controls)	1%		1%		0%		3%	
ΔR^2 (main effects)	32%		5%		0%		2% | 8% | 2%	
ΔR^2 (interaction)	2%		10%		0%			

Notes: $N = 405$. Unstandardized coefficients are reported.
* $p < .05$

FIGURE 5
Study 3: Moderating Effect of Conscientiousness on the Relationship of Algorithm Work and Role Breadth Self-Efficacy



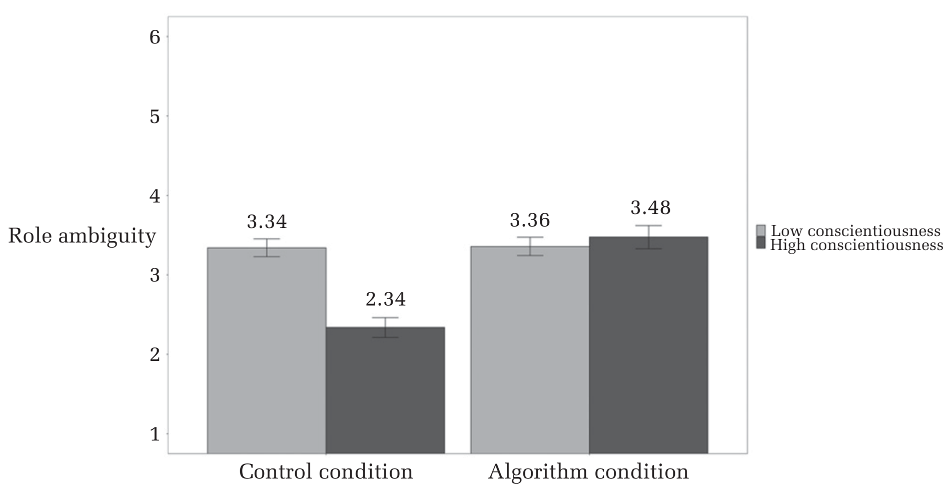
Notes: Error bars show +/− 1 standard error. Low/high conscientiousness mean 1 standard deviation below/above the mean.

sample, and increases our performance measure robustness with independent performance ratings. The results of this study—combined with the two prior—help alleviate concerns regarding (a) the causal inferences we draw from our model; (b) the generalizability of findings across different industries, job, national cultures, and types of intelligent machine; (c) the validity of our theory across levels of analysis; (d) the legitimacy of our measurement scales; and (e) the robustness of our other-reported measures of performance (i.e., coworker report for Study 1, supervisor report for Study 2, independent judge report for Study 3).

GENERAL DISCUSSION

During the 20th century, organizations experienced massive and varied technological change (Cooper & Kaplinsky, 2005; Greenwood, 1997). Common across these technologies was their *user-driven*

FIGURE 6
Study 3: Moderating Effect of Conscientiousness on the Relationship between Algorithm Work and Role Ambiguity



Notes: Error bars show +/− 1 standard error. Low/high conscientiousness mean 1 standard deviation below/above the mean.

nature (e.g., Dosi & Galambos, 2013; Mowery, 2009). Through this change, conscientious employees thrived (e.g., Barrick & Mount, 2000; Dyar, 1961)—due in no small part to their ability to work with these technologies (e.g., Young & Menter, 1973). That is, the orderly nature of these employees complements the user-directed features of traditional technology, which allows them to effectively work with these machines. Thus, a consensus shared among both academics and practitioners is that conscientiousness is one of the most important traits employees can possess (e.g., Behling, 1998; Gellatly, 1996; Li et al., 2014).

In some ways, the Fourth Industrial Revolution of the 21st century is no different than the Third Industrial Revolution of the 20th century, as technological changes continue to occur at work. However, this is now the era of intelligent machines that require less direct user input (McAfee & Brynjolfsson, 2017). As the Fourth Industrial Revolution unfolds, it may be tempting to assume that conscientious (in particular, orderly) employees will continue to work well with this new generation of machines. However, pilot data conducted with 196 investment bankers in an European investment bank revealed that more orderly employees reported working less well with intelligent ($r = -.17$, $p = .016$), compared to traditional, technology ($r = .27$, $p < .001$).

These preliminary insights reinforce our position (rooted in the intersection of role and complementarity theory) that the existing consensus about conscientious employees and their ability to effectively work with modern technology may need to be revisited. That is, the drive of conscientious employees to create order may be non-complementary to 21st-century intelligent machines, which are designed to autonomously do the same. Integrating this expectation with role theory, we predicted that more conscientious (orderly) employees (compared to less) not only do not reap the benefits of working with these modern technologies, but also that they may experience greater difficulties as well. To that end, we hypothesized that these employees would experience reduced role breadth self-efficacy and greater role ambiguity—with subsequent consequences for task performance. Results across three different studies (i.e., field study, field experiment, and online experiment) with distinct samples in Malaysia, Taiwan, and the United States largely supported these expectations. We hasten to note, however, that our results were more consistent with regard to role ambiguity than role breadth self-efficacy (i.e., despite all hypotheses being supported in Study 3, there were some unsupported findings with this construct in Studies 1 and 2). We turn now to the implications of our research for theory and practice.

Theoretical Implications

The most significant implication lies in our refinement of conventional wisdom regarding conscientiousness. While we acknowledge the consensus that conscientious is "the most valid personality predictor" of performance (Dudley et al., 2006: 40), we submit that this consensus requires an important degree of contextualization with regard to the types of technology used by these employees. As our results show, conscientious (orderly) employees may experience lower levels of efficacy and higher levels of ambiguity when it comes to both understanding and going beyond the expectations of their work roles. As intelligent machines become more prevalent in different types of jobs and organizations (Brynjolfsson & McAfee, 2014; Davenport & Ronanki, 2018), our findings offer novel insights for scholars and practitioners alike, and as such have the potential to change the conversation regarding conscientiousness in the modern workplace.

Our second implication both follows, and broadens out from, our first. One goal of the Special Research Forum is to introduce readers to topics that are important to scholars outside our field, but currently understudied by those in management. We see the changes currently occurring in the workplace due to the Fourth Industrial Revolution as such a topic. As it pertains to our paper, this vision allowed us to address a question that has to this point largely remained unanswered: *For whom* will the coupling of employees and intelligent machines be more (Raisch & Krakowski, 2021; Wilson & Daugherty, 2018) versus less (e.g., Dietvorst et al., 2015; Efendić et al., 2020; Lawless et al., 2019) beneficial? By elucidating conscientiousness (orderliness) as an answer to this question, our research showed that conventional wisdom on this construct might, going forward, be somewhat tenuous. We believe that there are likely many other such pieces of conventional wisdom that may also be in need of revisiting in the coming years.

Third, our integration of complementarity theory (Carson, 1969; Kiesler, 1983) with role theory (Kahn & Quinn, 1970; Kahn et al., 1964), in conjunction with the context in which our research is situated, enhances both theories. Regarding complementarity theory, our integrative framework extends this beyond the *human-to-human* work interactions in which it is often applied (e.g., Grijalva & Harms, 2014; Hu & Judge, 2017), thus revealing potential implications for the future of research on interactions between human and non-human entities. Indeed, our focus on complementarity theory may have implications for ongoing conversations regarding why employees—or external stakeholders such as customers—react aversively toward intelligent machines, particularly those that have human-like characteristics (Kim, Schmitt, & Thalmann, 2019; Strait et al., 2017). Viewing this phenomenon through complementarity theory suggests these negative reactions could arise because they both possess similar, anthropomorphized features, and, as such, there is non-complementarity in this interaction. Thus, our research provides timely insights for organizational scholars to advance the application of complementarity theory in the era of smart technology (e.g., von Krogh, 2018).

Practical Implications

Our research has important and timely practical implications for organizations. First, scholars have long extolled the importance of selecting for conscientiousness (Hogan & Ones, 1997; Jackson & Roberts, 2017; Mike, Harris, Roberts, & Jackson, 2015). Indeed, scholarly research, practitioner papers, and academic textbooks all endorse this trait as one of the most consistent and powerful predictors of employees' performance across jobs (Mount & Barrick, 1998; Noe et al., 2020). Yet, as our results indicate, the 20th-century consensus about the presumed effectiveness of conscientiousness employees may need to be refined when it comes to working alongside intelligent machines. Thus, our findings have important implications in terms of recruitment, selection, and actual work practices for the 21st-century workplace. Of note, while we frame the recommendations below in terms of conscientiousness, it is critical to be aware that we are generalizing from our results that specifically reflect the orderliness subdimension of conscientiousness, and our conclusions should be considered in that light.

For recruitment and selection, managers may not want to emphasize conscientiousness explicitly when posting for jobs that involve working with intelligent machines. This is because our results suggest the presumed benefits that arise from the orderly nature of these employees may be attenuated when such employees are paired with this technology at work. Similarly, applicant screening often involves personality tests (Diekmann & König, 2015), wherein hiring managers are advised to filter out employees low in conscientiousness (Barrick & Mount, 2000). Our findings could suggest otherwise, which may help expand the applicant pool. Going further, if conscientiousness (or at least, orderliness) is deemphasized as we suggest, we recommend the inclusion of work-sample tasks in the selection process, wherein candidates could be paired with intelligent machines to perform work tasks (e.g., Sackett, Zedeck, & Fogli, 1988). This would give managers the chance to observe how employees work with this technology before hiring. In sum, for companies that have incorporated smart technology into their operations, or plan to do so, we advocate for a reassessment of the role of conscientiousness in recruitment and selection.

As it relates to employee work arrangements, our findings point to a mismatch that organizations may wish to remedy. The consensus developed over the last century might suggest conscientious employees should work best with intelligent technology. Yet, our findings suggest such pairings may be suboptimal, which could lead job redesign efforts to fail when it comes to human–machine integration (Murray et al., 2021). Thus, we recommend that managers pair intelligent machines with employees lower in conscientiousness (or at least orderliness) when possible, as they may be better positioned to benefit from working with these machines and reap the corresponding performance increases. In this way, organizations can more effectively augment the performance of less conscientious employees by seeking complementarity in actual work arrangements (e.g., Dryer & Horowitz, 1997; Estroff & Nowicki, 1992; Sadler et al., 2011).

Limitations and Future Directions

Each study has notable strengths and weaknesses. For example, Study 1 has strong external validity given our use of actual employees who work daily with artificial intelligence. Yet, this study has potential limitations in terms of generalizability (e.g., Study 1 was conducted in a single organization), our ability to draw causal inferences, and our use of shortened scales. Studies 2 and 3 address many such limitations by testing our hypotheses in different contexts, using experimental designs, and using all scale items. Yet, these studies are, on their own, limited as well. For example, Study 2 suffers from similar generalizability concerns as Study 1 (i.e., also conducted with employees of a single organization in an Eastern context), whereas Study 3 relies on participants from an online sample pool. Importantly, many of the limitations in a given study are largely offset by the design of another (e.g., Zipay, Mitchell, Baer, Sessions, & Bies, 2021).

We want to draw specific attention to the measurement source of performance across the three studies. In general, obtaining other reports in ESM studies (i.e., Study 1) is desirable when feasible (Gabriel et al., 2019a; McClean, Barnes, Courtright, & Johnson, 2019). Yet, the daily nature of ESM studies makes it difficult to obtain these reports, particularly for performance (typically self-reported; Mitchell et al., 2019; Parke, Weinhardt, Brodsky, Tangirala, & DeVoe, 2018), as the designated other must be in a position to observe and report on focal participant behaviors—otherwise such reports are "deficient" (Gabriel et al., 2019a: 990). Participants in Study 1 work in close proximity, which made it feasible to get these reports (e.g., Trougakos et al., 2015). But, this does not speak to whether coworkers are qualified to rate performance. Studies 2 and 3 help assuage such concerns however, given the convergent findings from supervisor reports of performance in Study 2 and independent judge ratings in Study 3.

Beyond this, other limitations remain that it behooves us to acknowledge. For example, while all hypotheses were supported in Study 3, different hypotheses went unsupported in Studies 1 and 2. In Study 1, conscientiousness did not moderate the relationship between using artificial intelligence and role breadth self-efficacy. One possible explanation pertains to these participants' work; these individuals work with artificial intelligence to evaluate whether public employees are following government regulations. Since this work entails many rules and policies, it may constrain the moderating effect of conscientiousness. This type of work contrasts with the service jobs of Study 2, which are more open-ended in terms of how best to work with intelligent machines to satisfy customers. Thus, the nature of the job itself may be an additional boundary condition to the theory we develop. Alternatively, there may be an empirical explanation in that moderating effects are known to be harder to find in field studies relative to experimental studies (McClelland & Judd, 1993). Thus, further investigation will be necessary to identify which of the potential explanations for the null result we found is more likely correct.

A similar question arises in Study 2, as role breadth self-efficacy was not associated with service performance. One explanation could lie in the confluence of context and the relatively short length of the study. Our arguments for this relationship suggest that expanding one's work positively affects performance (Griffin, Parker, & Mason, 2010). For service employees in the short term, however, perhaps such role expansion runs counter to the parts of their job that are visible to supervisors (leading to the null result between role breadth self-efficacy and service performance). In this way, the positive effects of role breadth self-efficacy may only be visible over a longer time horizon. More broadly, there are many ways to interpret a null effect, thus future research is needed to probe these effects further. We do note that our predictions were largely supported across our studies, which should generally provide confidence in the theory we develop and set the stage for research to more concretely identify boundary conditions.

There are other opportunities for future research. Underlying our arguments is that employees may be reacting to particular functions, or dimensions, of intelligent machines (i.e., the quality of their output, or their user-friendliness [Haenlein, Kaplan, Tan, & Zhang, 2019; Osoba & Welser, 2017]). As we theorize about intelligent machines at a broad level, we could not explore whether the effects we propose may be impacted by whether a specific machine offers higher- or lower-quality output, or is viewed as user-friendly. Yet, such characteristics could change the relationships we identify. For example, conscientious employees could potentially appreciate these machines if their output was consistently of high quality, or if their decisions were consistently aligned with the employee's preferences (e.g., Arrieta et al., 2020; Suen et al., 2019). Thus, we encourage scholars to develop a means to classify the richness of the user experience with intelligent machines (e.g., Daft & Lengel, 1984), to better understand their more nuanced aspects and how this may impact the relationships that we find herein.

We also want to draw attention to a critical issue for future research involving intelligent machines—that the way in which the employees and intelligent machines work together is not homogenous across types of machine, jobs, companies, or industries. Consider Study 1, which takes a within-individual view of employees and their usage of intelligent machines. While there are components of these employees' job that do not require an intelligent machine, overall, the job cannot be performed without working with intelligent machines to some degree. Thus, a within-individual perspective on their work was appropriate, and provides useful insight into the outcomes that these employees experience. Studies 2 and 3, in contrast, take a between-individual perspective on using intelligent machines, because the job performed by these participants can be done either *with or without* the assistance of an intelligent machine. A strength of our theorizing is that our hypothesized relationships largely hold across both levels of analysis, as well as nature of how intelligent machines are utilized. However, such convergence is not, nor should be, an assumed feature of all relationships that involve intelligent machines. Accordingly we advocate for scholars conducting research in this space to simultaneously consider how their hypothesized effects either align, or do not, across levels of analysis (Voelkle et al., 2014).

Lastly, an extension to our research can be made via a trait activation lens. Prior research argues conscientious employees prefer conscientious leaders (Colbert & Witt, 2009; Guay, Kim, Oh, & Vogel, 2019), which initially is counter to complementarity theory. However, this neglects the role of hierarchy. As Guay et al. (2019: 184) noted, conscientious employees seek "validation" from conscientious supervisors who not only may "recognize, reinforce, and reward" employees for these traits, but also may create an facilitative environment for these employees. As the intelligent machines in our research are coworkers of the employee, not their supervisor, these machines may be unable to provide such validation for these employees.

Conclusion

In the 20th century, conscientiousness came to be seen as the most prominent personality trait in terms of performance, due in part to these employees' proficiency with the technology of that century. Yet 21st-century intelligent machines give reason to doubt this consensus. Indeed, we find that working with intelligent machines may be non-complementary for conscientious employees, thus creating a context wherein these employees' performance is not what would otherwise be expected. Our research aims at joining the ongoing conversation on the new era of work, and should spark more research on intelligent machines and the employees who use them.

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