Impact of COVID-19 outbreak on employee performance – Moderating role of industry 4.0 base technologies

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ABSTRACT

COVID-19 outbreak has implied significant changes in the way service organizations work, affecting employees' routine and activities. At the same time, the advent of Industry 4.0 (I4.0) introduced new technologies that might facilitate such activities, mitigating the COVID-19's implications. The objective of this research is two-fold. First, we aim at examining the impact of COVID-19's work implications on employees' performance (i.e. output quality and delivery). Second, we seek to verify the moderating role of I4.0 base technologies on this relationship. We surveyed 106 employees of different service organizations who have been working remotely during the pandemic and analyzed their responses through multivariate techniques. Results revealed that COVID-19's work implications (i.e. home office work environment, job insecurity and virtual connection) do impact employee's performance, although not at the same extent. Further, we found that I4.0 technologies moderate the enhancement of employee's performance. However, the orientation and intensity of such moderation may vary according to the performance metric and work implication under analysis. As COVID-19 outbreak inevitably pushed new ways of working that can become an integral part of the post-pandemic world, our research provides important theoretical and practical implications for improving employee's performance through the digitalization of service organizations.

1. Introduction

COVID-19 outbreak has pushed almost all the employees around the world to work in a completely different setting in comparison to what it used to be before. COVID-19 triggered interventions such as social distancing, travel restrictions, virtual or remote work, and skeleton crews have constrained the continuance of earlier processes, thereby changing the way employees work (Gallup, 2020; Tortorella et al., 2020a). Such interventions triggered by COVID-19 outbreak introduced employee behavioral changes, which can transition with multiple lockdowns from temporary to long-lasting. Line managers, team leaders and human resources professionals are very concerned about such behavioral changes as they can influence employees' emotional, cognitive, and physical wellbeing, which can ultimately impact their deliverables and performance (Graves and Karabayeva, 2020).

Clearly, the absorption of COVID-19 triggered interventions by the organizations to contain the its impact on the performance of employees. However, the direction of this impact is unclear, as arguments

exist for both negative and positive directions. Supporting the negative impact, a recent Deloitte survey in Chinese firms indicated that 46% of them expect a reduction in performance due to COVID-19 (Boichenko and Tymchenko, 2020). Increased stress, inadequate infrastructure, missing work environment/colleagues, unrealistic performance expectations, impaired manager-employee relationship, and difficulty establishing trust with colleagues are the downside of virtual work environment (Graves and Karabayeva, 2020), which can negatively impact on employees' performance. Caputo and Hyland (2020), through a focus group conducted with a sample of 256 employees (mostly from U.S. firm), indicated that four out of ten respondents felt that the pandemic would reduce cross-functional collaboration, and 36% of the respondents worried about how remote work would impact their work-life balance.

Supporting the positive impact, HSBC (2017) revealed that virtual work is more likely to increase worker productivity than financial incentives. Research also showed that firms providing a better work life balance through virtual work options pave way for more productive

workforce as employees feel more motivated (Stevens, 2019). Graves and Karabayeva (2020) stated that virtual work provides employees with flexibility in work, increased availability of time due to the absence of commuting, and more importantly access to better talent around the globe that can increase the average individual performance. Considering the above arguments for mixed impact of COVID-19 outbreak on employee performance leads to our first research question (RQ):

RQ$_1$: What is the impact of work implications of COVID-19 outbreak on employees' performance?

Another aspect that lacks clarity is the impact of Industry 4.0 (I4.0) adoption on the linkage between the work implications of COVID-19 outbreak and employees' performance. I4.0 refers to the dawn of a new industrial revolution introduced by the emergence, advancement, and convergence of a number of technologies such as additive manufacturing, Internet of Things (IoT), blockchain, advanced robotics and artificial intelligence (Tortorella and Fettermann, 2018; Ivanov et al., 2019). These technologies have enhanced employees and organizations performance by establishing real-time connection between the digital and physical systems. I4.0 is not only capable of reducing costs, enhancing flexibility, increasing speed, and improving quality, but can possibly dampen the tensions inherent between these key operational priorities and, thereby, influence performance (Olsen and Tomlin, 2020). Linking digital and physical systems using I4.0 is expected to affect every corner of the operations management (McKinsey 2015) and will also impact the way employees deal with value-adding processes, especially in the times after the outbreak of COVID-19. Due to the scarcity of studies that examine the I4.0's impact on the relationship between COVID-19's work implications and employees' performance, the below-stated research question was raised:

RQ$_2$: What is the impact of I4.0 technologies on the relationship between COVID-19's work implications and employees' performance?

We answer these two research questions by building the conceptual model using social construction of technology (SCOT) theoretical lens. SCOT theory assumes that the ways in which a technology is used cannot be deciphered without understanding how that technology is embedded in its social context (Bijker et al., 1987; Douglas, 2012). It argues that technology does not determine human behavior, instead technology is shaped by the human action (Pinch and Bijker, 1984, 1986; Bijker, 2008). To test the hypotheses developed, we collected data from employees of different service sector firms who have started working from home post COVID-19 outbreak. We received 106 valid responses and analyzed them using multivariate techniques.

The contributions of this study are two-fold. First, our results have shown that the work implications of COVID-19 pandemic have a direct impact on employees' performance, especially when considering home office environment. Further, I4.0 base technologies do moderate the work implications originated by the COVID-19 outbreak on employees' performance, although the orientation of such moderation seems to vary according to the work implication under analysis. To the extent of our knowledge, no similar studies have been conducted, and this is the first research that has empirically evidenced such effects, whose insights might also contribute to the post-pandemic period. Second, this research provides indications that service organizations might need to rethink their processes and routines for the post-pandemic period based on the lessons learned from the COVID-19's work implications. This is especially relevant for organizations that concurrently adopt I4.0 base technologies and virtual connection practices, which might enhance employees' performance. This insight is expected to add value to team leaders and line managers who face difficulty in containing the negative impact of COVID-19 pandemic on employee performance.

2. Theoretical background and hypotheses development

Majority of the attention in operations management research so far has been directed towards understanding the impact of COVID-19 outbreak on organizations. For example, Ivanov (2020) developed a

viable model by integrating agility, resilience and sustainability perspectives based on the lessons learnt from COVID-19 pandemic. Saileshsingh and Subramanian (2020) introduced ambiguity by studying 2011 Thai Flood and COVID-19 pandemic events and developed ambiguity-coping mechanisms. Remko (2020) suggested a pathway for developing more resilient post-COVID-19 operations. Based on a structured literature review, Queiroz et al. (2020) synthesized the impacts of epidemic outbreaks on operations amid the COVID-19 pandemic. However, impact of the pandemic on the management of processes and operations, and its associated stakeholders such as employees are yet to be investigated, which has been chosen as the focus of this research.

According to a policy brief by International Labor Organization (ILO, 2020), COVID-19 pandemic has turned the world of work upside down. Unanticipated change introduced by exogenous events such as the outbreak of COVID-19 is expected to partially paralyze organizations and their respective employees, and force them into vulnerable zones (Williams et al., 2017). Getting pushed into these zones can trigger immediate and severe issues that can negatively impact business-to-business (B2B) sales employee's performance (Hartmann and Lussier, 2020). Some of them were issues stemming from greater remote working and physical unavailability, cancellations and postponing of important meetings and events, travel restrictions and border shutdowns by different countries, and greater stakeholder mental and physical health illnesses, among others. These issues experienced by employees will reduce their ability and willingness to perform the existing tasks and new tasks. Employees continuing to work remotely after COVID-19 outbreak have higher chances of experiencing anxiety, frustration, and burnout, which on getting accumulated can affect their productivity and engagement, leading to delivery of poor-quality output prone to errors.

Performance management systems are adopted with an objective to create alignment and shared understanding of the deliverables and the pathways (e.g. trainings, mentorship) to achieve those deliverables. The relevance and validity of pre-established performance management systems are lost in a crisis hit context, warranting its revision by contextualizing to the new normal circumstances (Maley, 2013; Gunnigle et al., 2019). The fading of relevance and validity of such systems leaves the employees without alignment and shared understanding of deliverables, leading to their sub-optimal performance. This is more so true in the current context post the outbreak of COVID-19. Hartmann and Lussier (2020) studied the impact of COVID-19 outbreak on B2B sales employee's performance based on the review of practitioner-oriented articles, interview of B2B organization's employees, and a webinar with sales professionals. Using Leavitt's model of organizational change and sociotechnical systems theory, they synthesized a rich discussion on the challenges introduced by COVID-19 outbreak that can reduce the performance of B2B sales employee. Considering these arguments from literature and extending to all categories of employees in an organization, we incline towards negative impact of COVID-19 outbreak and propose our first hypothesis as:

H1. Work implications of COVID-19 outbreak are negatively related to employees' performance.

To hypothesize the impact of I4.0 base technologies on the relationship between work implications of COVID-19 outbreak on employee's performance, we rely on social construction of technology (SCOT) theoretical lens. SCOT theory explains how a variety of social factors and forces shape technological development that is often nonlinear, technological change, and the meanings associated with technology (Pinch and Bijker, 1984, 1986; Bijker, 2008). Leonardi and Barley (2010) clustered the research on SCOT implementation into five perspectives, namely perception, interpretation, appropriation, enactment, and alignment, and explained the phase of implementation, social phenomenon constructed, and construction process for each perspective. van Baalen et al. (2016) extended SCOT to digital world and treated its users as technological change agents. Different groups of users are

expected to adopt, apply and share the meanings of the technology, define the trajectory of the technology development, and interpret its artifact to conduct negotiation on its designs (Klein and Kleinman, 2002; Kwok and Koh, 2020).

I4.0 technologies enable digitized and connected value streams that can transform established firms into smart and autonomous value delivery (Arnold et al., 2016). I4.0 technologies deliver real-time-capable horizontal and vertical internet-based connectedness of people, machines, and objects, as well as information and communication technologies for the dynamic management of complex business processes (Bauer et al., 2015; Müller et al., 2018). I4.0 base technologies encapsulates technologies that provide connectivity and intelligence to the front-end technologies which is arranged in four main dimensions, namely smart manufacturing, smart products, smart supply chain and smart working (Frank et al., 2019). SCOT makes use of the notions of relevant social groups, interpretative flexibility, stabilization, and closure (Bijker, 2008). In the case of I4.0 technology, organizations and their stakeholders are the relevant social groups that conceptualize the utility of automation to extract value and enhance performance. They continue to brainstorm the design of I4.0 technology until reaching the point of stabilization, where coalescence can be achieved around the design. Small adaptations are made to the stabilized I4.0 architecture to accommodate industry specifications, application areas and exogenous events such as COVID-19, so that it can convincingly fit their needs.

Organizations with greater digital maturity and automation through the integration of I4.0 technologies have benefited significantly from it after COVID-19 outbreak as they were been able to sustain the productivity levels effectively. After the outbreak of COVID-19, IEEE (2020) implies that adoption of virtual reality, augmented reality, holographic displays and immersive collaboration spaces enabled by tele-presence technologies will see rapid rise in firms as they demand advanced at-a-distance collaboration tools. Javaid et al. (2020) explained how different technologies of I4.0 such as artificial intelligence, internet of things, big data, virtual reality, holography, cloud computing, autonomous robot, 3D scanning, 3D printing, and biosensors, can be used to efficiently manage the interventions of COVID-19. To demonstrate the extent of automation that can be expected through the adoption of I4.0 technology in the post-COVID world, IEEE (2020) state that *"A B2B sale used to require a handshake at an expensive steakhouse; now, it will be done through a food delivery app that serves the steak and wine to people's new home offices enabled by immersive collaboration spaces, that exist only on a server in a lights-out data center running on a self-healing network."*

Developing on SCOT theory, technologies are adopted and used by employees because they contribute towards achieving human purposes and improve social world or to advance the interests of individuals and social groups. Conforming to this, I4.0 base technologies have been widely adopted and pervasively used by employees after the outbreak of COVID-19 as it satisfies the automation requirements of different stakeholders. According to ILO (2020), outbreak of COVID-19 has accelerated the digitization trend and adoption of I4.0 technologies (including network technology, Big Data, 3-D printing, artificial intelligence and robotics) auguring a promising future of greater flexibility

and sustainability, that can enable employees to better manage their deliverables. Considering these arguments based on SCOT theory, we propose our second hypothesis as:

H2. I4.0 base technologies moderate the relationship between COVID-19's work implications and employees' performance, such that the negative effect is lesser with increase in the adoption level of I4.0 base technologies.

Fig. 1 presents the hypothesized theoretical model. As both the COVID-19 work implications and I4.0 technologies are recent phenomena whose relationship is uncertain, the moderation seems more suitable approach, since it tests for interactions that affect when relationships between variables occur rather than testing a causal link between these variables (Cohen, 2008). In this sense, in the hypothesized model we considered the COVID-19's work implications as the independent variables and I4.0 base technologies as the moderators of the relationship with performance metrics.

3. Method

3.1. Instrument development

The questionnaire consisted of four parts with their respective measures (see Appendix). First, we collected information of respondents and their organizations. In this initial part, we also included a statement that explicitly indicated the anonymity and confidentiality nature of the study, and that there was no better answer. Second, we asked respondents about the adoption level of I4.0 base technologies in their organizations. For that, we used the four base technologies: (*i*) Big Data, (*ii*) Internet of Things (IoT), (*iii*) Cloud Computing, and (*iv*) Analytics (e. g. machine learning and data mining). Those technologies were suggested and empirically validated by Frank et al. (2019), which identified implementation patterns for Industry 4.0. IoT, Big Data, Cloud Computing and Analytics provide a solid basis on which other front-end technologies can build on, being utilized in other investigations on I4.0 (e.g. Tortorella et al., 2020b). Therefore, we understand that, since I4.0 is still at its early stages in most organizations and given the high pervasiveness of those base technologies, they would be more easily found in the targeted sample. A 6-point Likert scale was utilized, varying from 1 (not implemented) to 6 (fully implemented). Those measures were also adopted by previous studies that encompassed I4.0 (e.g. Dubey et al., 2019; Tortorella et al., 2020b). The subsequent part evaluated the work implications of COVID-19 outbreak. Fifteen implications were stated and listed based on studies from Qiu et al. (2020), Nicola et al. (2020), Le_____nard and Lo (2020) and Zhang et al. (2020). Analogously, we applied a Likert scale that ranges from 1 (fully disagree) to 6 (fully agree) to identify respondents' agreement level. Finally, in the fourth part, respondents indicated their own performance improvement level during the past two months. Two individual performance measures were used: quality and delivery. These measures were assessed based on a Likert scale where 1 denoted a 'significantly worsened' performance, and 6 referred to a 'significantly improved' performance. This part was
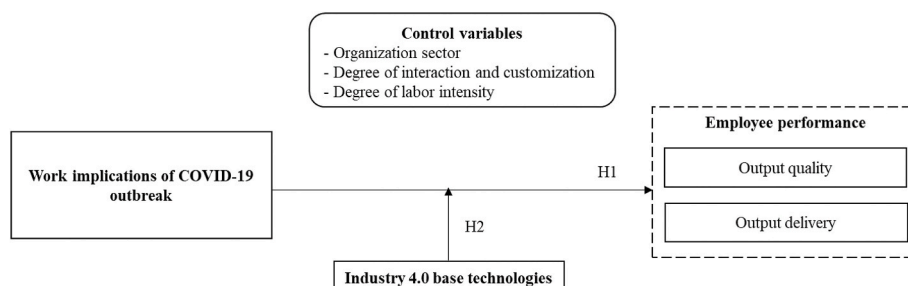

Fig. 1. Hypothesized theoretical model.

located far from the previous ones, where the independent and potential moderating variables were placed. Such countermeasure aimed at avoiding common method bias (Podsakoff and Organ, 1986; Podsakoff et al., 2003). Two academicians pre-tested the questionnaire so that content and face validity were checked. Based on their inputs, some terms and statements were revised to mitigate misinterpretations and erroneous responses.

3.2. Sample selection and data collection

For selecting the sample, we used a non-random approach with two main selection criteria (Smith, 1983). First, respondents should be working remotely to service organizations during COVID-19 pandemic. The establishment of this criterion would ensure that the proper working context is in place. We included a question in the email with the questionnaire sent to potential respondents, so that we could disregard those who did not meet this criterion. Further, all respondents should perform either a coordinator, supervisor, manager, or director role within their organizations. The assumption was that respondents playing these roles would have a more holistic and systemic view of their organization, mitigating myopic perceptions of the *status quo*. No restriction related to sector, ownership (i.e. public or private) or type (i.e. transnational or national) were determined, due to the wide diversity of service organizations.

Emails with the questionnaire were sent in April 2020 to 558 potential respondents initially identified from the authors' network in India. After that, a follow-up email was sent in the beginning of May 2020 to reinforce invitation to respond to the survey. 106 valid responses comprised the final sample, representing a 19% response rate (higher than the 15% rate recommended by Hair et al., 2014). The dataset was checked for non-response bias between respondents who answered in April (early respondents; $n_1 = 49$) and the ones who answered in May (late respondents; $n_2 = 57$). Levene's test for equality of variances and a *t*-test for equality of means (Armstrong and Overton, 1977) were applied, and results did not indicate significant differences in means and variances between groups. Moreover, Harman's single-factor test with an exploratory factor analysis was used to complementarily verify existence of common method bias (Malhotra et al., 2006). The test including all independent, moderating, and dependent variables resulted a first factor that accounted for 22.35% of the total variance. The absence of a single factor explaining most of the variance supported the assumption that issues related to common method bias could be disregarded.

Regarding respondents' characteristics, 67.9% were either supervisors or coordinators, and 59.4% had less than 5 years of experience. With respect to the service organizations encompassed in the dataset, 57.5% were transnational (located in multiple countries); 86.8% were private; 61.3% had less than 5000 employees; and 35.8% of them were from the infrastructure sector (e.g. communications, transportation, utilities, banking). In terms of the degree of interaction and customization, 85.8% of respondents claimed that their service organizations presented a high level, and 71.7% informed their organizations had a high degree of labor intensity. According to Fitzsimmons et al. (2008), organizations that display high labor intensity and interaction/customization are called 'professional services' as they provide individual attention by highly trained specialists.

3.3. Validity and reliability of constructs

In this step, we conducted two Exploratory Factor Analysis (EFA) using Principal Component (PC) extraction to identify and validate constructs based on the collected data. EFA is generally adopted in situations where a scale needs to be developed, helping the identification of latent constructs of variables (Fabrigar et al., 1999). EFA is also useful when hypotheses or patterns of measured variables are not previously known (Finch and West, 1997) (Table 1).

Table 1

Sample characteristics ($n = 106$).

Respondent's gender			Organization sector		
Male	76	71.7%	Financial services	16	15.1%
Female	30	28.3%	Government Services	18	17.0%
Respondent's role			Distribution Services	25	23.6%
Supervisor or Coordinator	72	67.9%	Personal Services	9	8.5%
Manager or Director	34	32.1%	Infrastructure Services	38	35.8%
Respondent's experience			**Organization degree of interaction and customization**		
<5 years	63	59.4%	Low	15	14.2%
>5 years	43	40.6%	High	91	85.8%
Organization size			**Organization degree of labor intensity**		
<5000 employees	65	61.3%	Low	30	28.3%
>5000 employees	41	38.7%	High	76	71.7%
Organization ownership			**Organization type**		
Public	14	13.2%	Transnational	61	57.5%
Private	92	86.8%	National	45	42.5%

The first EFA was performed with I4.0 base technologies, as shown in Table 2. All four digital technologies resulted in high loadings in the first PC, with an eigenvalue of 2.85 and accounting for 71.13% of the total variance in responses. Construct reliability was tested through the Cronbach's alpha, whose result ($\alpha = 0.856$) overcame the 0.6 threshold indicating high reliability in responses (Meyers et al., 2006). Responses for this construct were determined calculating the weighted average of original responses using factor loadings as weights.

The second EFA utilized responses on the agreement level of work implications caused from COVID-19 outbreak. Using a varimax rotation, we found three PCs with eigenvalues larger than 1 (4.30, 3.83 and 2.13, respectively) and representing an accumulated variance of 68.31% of the measures. Only factor loadings above 0.45 were considered (Tabachnick et al., 2007). We replicated the results utilizing an oblique rotation as a check for orthogonality and the extracted components were similar. Unidimensionality of components was verified and confirmed applying Principal Component Analysis at a component level. We assessed reliability determining Cronbach's alpha. Results in Table 3 showed high reliability (i.e. $\alpha > 0.6$) (Meyers et al., 2006).

Measures that loaded in the first component were all related to the economic impact caused by COVID-19 outbreak. Due to social distancing restrictions, market consumption has deaccelerated in many sectors (Zhang et al., 2020). Additionally, the utilization of existing resources has been reoriented to basic needs supply, such as food (Hobbs, 2020). Thus, most organizations have faced a significant reduction in

Table 2

EFA to validate the I4.0 base technologies construct (Adapted from Frank et al., 2019).

Variables	Mean	Std. Dev.	Communalities	Base Technologies [BASE_TECH]
Big data	3.49	1.78	0.79	**0.890**
Internet of Things (IoT)	3.68	1.79	0.63	**0.794**
Cloud computing	3.76	1.84	0.73	**0.853**
Analytics (e.g. machine learning and data mining)	3.83	1.77	0.70	**0.834**
Extraction sums of squared loadings				2.85
% of variance				71.13
Cronbach's alpha				0.856
KMO measure of sampling adequacy				0.812
Bartlett's test of sphericity (χ^2/df)				196.450/6**

Notes: Extraction method: Principal Component Analysis; ** p-value < 0.01.

Table 3

EFA to validate constructs of COVID-19's work implications (rotated component matrix).

Variables	Mean	Std. Dev.	Communalities	1	2	3	Denomination
I do not face delay in receiving information from my team	3.24	1.64	0.76	**0.774**			Job insecurity [JOB INS]
I do not find my department or division's future uncertain	3.13	1.72	0.76	**0.816**			
I cannot be moved to a lower level job within the organization	2.66	1.78	0.80	**0.890**			
I cannot lose my job and be laid off permanently	2.99	1.84	0.79	**0.887**			
I cannot lose my job by being pressured to accept early retirement	2.80	1.84	0.82	**0.901**			
I have more frequently used email to communicate with my suppliers, customers and/or team members	5.08	1.31	0.64		**0.699**		Home office environment [HOME]
I have more frequently used websites to communicate with my suppliers, customers and/or team members	3.96	1.88	0.46		**0.459**		
My work environment is neat and organized	4.88	1.22	0.71		**0.845**		
My work environment presents the necessary infrastructure to support my activities	4.81	1.29	0.75		**0.859**		
My work environment allows me to properly concentrate and focus on my daily duties	4.74	1.22	0.79		**0.892**		
My work environment allows me to have a flexible routine (i.e. flexible hours)	4.81	1.38	0.41		**0.599**		
I have more frequently used the telephone to communicate with my suppliers, customers and/or team members	4.84	1.60	0.56			**0.645**	Virtual connection [VIRTUAL]
I have more frequently used online platforms to communicate with my suppliers, customers and/or team members	5.10	1.39	0.64		0.598	**0.525**	
I significantly do not miss the physical interaction with my colleagues	4.29	1.62	0.65			**0.774**	
I do not face difficulty in approaching my coworkers	3.21	1.70	0.67	0.606		**0.548**	
Extraction sums of squared loadings				5.04	3.86	1.37	
% of variance				33.58	27.73	9.14	
Rotation sums of squared loadings				4.30	3.83	2.13	
% of variance				28.69	25.40	14.22	
Cronbach's alpha				0.843	0.805	0.821	
KMO measure of sampling adequacy				0.807			
Bartlett's test of sphericity (χ^2/df)				1041.913/105**			

Notes: Extraction method: Principal Component Analysis; Rotation Method: Varimax with Kaiser normalization; ** p-value < 0.01.

their demands, which caused a decrease in revenue and aggravated unemployment in most countries (Nicola et al., 2020). This construct then represents such sense of *job instability and sense of market insecurity* [JOB_INS] entailed by COVID-19 outbreak.

The second construct was consisted of work implications associated with *home office environment*. COVID-19 pandemic has forced organizations to restructure their processes and so that their employees could work remotely from home, avoiding an accentuated exposition and reducing the odds of a larger contamination (Nicola et al., 2020). In this scenario, people had to rearrange their work environment to perform their activities from home accordingly. Measures that loaded in this construct were grouped and assumed to represent pandemic's effects related to *home office environment* [HOME].

The third construct grouped items that were associated with work communication and information sharing. One of the main impediments entailed by COVID-19 outbreak has been related to communication. As physical interaction has been minimized, online platforms have been more extensively utilized as means to curb such restriction. In this sense, service organizations have encouraged virtual connections to enhance communication and mitigate social distancing effects on employees and teams. Hence, the underlying measures of this construct represent the virtual connection [VIRTUAL] motivated by COVID-19 pandemic.

Finally, we determined the pairwise correlations for all constructs

and their composite reliability (CR) (see Table 4). Significant correlation coefficients (*p*-value < 0.05) were found positive, indicating the nature of variables' interaction. CR values were larger than 0.7, confirming the convergent validity of constructs (Hair et al., 2014). Therefore, values for each validated construct were calculated based on their corresponding factor loadings and given in a continuous scale.

3.4. Data analysis

Next, we performed a set of Ordinary Least Square (OLS) hierarchical linear regression models to test our hypotheses. Each performance measure was individually examined in the regression models. Model 1 encompassed 'employee output quality' as the dependent variable. Thus, in Model 1A we only included the effect of the control variables (i. e. organization sector, degree of interaction and customization, and degree of labor intensity). Model 1B included the direct effect of the three constructs of COVID-19's implications and the I4.0 base technologies construct. Finally, Model 1C entailed adding the moderating effects of I4.0 base technologies. Model 2 referred to 'employee output delivery' as dependent variable. Analogously, Models 2A, 2B and 2C regressed this dependent variable on control variables, control and independent variables, and control, independent and interaction terms, respectively.

Table 4

Pearson correlation coefficients and composite reliability (CR).

	1	2	3	4	5	6	7	8	9	CR
1-Organization sector	–	0.237*	0.169	−0.058	0.212*	0.073	0.193*	0.116	0.147	–
2-Degree of interaction and customization		–	0.406**	−0.063	0.147	0.201*	0.133	0.153	0.083	–
3-Degree of labor intensity			–	0.059	0.157	−0.013	0.148	0.189	0.179	–
4-JOB_INS				–	0.094	0.401**	0.063	0.128	0.157	0.901
5-HOME					–	0.447**	0.454**	0.612**	0.605**	0.876
6-VIRTUAL						–	0.113	0.386**	0.368**	0.854
7-BASE_TECH							–	0.366**	0.358**	0.889
8-Employee output quality								–	0.887**	–
9-Employee output delivery									–	–

Determining a minimum representative sample size at which the results of a regression analysis would be unchanged from those obtained with larger sample sizes has been a major practical concern for multivariate data analysis techniques application (Forcino, 2012). Although researchers must collect a sample size that is large enough to be representative, once that sample size has been obtained, additional samples should not alter the outcome of a multivariate analysis, and such additional material can be considered a form of over-sampling (Forcino et al., 2015). There is no certain rule of thumb to determine the sample size. Some researchers do, however, support a rule of thumb when using the sample size. In regression analysis, which is the procedure conducted in our study, many researchers (e.g. Concato et al., 1995; Peduzzi et al., 1995; Vittinghoff and McCulloch, 2007) say that there should be at least 10 observations per variable. In our regression analysis, the most critical models were 1C and 2C, which regressed the respective dependent variables on control, independent and interaction terms. As our sample size is 106 respondents, we met the 10 to 1 ratio between sample size and independent variables indicated. Other survey-based studies recently published that approached novel phenomena utilized a similar sample size to perform their multivariate data analyses, such as Frank et al. (2019) which had a 92-respondent sample, Tortorella et al. (2017) with a sample of 89 companies, Marodin et al. (2018) with a sample of 110 responses, Marodin et al. (2016) with a dataset comprised by 64 respondents, and Godinho Filho et al. (2016) with 52 responses.

Multicollinearity on the estimated coefficients was examined using the variance inflation factors (VIF) for all variables, which were all below five (Belsley et al., 2005). Assumptions related to normality, linearity and homoscedasticity were verified between independent, moderating and dependent variable (Hair et al., 2014). Residuals were evaluated to verify normality of the error term distribution. Linearity was assessed with plots of partial regression for each model. Homoscedasticity was visually examined by plotting standardized residuals against predicted value. All tests confirmed the required assumptions for the OLS regression analyses.

4. Results and discussion

Table 5 displays the results for the standardized $\widehat{\beta}$ coefficients of the regression analyses. For Model 1A (only control variables), no significant results were found. When adding the independent variables to the model (Model 1B), the prediction of 'employee output quality' was significantly explained (F-value = 9.877; p-value < 0.01; R^2 = 0.414) by HOME construct ($\widehat{\beta}$ = 0.474; p-value < 0.01). However, as the interaction terms (moderating variables) were inserted, Model 1C showed a significant change in R^2, explaining 45.3% of the variance (F-value = 7.878; p-value < 0.01). In Model 1C, HOME remained positively

associated ($\widehat{\beta}$ = 0.513; p-value < 0.01) with employee output quality. Regarding the interaction terms, results suggested that BASE_TECH has a positive moderation on the effect of VIRTUAL ($\widehat{\beta}$ = 0.197; p-value < 0.10) on employee output quality. In opposition, BASE_TECH seems to negatively moderate the effects of both HOME ($\widehat{\beta}$ = −0.208; p-value < 0.05) and JOB_INS = −0.157; p-value < 0.10).

With regards to 'employee output delivery', results for the hierarchical linear regression analyses indicated that Model 2B (F-value = 9.491; p-value < 0.01; R^2 = 0.404) was the selected one, since no significant change in R^2 occurred in Model 2C. In other words, as Model 2B only included control and independent variables, no significant moderation was found for the performance improvement of employee output delivery. In fact, only HOME presented a significant positive association ($\widehat{\beta}$ = 0.476; p-value < 0.01) with this performance measure. These results do not bear H_1 and partially support H_2.

The positive direct impact of HOME on both employee output quality and delivery was contrary to the hypothesized negative effect of COVID-19's work implications (H_1). As service organizations had to quickly adapt to the new normal implied by the pandemic, individuals' performance was expected to worsen since their readiness level would not match the current requirements. However, the counterintuitive positive impact of *home office environment* pointed in our analyses somewhat converges to previous indications from MacEachen et al. (2008) and Bloom (2014). In general, these studies suggested that when employees work remotely from their homes there is a higher likelihood of increasing both productivity and job satisfaction. Our results expand such findings indicating that employee output quality is also prone to improve when service organizations adopt home office policies. Further, our findings suggest that employees do not lack the required infrastructure and discipline to work from their home, since the sudden change to home office environment implied by the pandemic positively influenced their performances.

Regarding the moderating role of BASE_TECH, two different outcomes were observed. I4.0 base technologies (e.g. IoT, big data, cloud computing and machine learning) are supposed to facilitate communication and information sharing among agents (Frank et al., 2019; Shou et al., 2019), support and catalyze more assertive decision-making (Tortorella et al., 2019; Ancarani et al., 2019), and eventually act on issues related to services, processes or products by autonomously addressing proper countermeasures (Lam et al., 2019; Koh et al., 2019). In this sense, the extensive adoption of such technologies was assumed to mitigate potentially negative impacts of the pandemic on employees' performance, hence, moderating this relationship as hypothesized in H_2. Thus, the positive moderation found for the VIRTUAL construct was naturally expected, as this construct deals with work communication and information sharing implied by the COVID-19 outbreak.

Table 5
Standardized $\widehat{\beta}$ coefficients of the hierarchical regression models.

Variables	Employee output quality			Employee output delivery		
	Model 1A	Model 1B	Model 1C	Model 2A	Model 2B	Model 2C
Organization sector	0.073	−0.038	−0.057	0.123	0.015	−0.007
Degree of interaction and customization	0.077	0.002	−0.011	−0.013	−0.080	−0.087
Degree of labor intensity	0.145	0.104	0.093	0.163	0.117	0.107
HOME		0.474***	0.513***		0.476***	0.498***
VIRTUAL		0.163	0.135		0.144	0.133
JOB_INS		0.002	0.000		0.036	0.047
BASE_TECH		0.124	0.145		0.114	0.123
HOME x BASE_TECH			−0.208**			−0.148
VIRTUAL x BASE_TECH			0.197*			0.123
JOB_INS x BASE_TECH			−0.157*			−0.156
F-value	1.705	9.877***	7.878***	1.649	9.491***	7.215***
R^2	0.048	0.414	0.453	0.046	0.404	0.432
Adjusted R^2	0.020	0.372	0.396	0.018	0.361	0.372
Change in R^2		0.366***	0.040*		0.358***	0.028

Notes: * p-value < 0.10; ** p-value < 0.05; *** p-value < 0.01.

On the other hand, the negative moderation of BASE_TECH on the relationships between HOME or JOB_INS and employee output quality was contrary to expectation. Although surprising, these negative interactions are aligned with findings from Tortorella et al. (2020b), which indicated that organizations might find larger benefits from the adoption of I4.0 base technologies at an organization level rather than at a team or individual level. Frank et al. (2019) has pointed that the understanding about I4.0 base technologies still needs to be enhanced, since managers are more familiar with their I4.0 smart functionalities and applications rather than the technologies that underpin them. This fact may also help to explain the negative moderation of BASE_TECH. Thus, we argue that the negative moderation on the effects of both *home office environment* and *job insecurity* may occur due to the combination of poor managerial comprehension of I4.0 base technologies and the fact that these technologies are more prone to be used in organizational macro-processes that do not directly relate (or distantly relate) to employee output quality. This argument is also supported by the lack of significant moderation found for employee output delivery. Fig. 2 summarizes the results obtained by capturing the empirically significant relationships.

5. Conclusion

The objective of our research was to provide an understanding of how the outbreak of COVID-19 could impact employee's performance (RQ_1) and the moderating role performed by I4.0 base technologies adoption (RQ_2). To answer those questions, we collected data from employees of different service sector firms in India who have been working remotely during the COVID-19 outbreak. We received 106 valid responses and analyzed them using multivariate techniques.

Answering RQ_1, our results revealed that home office work environment enhances output quality and delivery performance of employees. In the sample studied, we did not find any significant direct impact of job instability and sense of market insecurity and virtual connection on employee performance. Regarding RQ_2, our research indicated that I4.0 base technologies adoption (*i*) negatively moderates the relationship between home office work environment and output quality, (*ii*) positively moderates the relationship between virtual connectedness and output quality, and (*iii*) negatively moderates the relationship between job insecurity and output quality. No significant moderation of I4.0 base technologies was observed for output delivery performance. These findings have significant implications to both theory and practice, being discussed more in-depth next.

5.1. Theoretical implications

From a theoretical perspective, three outcomes are worth mentioning. First, we have empirically verified three constructs of COVID-19's work implications; they are: (*i*) job insecurity, (*ii*) home office environment and (*iii*) virtual connection. As COVID-19 pandemic is a recent phenomenon, the existence of clear definitional constructs to base research on is scarce, entailing a fragmented research field. Hence, a theoretical contribution of this study refers to the identification of three specific work implications constructs, which were validated by orthogonal components extraction and complemented previous research indications (e.g. Tortorella et al., 2020a). As these work implications constructs were initially derived from the literature and validated based on practitioners' perceptions, their identification raises a practical framework anchored on a theoretical background. Thus, instead of addressing a wide range of work implications from the COVID-19, which tends to consume unnecessary efforts, these constructs allow focusing on more common and elementary work implications from COVID-19.

Second, our results have shown that the work implications of COVID-19 pandemic have a direct impact on employees' performance, especially when considering home office environment. Counterintuitively, working remotely appears to positively influence employees' performance. Surprisingly, no significant direct effect was found for job insecurity and virtual connection. The explanation of this result might favor two different theoretical views. On the one hand, it may indicate that the variation in individual employee's performance is not so vulnerable to the working condition, relying much more on individual employee's factors, such as adaptability and intrinsic motivation (Diamantidis and Chatzoglou, 2019). On the other hand, the effect of COVID-19's work implications on employees' performance may be mitigated when other organizational factors are properly in place. This is view is much aligned with Li et al.'s (2019) findings, which posed that organizational factors, e.g. leadership and culture, are key to employees' turnover intention.

Finally, I4.0 base technologies do moderate the work implications originated by the COVID-19 outbreak on employees' performance. Nevertheless, the orientation of such moderation seems to vary according to the construct under analysis. Moreover, the moderating role of I4.0 base technologies is more pervasive on quality performance of employees than on delivery performance. The duality in results suggests that the benefits from implementing I4.0 base technologies are still poorly understood, with emphasis to service organizations. Although the advent of the Fourth Industrial Revolution has led organizations to increase their interconnectivity and automation levels, so that higher levels of modularization, flexibility, resilience, and performance can be achieved (Frank et al., 2019; Kusiak, 2020), many service organizations still struggle to grasp the concepts of I4.0 (Bonamigo and Frech, 2020).
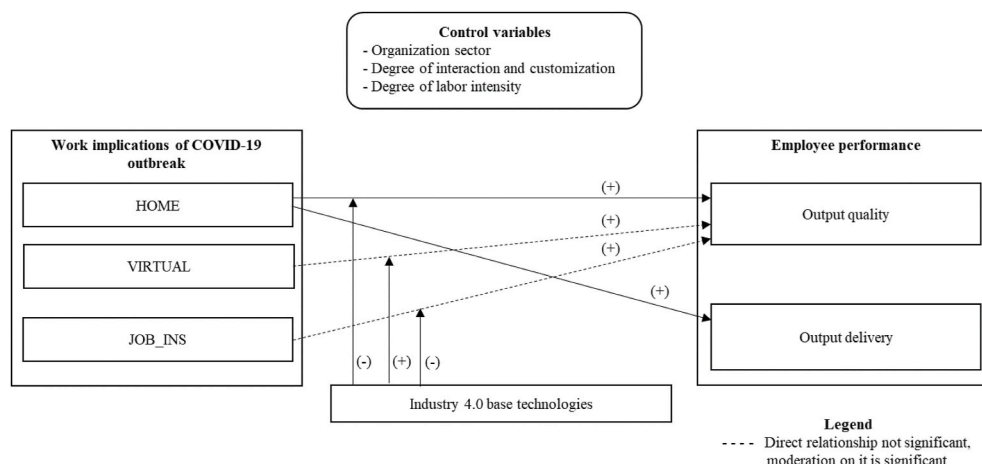

Fig. 2. Empirically significant relationships.

Our research unveils further roles played by I4.0 technologies in service organizations, especially when considering the "new normal" implied by the COVID-19. To the extent of our knowledge, no similar studies have been conducted and this is the first research that has empirically evidenced such effects, whose insights might also contribute to the post-pandemic period.

5.2. Practice implications

Regarding practical contributions, our research raised arguments to managers of service organizations that are implementing I4.0 technologies and working remotely during the COVID-19 outbreak. Our findings indicate that service organizations might need to rethink their processes and routines for the post-pandemic period based on the lessons learned from the COVID-19's work implications. For instance, the reinforcement of home office environment appears to be an interesting alternative to enhance performance of the employees of these organizations. Furthermore, our results indicate that organizations concurrently adopting I4.0 base technologies and virtual connection practices might improve employees' performance, especially in terms of quality output. This insight is expected to add value to team leaders and line managers who face difficulty in containing the negative impact of COVID-19 pandemic on employee's performance. Such indications might be valuable not only during the pandemic outbreak, but also be a legacy to the service industry context for the post-pandemic world.

This study has also highlighted that there are still many opportunities with respect to I4.0 implementation in service organizations. More specifically, we found service organizations that are adopting I4.0 base technologies to be underutilizing their capacity, hence, blurring the perception of their benefits to individual performance. This was particularly observed during the COVID-19 pandemic, which has entailed several changes to the way organizations work. In this sense, service organizations are unlikely to be fully benefitting from I4.0 adoption to conduct the 'new normal' routines implied by the COVID-19 outbreak. Because, this finding was obtained using the very basic technologies of I4.0, we highlight the infancy of the topic and the low maturity displayed by most service organizations in terms of I4.0. This indicates the opportunity for more extensive digitalization efforts of service industry's processes and activities so that it becomes possible to cope and benefit with the inevitable work implications from the severe disruptive events, such as the COVID-19 pandemic. Examples of these digitalization efforts would encompass the integration of other technologies, such as blockchain, collaborative robots, and augmented reality. Results also indicate that it is important to regularly monitor and assess the impact of such digitization efforts on the relationship between work implications and employee performance as it can at times fail to deliver the intended outcome. The regular assessment is expected to guide the team on revisiting their configurations of digital technologies and fine-tune it to best fit their capabilities and requirements.

5.3. Limitations and future research

A few limitations of this study are worth mentioning. First, because the COVID-19 outbreak is a recent phenomenon, perceptions related to performance improvement are subtle and may lead to misguided results. Although this is a relevant limitation of our study, we curbed such issue by restricting the unit of analysis to employee's performance. This allows respondents to have a clearer opinion about their own performance results during the pandemic, avoiding misguided responses on the organizational performance. Hence, future studies could encompass organizational performance metrics and expand the unit of analysis to the organization itself. This would enable a broader generalization of findings and more holistic approach. Longitudinal empirical studies are also recommended as a means to observe the pandemic implications in the longer term. Second, the nature of service firms is extremely broad. Even though we performed a non-random data collection with pre-

established selection criteria, the distribution of respondents varied. In this sense, our findings may be limited by the characteristics of the study sample. Further research could increase the dataset not only in terms of number of responses, but also in relation to the diversity of services. This could provide different and new insights to the field, complementing our research findings. Finally, we studied the moderation of I4.0 base technologies, on which smart functionalities and applications are supposed to be built. As observed in our study, managers are more likely to perceive the benefits of I4.0 adoption when discussing the smart functionalities and applications (also denoted as front-end technologies by Frank et al., 2019), undermining the empirical examination of the role of I4.0 base technologies. Therefore, subsequent studies could conduct the analysis of such I4.0 front-end technologies in service organizations that are working remotely during the COVID-19 outbreak. A deeper understanding of the role played by I4.0 in extremely disruptive moments (such as the pandemic) could be an additional motivation to managers to move forward towards the fourth industrial revolution era.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijpe.2021.108075.

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