Impact of Industry 4.0 adoption on workload demands in contact centers

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Abstract

This paper examines the impact of Industry 4.0 (I4.0) technologies on employees workloads in contact centers. For that, we adopted the NASA task load index (TLX) questionnaire to assess the workload of 100 employees from different contact centers in India that have been adopting I4.0 technologies. The collected data is analyzed through multivariate techniques. This research is grounded on concepts from the multiple resource theory. Our findings indicate positive and negative effects of I4.0 on employees workloads, conditioned on the adopted technologies (i.e., Internet-of-Things, cloud computing, big data, machine learning/artificial intelligence, remote monitoring, and wireless sensors) and workload dimensions considered (i.e., mental demand, physical demand, temporal demand, overall performance, effort, and frustration level). Identifying I4.0's impacts on employees workloads allows planning of managerial efforts to mitigate potential issues while setting clear expectations related to the digital transformation of contact centers' processes and services.

Keywords: Industry 4.0, Workload dimensions, Ergonomics, NASA-TLX, Contact centers, Call centers.

1. Introduction

Industry 4.0 (I4.0) has raised new management paradigms. With the increased level of interconnectivity and automation, organizations have been restructuring and revising their processes, products, services, and business models to achieve superior performance results (Wagire et al., 2020; Tortorella et al., 2021a). The integration of disruptive digital technologies, e.g. big data, cloud computing, Internet-of-Things (IoT), and artificial intelligence (AI), has been changing the landscape of organizations and supply chains, yielding operational benefits while imposing additional challenges (Sony et al., 2021). As organizations increase their awareness of I4.0, understanding its actual benefits and challenges becomes clearer (Veile et al., 2020), especially regarding the implications of human factors (Tortorella et al., 2021b).

The impacts of I4.0 adoption on employees workload and ergonomics are still underexplored in the literature (Kadir et al., 2019; Costa and Portioli-Staudacher, 2021), and the few existing studies (e.g., Laudante, 2017; Broday, 2020; Virmani and Salve, 2021; Reiman et al., 2021) raise contradictory arguments on the relationship between I4.0 and employees workload. On the one hand, I4.0 technologies allegedly allow the automation of repetitive and monotonous activities, increasing the diversity of movements and responsibilities and positively affecting the workplace. On the other hand, as I4.0 facilitates real-time data collection and information sharing across processes, decision-making takes place in shorter feedback loops, possibly increasing the temporal demand on employees and negatively affecting their workload. The relevance and extent of this relationship may be amplified when considering workplaces that are traditionally known for high workloads, such as call centers (Sprigg et al., 2007; Khattak, 2021).

The relevance of call centers has significantly grown since the Bell Telephone Company started to use operators to connect calls (Pinedo et al., 2000). The role played by call centers has also changed over the years, expanding from providing information (e.g., phone numbers and flight schedules) to carrying out more complex activities (e.g., giving medical advice and opening bank accounts) (Choi, 2017). The advent of new technologies and the increasing need for multiple information access channels have also fostered the use of other communication means besides the telephone, such as web chats, SMS and Whatsapp messages, and video chat assistance (Bernhard and Wihlborg, 2015; Knauer, 2019; Levant, 2020). The diversity of communication avenues led to renaming 'call centers' as 'contact centers' (Parikh, 2016). Despite the changes and technological advances, employees workload remains an important concern in such work environments (Baseman et al., 2018). The paucity of studies combined with the contradictory evidence reported in the literature on the impact of emerging I4.0 technologies on the workload of contact centers' employees gave rise to the following research question:

RQ. How do I4.0 technologies impact employees workload in contact centers?

To answer that, we conducted a survey with 100 employees from different contact centers in India. As one of the countries with the largest number of call/contact centers in the world, employing more than 3.1 million workers (White, 2018) and with an existing infrastructure characterized by extensive utilization of emerging digital technologies (D'Cruz and Noronha, 2013; D'Sa-Wilson, 2021), India offers the perfect scenario for this research. The workload demands were assessed through the NASA task load index (NASA-TLX) (NASA, 1986), a widely known scale used by academics and practitioners. The adoption level of base technologies (Frank et al., 2019a) was used as a proxy for I4.0, following the procedure reported in studies of similar nature (e.g., Rossini et al., 2019; Tortorella et al., 2021c). The collected data were analyzed using multivariate techniques.

Our study was framed by Wickens' (1984) multiple resource theory (MRT) model, which postulates that individuals possess a limited set of resources for mental processes. MRT concepts explain the difficulty of running single-tasks and how dual-task performance can be undermined by doing similar tasks (Basil, 2012). In addition to the contributions to theory, this research presents some relevant practical implications. Identifying I4.0's impacts on employee workloads allows for anticipating managerial efforts to mitigate potential issues while setting clear expectations related to the workplace's digital transformation.

2. Background and hypotheses

2.1. I4.0

The fourth industrial revolution (also known as Industry 4.0 or I4.0) aims at enhancing automation and the use of computers in industrial environments. I4.0 relies on smart and autonomous systems that use data mining and sharing and machine learning methods (Xu et al., 2018; Tortorella et al., 2020). These have been applied in a . I4.0 refers to a new paradigm in the organization and monitoring of the value chains, enabling autonomous decision-making processes, control of assets and processes in real-time, developing of value creation networks connected in real-time based on early involvement of stakeholders, and vertical and horizontal integration (Olsen et al., 2020; Dos Santos et al., 2021). The digital transformation fostered by I4.0 has been producing significant impacts on a variety of industry sectors, such as automotive (Lin et al., 2018), healthcare (Rosa et al., 2021), food (Kayikci et al., 2020), and construction (Dallasega et al., 2018).

Besides the incorporation of a portfolio of digital technologies, I4.0 encompasses a set of design principles that guide its implementation (Hermann et al., 2016; Basl, 2016; Cañas et al., 2021); they are: (*i*) interconnection, which is the ability of machines, devices, sensors, and people to connect and intercommunicate through IoT; (*ii*) information transparency, which represents the widespread availability of comprehensive information to support decisions; (*iii*) technical assistance, which is the systems' ability to underpin decision-making and problem-solving, and in the execution of dangerous tasks; and (*iv*) decentralized decisions, which is the systems' ability to perform tasks and decide autonomously. I4.0 may also be characterized by other aspects, such as (*i*) velocity, which denotes the increasingly speed at which organizations are impacted, (*ii*) scope, which refers to the large number of impacted sectors, and (*iii*) paradigm shift in technology policy, which comprises the novel policies designed to support the inherent innovations from I4.0 (Schwab, 2015).

Regarding the existing challenges for a successful I4.0 adoption, Mohamed (2018) emphasized the uncertainties about financial benefits due to the scarcity of evidence that justifies investments in I4.0. The absence of a strategical approach to organizing the initiatives across different organizational levels may also pose a barrier to a more extensive implementation (Olsen et al., 2020). Other challenges for I4.0 adoption include cybersecurity concerns with third-party providers (Prinsloo et al., 2019), high capital expenditures and financial constraints (Masood and Sonntag, 2020), and information technology infrastructure and government support (Sung, 2018).

In terms of human aspects, I4.0 adoption requires specific skills and qualifications (e.g., data analytics and programming capabilities) that may not be available in the existing workforce (Tommasi et al., 2021). That undermines the inclusion of workers whose abilities do not meet the necessities of this new management paradigm, impairing I4.0's pervasiveness across different socio-economic contexts (Tortorella et al., 2021c). I4.0 can have a profound impact on how work tasks are executed (Neumann et al., 2021). Kadir et al. (2019) indicated that the existing research about the impact of I4.0 on workers is mostly based on speculation, with very few studies presenting empirical results. Cimini et al. (2021) showed that the application of I4.0 technologies to logistics could either replace some tasks, augment workers' capacity, or even present no impact at all. Particularly for complex tasks in which replacing the operators is more difficult, I4.0 technologies should be used to assist operators while executing them (Badri et al., 2018).

2.2. Workload assessment

The workload is the amount of work an individual must perform in a given time. The actual amount of performed work may differ from the individual's perception of the workload (Jex, 1998). Workloads may also vary across individuals performing the same task due to distinctions in capabilities, efforts, attitudes, cognition, skills, limitations, and states of situational awareness, complacency, fatigue, boredom, anxiety, and stress (Lean and Shan, 2012). Shifts in human performance and behavior derived from mental demands might be directly associated with physiological and biochemical shifts, which depend on nervous regulation (Zink, 2000; Silva et al., 2016). Thus, assessing a person's workload is crucial in designing socio-technical systems. In evaluating employees workload during the design of a new workplace or iteration of an existing one, issues such as bottlenecks and overburden might emerge (Feitelson, 2015). As employees are a central part of socio-technical systems, it is necessary to address those issues to enhance their working conditions and efficiency (Tortorella et al., 2017; 2019).

Qualitative and quantitative evidence should be gathered when assessing whether a workplace has the proper design and reasonable workload. Such evidence may be obtained from various sources (Macleod, 2003; Young et al., 2015). Nevertheless, assessing employees workload is not a new problem, and several researchers have proposed different methods and techniques to conduct it. For instance, the RNUR (Regie Nationale des Usines Renault) or job-profile method of Renault (1976) was conceived with the National Control of Factories in France and assesses the demands of general work activities from the expert's perspective. Very popular in the automotive industry, the Peripheral Detection Task (PDT) measures workload indirectly through visual attention. As workload increases, visual attention narrows, and people tend not to perceive peripheral visual stimuli (van Winsum et al., 1999).

Self-reporting techniques, such as the Modified Cooper-Harper scale (Cooper and Harper, 1969), Subjective Workload Assessment Technique (Reid and Nygren, 1988), NASA-TLX

(NASA, 1986), Workload Profile (Tsang and Velazquez, 1996), Overall Workload scale (Hill et al., 1992), and Rating Scale Mental Effort (Zijlstra, 1993), are well-known and widely adopted. These scales are based on multi-dimensions rated by the workers. Despite the criticism for being overcomplicated, these scales are non-intrusive and provide adequate accuracy and validity (Rubio et al. 2004). Most recently, there has been a spread of physiological measures to assess the workload. Heart rate variation, blood pressure, brain activity regions, electroencephalogram power density spectra, and facial muscles are examples of physiological measures that indicate the individual workload state (Young et al., 2015). Despite the advances in the technologies employed to measure these metrics, the techniques are still considered intrusive and may affect the quality of the data (Liu et al., 2018).

In particular, the NASA-TLX (NASA, 1986) allows the workload estimation from workers doing an activity or immediately afterward. It employs different dimensions to assess mental demand, physical demand, temporal demand, frustration, effort, and performance. It is one of the most used methods to assess mental workload in experimental research as it diagnoses the sources that contribute to mental workload (Şeker, 2014; Rizzo et al., 2016; Mansikka et al., 2019). It has been adopted in several studies and used in various contexts, such as aviation, healthcare, and other complex socio-technical domains (Colligan et al., 2015), highlighting its pervasiveness in human factors research. In summary, despite the prolific literature evidence, there seems to be no consensus on the concept of workload and, hence, not an agreed method for evaluating or modeling it.

2.3. The integration of technologies in contact centers

A contact center usually encompasses many technologies that help enhance the customer experience, improve operational efficiency, and reduce costs. Over the last years, contact centers have been increasing technology adoption in their processes and services. Nevertheless, contact centers display important differences concerning the technologies used, and the skills demanded to handle them (Zweig et al., 2006; Darcy et al., 2017). Despite the technology-oriented initiatives, their impacts on the employees workload, which is already highly stressed, are still unknown (Sieben et al., 2009; Arzbächer et al., 2017). In general, there is concern that technological advances may aggravate stress, reduce job performance, contribute to ill-structured coping approaches, and reduce employee retention and morale in the workplace (Prichard et al., 2014; Baseman et al., 2018).

The event of I4.0 has accelerated the digital transformation of workplaces, providing a basis for further technological advances and improved services (Narayanamurthy and Tortorella, 2021). I4.0 technologies have significantly increased the rate and speed of information exchange, which is likely to enhance the awareness of customers' issues and allow contact centers to make more assertive decisions and recommendations (Kibria et al., 2018; Kahn et al., 2020). However, the greater availability of information may also lead to higher customers' expectations of more efficient services and processes (Frank et al., 2019b). The operation of contact centers may be significantly affected to meet such demands, particularly regarding employees workload.

According to the MRT model, workers process information using multiple (rather than single) resources simultaneously. Depending on the task's nature, information will be processed sequentially (e.g., when distinct activities demand the same set of resources) or in parallel (e.g., when the activities require different resources) (Wickens, 1984; 2008). Consequently, increases in employees workload may not always lead to poorer performance (Nachreiner, 1995; Fallahi et al., 2016). As I4.0 technologies have often been considered enablers of better organizational performance (Sony et al., 2021; Narayanamurthy and Tortorella, 2021), one tends to assume that they also present a positive impact on employees workload. To better investigate the effects of I4.0 on employees workloads in contact centers, we propose the following hypotheses based on NASA-TLX dimensions (i.e., mental demand, physical demand, temporal demand, overall performance, effort, and frustration levels):

H_1. The adoption of I4.0 technologies reduces the mental demand in contact centers.

H_2. The adoption of I4.0 technologies reduces the physical demand in contact centers.

H_3. The adoption of I4.0 technologies reduces the temporal demand in contact centers.

H_4. The adoption of I4.0 technologies increases the overall performance in contact centers.

H_5. The adoption of I4.0 technologies reduces the effort in contact centers.

H_6. The adoption of I4.0 technologies reduces the frustration level in contact centers.

The hypothesized model is displayed in Figure 1. Note that since the dimension 'overall performance' has a different target than the others (i.e., the higher, the better), its hypothesized relationship with I4.0 technologies is claimed to be positive rather than negative.

Figure 1 – Hypothesized model in the research

3. Method

The exploratory nature of this research motivated the utilization of an empirical approach, which allows acquiring knowledge through direct and/or indirect observation (Goodwin, 2005). Quantifying empirical evidence collected from non-random participants who meet specific selection criteria is a popular research technique (e.g., Tortorella et al., 2019). We adopted the online survey method for data collection due to its many advantages, such as higher representativeness, lower cost, good statistical significance, and standardized stimulus to participants (Forza, 2002). The proposed method consisted of three main steps: (*i*) instrument development, (*ii*) sample selection and data collection, and (*iii*) data analysis. These steps are explained in the subsequent sections.

3.1. Instrument development

The questionnaire applied in this study consisted of four parts (see Appendix). The first part comprised questions about participants' information. Employees' age was categorized as (*i*) ≤ 29 years old, (*ii*) between 30 and 39 years old, and (*iii*) ≥ 40 years old), while gender was dichotomized into male or female. Working shift was divided into 4 groups: (*i*) from 6 am to 12 pm, (*ii*) from 12 pm to 6 pm, (*iii*) from 6 pm to 12 am, and (*iv*) from 12 am to 6 am. Due to the high turnover traditionally found in this type of service organization (Tuten and Neidermeyer, 2004), respondents' working experience in the contact centers was divided into less than 1 year and more than 1 year. We also asked them to indicate the type of contact center according to three main categories: (*i*) inbound contact center (e.g., customer service, technical support, and emergency response), (*ii*) non-voice-based business process outsourcing (e.g., back-office support for data entry, chat support, and e-mail support), and (*iii*) web-enabled contact center (e.g., webchat, e-mail support, and quality analysis). This information allowed us to characterize the sample and determine the relevant control variables in our research. In the second and third parts, we assessed employees workload by incorporating the NASA-TLX questionnaire (NASA, 1986) into the survey. The NASA-TLX has been adopted in similar studies (e.g., Hart, 2006; Akyeampong et al., 2014; Galy et al., 2018), being acknowledged by both academics and practitioners, which justifies our choice. Participants were initially asked to rate their workload according to six dimensions (i.e., mental demand, physical demand, temporal demand, overall performance, effort, and frustration levels) within a 100-points range (second part of the questionnaire). Next, respondents were asked to perform 15 pairwise comparisons of those six dimensions, indicating which one was more relevant to the workload in their daily activities in the contact center (third part of the questionnaire). The number of times each dimension was chosen as more relevant is used as importance weights (Rubio et al., 2004). Weights were multiplied by scale scores for each dimension (obtained in the second part) and added up. The resulting sum was divided by 5 to get the dimension workload score varying from 0 to 100.

The last part of the survey assessed the adoption level of four I4.0 base technologies (Frank et al., 2019a) in the respondents' workplaces; they are IoT, cloud computing, big data, and machine learning/AI. According to practitioners' reports (e.g., Levant, 2020; Bai, 2021; CallMiner, 2021), those technologies can support the development of more effective processes and services, entailing significant improvements in contact centers' performance. Further, because the concept of those technologies could vary among participants, we inserted a brief definition in the questionnaire to avoid misinterpretation. A 5-point scale was used, in which a score of 1 denoted a technology 'not adopted' and 5' fully adopted'.

To avoid common method variance, we performed a few countermeasures related to the design of the questionnaire. In the instrument opening remarks, we inserted two statements informing respondents about the anonymity and confidentiality of the data and that there were no right/wrong answers (Podsakoff and Organ, 1986). We also located dependent variables (NASA-TLX workload dimensions) apart from independent variables (I4.0 technologies) (Podsakoff et al., 2003). We carried out Harman's single-factor test (Malhotra et al., 2006) utilizing all variables. Results indicated that the first factor only accounted for 25.03% of the total variance, allowing us to disregard issues related to common method variance.

3.2. Sample selection and data collection

We established the following criteria to select participants. First, as the focal point of our analysis was the person herself, all respondents should perform operational activities in contact centers. Second, to mitigate the effect of the socio-economic context, we only involved participants who worked in companies located in India. Although it may limit the generalization of our indications, it increases the internal validity of our findings and their extension to companies located in similar socio-economic contexts. Moreover, India has a large number of contact centers, representing approximately 8% of its gross domestic product (White, 2018). Third, due to our research purpose, the contact centers included in the dataset should have started adopting I4.0 technologies. We inserted an initial question asking participants whether their contact centers had initiated the I4.0 adoption to verify this selection criterion. They should provide examples to justify their answers. Based on the responses, we could judge whether the respondents were eligible or not.

The survey data was collected in September 2021 with the help of a market research firm. The firm used its proprietary panel network of registered users who were employees of contact centers in India as the sampling frame. A non-random sampling approach was adopted for the online survey. A personalized e-mail invitation with the embedded survey link was sent to 366 contact center employees with simple directions on how to access and complete the survey. To encourage participation and assure respondents' anonymity, follow-up e-mails were sent and all identifying information was removed before analysing the survey data, respectively.

We obtained a complete final sample of 100 respondents (27.32% response rate), 35 responses collected in the first two weeks of September, and 65 in the last two weeks. All contact centers have already initiated their digitalization, and some I4.0 technologies, such as machine learning/artificial intelligence, big data, Internet-of-Things, and cloud computing, stood out as the most frequently adopted ones. Most of the participants were male (75%), had been working for less than one year in the company (52%), 40% of them worked in the morning shift (from 6 am to 12 pm), and 48% were less than 29 years old. The sample was well-balanced concerning the types of contact centers, with 33% of respondents from inbound contact centers (e.g., customer service, technical support, emergency response), 33% from non-voice-based business process outsourcing (e.g., back-office support for data entry, chat support, e-mail support), and 34% from web-enabled contact centers (e.g., webchat, e-mail support, quality analysis), as displayed in Table 1.

Table 1 – Sample characteristics (n = 100)

3.3. Data analysis

We tested the theoretical model displayed in Figure 1 through a set of Ordinary Least Square (OLS) hierarchical linear regression models. For each NASA-TLX workload dimension (dependent variable), we examined two models. In the first model, dependent variables were individually regressed on control variables, such as employees' age, gender, working shift, time working for the company, and contacts/shift. The variable 'contacts/shift' was standardized to avoid scale effects (Hair et al., 2014). In the second model, each NASA-TLX workload dimension was regressed on the control and independent (I4.0 technologies) variables. If adding the independent variables yielded a significant increase in the prediction capacity of the model (measured by the change in R^2 value), the second model was chosen, and its variables' coefficients analyzed.

We also determined the variance inflation factors (VIF) for all variables to check for multicollinearity on the estimated coefficients. As all VIF values were below five, we disregarded multicollinearity between variables (Belsley et al., 2005). Additionally, we examined assumptions related to normality, linearity, and homoscedasticity between independent and dependent variables (Hair et al., 2014). To test normality, we assessed the residuals of the error term distribution. We analyzed linearity via plots of partial regression for each model. Finally, homoscedasticity was verified by plotting standardized residuals against the predicted values and examining them visually. All assumptions were satisfied, enabling the use of OLS regression results.

4. Results and discussion

Table 2 shows the means, standard deviations, and coefficients of the pairwise relationships of variables involved in our study. Of the 105 different pairwise relationships examined, 41 displayed significant coefficients (p-value < 0.05). Out of the 41, 27 were positive, indicating the direction of the relationship. In Table 3, we display the standardized $\hat{\beta}$ coefficients of the OLS hierarchical linear regression models. All models indicated a significant association between I4.0 base technologies and NASA-TLX dimensions, except for overall performance and effort levels (none of the regression models tested for these dimensions were significant, with p-values > 0.10). That suggests that, based on our sample of respondents, I4.0 technologies may not display perceptible effects on overall performance and effort levels, which may be affected by other variables not considered in our survey. Therefore, we could not validate hypotheses H_4 and H_5.

Table 2 – Pairwise correlations

Table 3 – Results of the OLS linear regression models (standardized $\hat{\beta}$ coefficients)

4.1. I4.0 technologies and mental demand

In the first model, mental demand was regressed on control variables (Model 1A) and I4.0 base technologies (Model 1B). Model 1B was chosen due to its significant increase in prediction capacity (change in R^2 = 0.396, p-value < 0.01; F-value = 12.962, p-value < 0.01). In addition to the positive association between mental demand and working shift ($\hat{\beta}$ = 0.213, p-value < 0.01) and gender ($\hat{\beta}$ = 0.136, p-value < 0.10), the adoption of big data also significantly increases the mental demand ($\hat{\beta}$ = 0.712, p-value < 0.01). In opposition, IoT adoption significantly decreases the mental demand ($\hat{\beta}$ = -0.231, p-value < 0.05) of the surveyed employees.

The adoption of IoT tends to generate new opportunities with regard to customer service in contact centers (Ives et al., 2016; Yerpude and Singhal, 2018). According to Vocalcom (2021), integrating IoT into contact centers will increase employees' proactivity, allow them to become specialized experts, and enhance customer self-service activities. That justifies the decrease in mental demand associated with IoT adoption observed in the model. In turn, the widespread processing and data collection through sensors in the IoT environment impose a challenge to workers, that may become overwhelmed by the wealth of information made available through big data analytics (Marjani et al., 2017). Big data extracts information from large and/or complex datasets (Schermann et al., 2014). Challenges to its adoption in the workplace include the visualization, sharing, querying, and updating of the information generated by datasets with sizes exceeding the capacity of usual software to process within an acceptable time and value (Madden, 2012; Harford, 2014). Handling this amount of data requires different skills and competencies that most employees may not be yet prepared for (Tommasi et al., 2021; Costa and Portioli-Staudacher, 2021), justifying the increase in mental demand derived from the use of big data. The mixed effects of IoT and big data on the mental demand of contact centers' employees allow us to partially validate H_1.

4.2. I4.0 technologies and physical demand

Regarding physical demand, the addition of I4.0 technologies as independent variables in the regression model significantly improved its prediction capacity (change in $R^2 = 0.094$, p-value < 0.05; F-value $= 2.498$, p-value < 0.05). In Model 2B, all significant coefficients were positively associated with physical demand. In other words, the employees' age ($\hat{\beta} = 0.212$, p-value < 0.10), number of contacts per shift ($\hat{\beta} = 0.247$, p-value < 0.05), and IoT adoption ($\hat{\beta} = 0.273$, p-value < 0.05) increase employees' physical demand in contact centers.

The increase of interconnectivity and data exchange supported by IoT tends to be more convenient to customers, as it allows contact centers to remotely develop and address solutions to issues that usually require a physical connection to a central company location (Ramaswamy, 2016; Soucy, 2021; Bai, 2021). Applications of IoT lead to automation of the work environment that reportedly minimizes human effort (Paul and Jeyaraj, 2019). However, the adoption of digital technologies, most notably IoT, leads to downsizing in some service industry sectors, e.g., banking (Tehubijuluw, 2017), or increasing the sharing of similar services by different businesses (Su et al., 2009). That imposes an additional workload on employees, justifying the positive association between IoT adoption and the level of physical demand and not allowing us to validate H_2.

4.3. I4.0 technologies and temporal demand

Model 3B (F-value $= 1.975$, p-value < 0.10) indicated that both the number of contacts per shift ($\hat{\beta} = 0.207$, p-value < 0.10) and the adoption of machine learning/AI ($\hat{\beta} = 0.207$, p-value < 0.10) are likely to increase temporal demand. The outcome for the number of contacts per shift was not surprising, as the volume flow is identified in the literature as one of the main burnoutinducing factors in contact centers (Castanheira and Chambel, 2010; Dellagi and Bouslama, 2014). In opposition, the result was somewhat counterintuitive since machine learning/AI provides means to analyze interactions so that employees from contact centers can better understand why customers are contacting them (Wallace and Whitt, 2005; Soucy, 2021).

By facilitating the approach of multiple communication channels, machine learning/AI could potentially save employees' time and reduce their temporal demand. Our findings contradict this rationale. An explanation for that would be related to MRT's concepts that state that individuals have a limited capacity for information processing (Hancock et al., 2007). Cognitive resources are limited, and a demand and supply issue happens when individuals perform two or more activities that demand the same resource (Wickens, 2008). In this sense, although machine learning/AI may save employees time by analyzing data and providing prompt replies, it may also push employees to more frequently give faster responses related to complex issues. This would raise the requirements and expectations on complex tasks, hence, increasing employees' temporal demand, especially when performing similar activities. Additionally, technology-induced downsizing and customers' mixed perceptions of being served by robots in contact centers (Lu et al., 2020) are likely postponers of the benefits of I4.0 on employees' temporal demand perceptions.

4.4. I4.0 technologies and frustration

Concerning frustration level, control variables working shift ($\hat{\beta} = -0.177$, *p*-value < 0.05), gender ($\hat{\beta}$ = -0.196, *p*-value < 0.05), and number of contacts per shift ($\hat{\beta}$ = -0.141, *p*-value $<$ 0.10) seem to have a negative effect on this workload dimension. In terms of I4.0 independent variables, both big data ($\hat{\beta}$ = -0.489, *p*-value < 0.01) and machine learning/AI ($\hat{\beta}$ = -0.157, *p*-

value < 0.10) are negatively associated with frustration level, i.e., their adoption is likely to reduce the frustration level of employees in contact centers.

Frustration level indicates how irritated, stressed, and annoyed versus content, relaxed, and complacent the employee feels when performing the activity (Hart, 2006). In a contact center environment, AI can benefit from massive datasets that contain critical information to automatically handle the more straightforward requests in real-time (Wang et al., 2020; Soucy, 2021). That enables employees to focus on high-level customer requests instead of dealing with ordinary contacts that might raise their frustration and boredom levels (Silva et al., 2016), which is aligned with MRT's notion that dual-task performance is more likely to be impaired by performing similar activities than dissimilar ones (Hancock et al., 2007). Our results empirically confirmed such an assumption, supporting H_6.

Concerning overall performance and effort levels, none of the tested regression models were significant (i.e., all p-values were above 0.10). These results suggest that I4.0 technologies may not have a relevant impact on these workload dimensions, being potentially affected by variables that were not encompassed in our study. Therefore, we did not find evidence to validate H_4 and H_5. In opposition, our findings supported H_1, H_2, and H_6. For H_3, even though we found a significant relationship between I4.0 technologies and temporal demand, the direction of this relationship was contrary to the hypothesis.

6. Conclusions

This research assessed the effect of I4.0 technologies on employees workloads in contact centers. We surveyed employees from different contact centers and assessed their workload and adoption level of I4.0 technologies. Our findings indicated that the effect of I4.0 on employees workloads varies according to the combination between technologies and workload dimensions, raising insightful implications for both theory and practice. Those contributions are further discussed in the following sections.

In terms of theoretical implications, this study sheds light on the relationship between I4.0 technologies' adoption and employees workload from the MRT perspective. Our findings suggest that integrating I4.0 base technologies into contact centers' processes and services may lead to different effects on employees workload, especially depending on the functionality of the I4.0 base technology. Such results corroborate MRT's assumption of the multiple set of resources with a limited capacity, as the adoption of different technologies may either push or relieve the same cognitive resources. In a repetitive workplace environment, such as a contact center, the adoption of the same base technology can either enhance the diversity of employees' tasks, reducing mental demand and frustration, or overwhelm them by increasing the frequency of complex activities that require similar skills, which is likely to worsen physical and temporal demands. To the best of our knowledge, this is the first study that approaches such a relationship, hence, being an original contribution to the body of knowledge.

In terms of practical contributions, understanding the association between I4.0 technologies and employees workload in contact centers allows for predicting when technology-supported tasks can be simultaneously performed or will interfere with each other. For example, assessing customers' problems with the support of IoT and big data reduces the mental effort and frustration levels, respectively. However, more extensive machine learning/AI adoption may add complexity to the solution. That is likely to reduce the time allocated for employees to solve the customer's problem since productivity is expected to increase proportionally to the investment made. Our investigation provides organizations with arguments to properly digitalize their contact centers without undermining the health or satisfaction of employees. Additionally, identifying the negative impacts of I4.0 technologies' adoption on employees workload avoids unnecessarily increases in the difficulty of an activity caused by its digitalization that can yield a lower performance in another activity. That raises managerial attention to drive digitalization efforts that can either lead to harmful underloaded workplaces or a healthy increase in employees workload. This may vary according to the implementation emphasis.

Although we carefully designed this research to allow the indication of sound findings, it has some limitations that are worth highlighting. First, concerning our sample, we only included respondents from Indian contact centers. It enhances the representativeness of our results in this context and avoids the influence of national cultural issues; however, it also impairs the generalization of our findings to other socio-economic contexts where contact centers also play relevant roles, such as the USA. Second, even though big data, cloud computing, IoT, and machine learning/AI establish a fundamental basis for I4.0 adoption, their combination and integration into processes and services originate the front-end technologies (Frank et al., 2019a). That might affect the extension of their impact on employees workloads. Therefore, future studies should enlarge and diversify the dataset and encompass the assessment of front-end technologies. Third, we did not investigate how respondents' profiles could influence our results. Although they all met the required selection criteria, there may be differences in their perceptions according to some specific characteristics, such as experience. Thus, a thorough investigation of how respondents' characteristics (e.g., gender, experience, and age) may impact the perception of the technologies is required. It is worth mentioning that other organizational aspects besides the control variables and technologies assessed in our investigation might also influence employees workload. Aspects such as leadership and organizational culture may also be critical factors for either aggravating or mitigating physical and mental stress. Further research could approach those topics together with I4.0 adoption, enabling a more holistic perspective of factors that affect employees workload in the digital transformation era. Finally, future studies could more deeply verify how I4.0 technologies have been adopted in contact centers. Complementary data collection methods (e.g., semi-structured interviews and focus groups) could be conducted, providing valuable additional insights.

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Appendix – Questionnaire

This survey aims at investigating the impact of technologies adoption on the ergonomics demands of contact centers' employees. We ensure the anonymity and confidentiality of your responses. There are no right or wrong answers.

Section 1: Demographics

This part of the survey will ask questions about you and your work.

Q1: What is your age group (in years)?
- Below 29
- 30-39
- 40-49

Q2: What is your gender?
- Female
- Male
- Other

Q3: How long have you been working for this company? [rounded years]

Q4: What type of contact center service services does your company provide?
- Inbound contact center (customer service, technical support, emergency response, etc.)
- Non-voice based BPO (back office support for data entry, chat support, e-mail support)
- Web-enabled contact center (webchat, e-mail support, quality analysis, etc.)

Q5: To which time of the day is your shift normally allocated?
- Morning (6 am -12 pm)
- Afternoon (12 pm – 6 pm)
- Night (6 pm – 12 am)
- Late night (12 am – 6 am)

Q6: How many contacts, on average, do you answer/work on/make per hour during a normal shift? [rounded unit]

Section 2: Subjective Workload: Rating

In this part, we will ask you to rate how you perceive your workload according to six aspects: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration level.

Q7: Keeping in mind the activities you perform on a daily basis, scroll across after reading the instructions for each question [0-low / 100-high].

0 10 20 30 40 50 60 70 80 90 100

7.1 Mental demand: how much mental and perceptual activity is required? (e.g., thinking, deciding, calculating, remembering, looking, searching)?	
7.2 Physical demand: how much physical activity is required (e.g., pushing, pulling, turning, controlling, activating)?	
7.3 Temporal demand: how much time pressure do you feel due to the rate or pace at which the tasks or task elements occur?	
7.4 Performance level: what is your success level in accomplishing the goals of the task set by your leaders or yourself?	
7.5 Effort level: how hard do you have to work (mentally or physically) to accomplish your level of performance?	
7.6 Frustration level: how insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?	

Section 3: Subjective Workload – Comparison

This part of the survey will ask how you compare the six dimensions, two by two.

Q8: Keeping in mind your daily activities in the contact center, which one is higher?

8.1 Effort level (1)
Performance level (2)

8.2 Temporal demand (1)
Effort level (2)

8.3 Performance level (1)
Frustration level (2)

8.4 Physical demand (1)
Performance level (2)

8.5 Temporal demand (1)
Frustration level (2)

8.6 Physical demand (1)
Frustration level (2)

8.7 Physical demand (1)
Temporal demand (2)

8.8 Temporal demand (1)
Mental demand (2)

8.9 Frustration level (1)
Effort level (2)

8.10 Performance level (1)
Temporal demand (2)

8.11 Mental demand (1)
Physical demand (2)

8.12 Frustration level (1)
Mental demand (2)

8.13 Performance level (1)

Mental demand (2)

8.14 Mental demand (1)

Effort level (2)

8.15 Effort level (1)

Physical demand (2)

Section 4: Technologies from Industry 4.0

In this part of the survey, we will ask you your perception regarding technologies from Industry 4.0.

Q9: Please, indicate below the adoption level of the following technologies in your workplace:
Scale: from 1 (not adopted) to 5 (fully adopted)

Technology	Definition	1	2	3	4	5
Internet-of-Things	Describes physical objects (or groups of such objects), that are embedded with sensors, processing ability, software, and other technologies, and that connect and exchange data with other devices and systems over the Internet or other communications networks.					
Cloud computing	Cloud computing is the on-demand availability of computer system resources, especially data storage (cloud storage) and computing power, without direct active management by the user.					
Big data	Big data is a field that treats ways to analyze, systematically extract information from, or otherwise deal with data sets that are too large or complex to be dealt with by traditional data-processing application software.					
Machine learning / Artificial intelligence	Machine learning is the study of computer algorithms that can improve automatically through experience and by the use of data. It is seen as a part of artificial intelligence.					

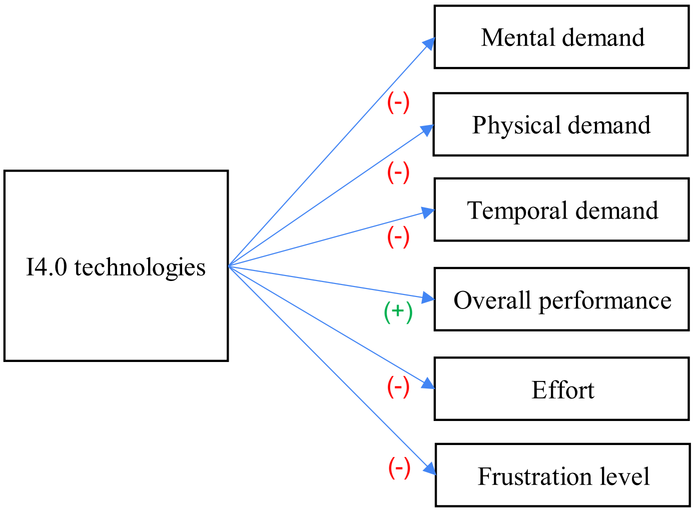

Figure 1 – Hypothesized model in the research

Table 1 – Sample characteristics (n = 100)

Gender	
Male	75
Female	25
Age	
Bellow 29 years old	48
Between 30 and 39 years old	46
More than 40 years old	6
Time working for the company	
Less than 1 year	52
More than 1 year	48
Working shift	
From 6 am to 12 pm	40
From 12 pm to 6 pm	25
From 6 pm to 12 am	31
From 12 am to 6 am	4
Type of contact center	
Inbound contact center	33
Non-voice-based BPO	33
Web-enabled contact center	34

Note: BPO = Business process outsourcing

Table 2 – Pairwise correlations

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1-Mental demand	-	0.025	0.088	0.367**	0.106	-0.690**	0.056	0.364**	0.648**	0.504**	0.017	0.225*	0.096	0.045	0.269**
2-Physical demand		-	0.058	0.168	-0.120	-0.263**	0.309**	0.261**	0.120	0.067	0.120	-0.071	0.130	-0.091	0.161
3-Temporal demand			-	-0.016	-0.160	-0.313**	0.033	0.176	0.200*	0.279**	-0.085	-0.028	0.083	0.147	0.289**
4-Overall performance				-	0.321**	-0.192	0.291**	0.303**	0.231**	0.140	0.009	0.037	0.048	0.044	0.104
5-Effort					-	-0.216*	0.312**	0.303**	0.228*	0.221*	0.007	-0.145	0.138	-0.052	0.045
6-Frustration level						-	-0.140	-0.427**	-0.633**	-0.539**	-0.104	-0.158	-0.169	-0.136	-0.329**
7-IoT							-	0.623**	0.435**	0.267**	0.084	-0.282**	0.113	-0.020	-0.003
8-Cloud computing								-	0.637**	0.506**	0.076	-0.075	0.152	-0.010	0.111
9-Big data									-	0.611**	0.205*	0.017	0.030	0.233*	0.311**
10-Machine learning/AI										-	0.053	0.057	0.140	0.047	0.272**
11-Age											-	0.206*	-0.249*	0.339**	-0.066
12-Shift												-	-0.316**	0.054	-0.099
13-Gender													-	0.018	0.024
14-Time working for the company														-	0.112
15-Contacts/shift															-
Mean	32.68	47.48	19.80	90.22	56.90	29.48	4.48	3.85	3.82	3.70	-	-	-	-	18.43
Standard deviation	26.63	21.63	12.57	9.95	24.09	31.15	0.82	1.02	1.17	1.07	-	-	-	-	14.96

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

Table 3 – Results of the OLS linear regression models (standardized $\hat{\beta}$ coefficients)

Variables	Mental demand		Physical demand		Temporal demand		Overall performance		Effort		Frustration level	
	Model 1A	Model 1B	Model 2A	Model 2B	Model 3A	Model 3B	Model 4A	Model 4B	Model 5A	Model 5B	Model 6A	Model 6B
Age	0.027	-0.081	0.253^{**}	0.212^{*}	-0.112	-0.132	0.049	-0.021	0.093	0.027	-0.132	-0.032
Working shift	0.311^{***}	0.213^{***}	-0.036	0.067	0.031	-0.010	0.068	0.149	-0.115	-0.073	-0.250^{**}	-0.177^{**}
Gender	0.194^{*}	0.136^{*}	0.180^{*}	0.165	0.056	-0.002	0.080	0.048	0.126	0.073	-0.272^{***}	-0.196^{**}
Time working for the company	-0.017	-0.121	-0.199^{*}	-0.156	0.152	0.175	0.079	-0.063	-0.085	-0.067	-0.034	0.027
Contacts/shift	0.299^{***}	0.047	0.192^{*}	0.247^{**}	0.266^{***}	0.207^{*}	0.121	0.108	0.047	-0.004	-0.352^{***}	-0.141^{*}
IoT		-0.231^{**}		0.273^{**}		-0.072		0.224^{*}		0.173		0.147
Cloud computing		0.001		0.159		0.147		0.155		0.103		-0.092
Big data		0.712^{***}		-0.123		-0.068		0.064		0.039		-0.489^{***}
Machine learning/AI		0.097		-0.109		0.208^{*}		-0.078		0.096		-0.157^{*}
F-value	3.822^{***}	12.962^{***}	2.217^{*}	2.498^{**}	2.386^{**}	1.975^{*}	0.440	1.596	0.806	1.622	5.283^{***}	10.831^{***}
R^2	0.169	0.564	0.105	0.200	0.113	0.165	0.023	0.138	0.041	0.140	0.219	0.520
Adjusted R^2	0.125	0.521	0.058	0.120	0.065	0.081	-0.029	0.051	-0.010	0.054	0.178	0.472
Change in R^2		0.396^{***}		0.094^{**}		0.052		0.115^{**}		0.098^{**}		0.301^{***}

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