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Mediating Effect of the Adoption of Industry 4.0 Technologies on the Relationship between Job Involvement and Job Performance of Millennials

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Abstract: Despite recent interest in Industry 4.0, little is known about the relationship between job involvement and job performance of millennial workers in companies. The present study addresses this knowledge gap by exploring the mediation of the adoption of Industry 4.0 technologies (IND) between job involvement (INV) and job performance (PRF). Data was collected from 241 employees of large Canadian companies. The structural equation model was used to test the mediation effect of IND and the relationship between INV and PRF. Results based on this model (SEM) revealed differences by gender. It was found that in men, INV was positively related to PRF and that in women, INV was positively related to IND, although it was also evident that millennial employees showed egalitarian gender attitudes by strongly perceiving IND positively with PRF. Furthermore, IND fully measured the relationship between INV and PRF in manufacturing firms but not in service firms. Years of work experience was also found to affect the mediation effect of IND between INV and PRF, while it was not significant for education level. This study also highlights demographic criteria such as the age, income, and status of millennial employees. Implications of these findings are discussed, and useful insights are provided on new I4.0 approaches that improve industrial processes. This research contributes to developing the Theory of Planned Behaviour and proposes that managers use current continuous improvement approaches, human-centred and consistent with new I4.0 technologies.

Keywords: Industry 4.0 technologies; job involvement; job performance; millennials; Canadian companies; gender

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1. Introduction

Industry 4.0 (I4.0) was born as a public–private initiative in Germany with the purpose of creating smart factories with the use of technologies (Sommer 2015). It was presented for the first time in 2011 at the Hanover Fair, immediately becoming the focus of the German government and many other European countries (Brettel et al. 2014). Although the industrial revolution before 4.0 focused on mass production, it focuses on technologies that merge the physical, digital, and biological (Schwab 2017).

I4.0 has been catalogued as the maturity of new information and communication technologies (ICT) applied to industrial processes and products (Awan et al. 2021; Diez-Olivan et al. 2018). In general, it is interpreted as the application of cyber-physical systems within industrial production (Ghobakhloo 2018), including integration with product life cycle and supply chain activities (Dalenogare et al. 2018; Wang et al. 2016). Therefore, I4.0 promises to transform jobs and working conditions (Rahman et al. 2020; Bettiol et al. 2021; Babatunde 2020; Nedelko 2021; Cunha et al. 2022), where companies have been forced to modify their human resources and therefore change the way employees carry out their daily activities (Bednar and Welch 2019; Febriani et al. 2020; Richard et al. 2020; Aguilar-Rodríguez et al. 2021).

In this sense, companies are replicating an I4.0 adoption model based on economies of scale (Dalenogare et al. 2018). Stachová et al. (2019) identified that companies with a higher level of maturity and innovation better manage their Innovation and Development (R&D) processes, as well as human resources. However, even though I4.0 promotes communication between people, machines, and resources (Dassisti et al. 2018; Baena et al. 2017) and contributes to the relationship with customers (Ayala et al. 2017; Bortolini et al. 2017; Dalenogare et al. 2018; Jeschke et al. 2017) when companies have an advanced level of implementation, the supply products and services could generate restrictive changes (Frank et al. 2019).

On the other hand, it has been determined that I4.0 technologies are the basis for measuring job performance (Aguado et al. 2019), since, by adopting them, knowledge (intellectual capital) is managed, with decision-making strategies (Abubakar et al. 2019; Stachová et al. 2019; Diez-Olivan et al. 2018; Posada et al. 2015), where workers embrace new skills and abilities (Wei et al. 2017) to better carry out their work. However, job involvement is also a conditioning factor for job performance, even more so, because it establishes the degree to which workers psychologically identify with their tasks (Ćulibrk et al. 2018; Al Naggar and Saad 2019; Blau 1985), being part of the personality and organizational climate (Diefendorff et al. 2002; Loke et al. 2016; Narayanamurthy and Tortorella 2021).

Despite this, research to date has not specifically addressed whether job involvement is due to characteristics that differentiate people in their work (Govender and Parumasur 2010; Reeve and Smith 2001; Rehman et al. 2020), or if it is caused by situations in the work environment (Vroom 1962), or by motivation and commitment (Michie et al. 2002; Ćulibrk et al. 2018). Therefore, there are still unknown findings that show a solid association between job involvement and job performance when incorporating I4.0. In this way, job involvement can influence the adoption of I4.0 and influence job performance. In fact, there could be differences based on the gender of the employees and the business sector in which they work. The report of the World Economic Forum (WEF 2018) showed that I4.0 presents a greater risk for positions held by women and has estimated that in 2026, in the United States alone, 1.4 million jobs will be affected by digitalization, and of these, 57% are jobs held by women.

In this way, (Johari and Yahya 2016) specified that tasks should be developed that consider the skills of workers as a basis to improve job involvement and performance. In addition, (Rehman et al. 2020) suggested that adequate leadership behaviour increases the level of job involvement, job commitment and employee satisfaction, which in turn triggers a better job retention rate and job performance (Albuquerque et al. 2021). Furthermore, in the context of I4.0, the challenges faced by all economies are particularly important, involving companies from all branches of economic activity (Veith and Costea 2019).

On the other hand, although the behaviour of workers depends on their emotions (Bhutta et al. 2021; Albuquerque et al. 2021; Johari and Yahya 2016; Rehman et al. 2020; Saputra and Hutajulu 2020), this may be different when companies concentrate a particular number of generational employees (silent generation, baby boomers, generation X, or millennials). This study pays special attention to the generational cohort of millennials (also known as generation Y, people born between 1980 and 2000: aged between 22 and 42 years) (Alexander and Sysko 2012; Howe and Strauss 2000), since recent contributions have revealed that corporations are increasingly hiring employees of this generation (Moreno et al. 2022; Saputra and Hutajulu 2020; Hebles et al. 2022), because they belong to a diverse multicultural environment (Deal et al. 2010). Millennials are experiencing the incorporation of new technologies, which influences their personality and changes in their behaviour (Naim and Lenka 2018).

This research, therefore, determines the mediation of the adoption of I4.0 technologies in the relationship between job involvement and job performance. In addition, this study analyses comparatives by gender, and the level of education and years of experience are included as control variables. This is conducted to determine potential development benefits in the context of I4.0. For this analysis, millennial workers from large Canadian companies certified as a Great Place to Work are studied through a structural equation model. Canada has been chosen based on its cultural differences, its recent history, and high level of economic development. This study assumes that workers involved with their tasks will make additional efforts to comply with organizational objectives and, therefore, will have better job performance, or, on the contrary, those who do not get involved with the company will have a lower job performance.

This research is relevant, since, in addition to providing empirical evidence on the behaviour of millennials as support for human resource management in their current and future permanence in companies (Gorman et al. 2004; Hebles et al. 2022), changes generated by the COVID-19 pandemic are making I4.0 technologies more important in the job performance of workers (Narayanamurthy and Tortorella 2021; Hebles et al. 2022). Therefore, this study highlights new contributions to the knowledge and technical skills that enhance the intellectual capital of employees. This research provides new findings for decision makers to emphasize the new continuous improvement approaches that should be consistent with the new technologies adopted.

This research provides scientific value in the knowledge of millennials as a support for human resource management so that organizations are bearers of lasting competitive advantages over time. Since ICTs are a substantial part of the professional development of millennials, they can be used to improve organizational performance and maximize productivity (Gorman et al. 2004; Hebles et al. 2022).

The following section provides a literature review as support for the proposed research model. Subsequently, the methodology is established in which the population and analysis are determined by the measurement instruments used in this study. Moreover, the results of this research, discussion, conclusion, implications, limitations, and recommendations for future research studies are presented. The research methodology flowchart is in Appendix A.

2. Literature Review and Hypothesis Development

2.1. Job Involvement and Job Performance

According to (Ajzen 1991), through the Theory of Planned Behaviour, people have attitudes that announce their behaviour, where these attitudes arise from cognitive, affective, and behavioural mechanisms. For this reason, before an individual act, they will carry out a detailed and rational analysis of the implications of carrying out a specific behaviour (Ajzen 2011). In this way, employees will have beliefs (individual and subjective norms), which lead to attitudes and intentions that would predict their behaviour and, therefore, their job involvement (Ajzen 1991, 2002, 2011).

Various studies have shown a significant relationship between job involvement and job performance (Ali-Chughtai 2008; Bhutta et al. 2021; Brown and Leigh 1996; Diefendorff et al. 2002; Li et al. 2015; Loke et al. 2016; Qaiser-Danish et al. 2015; Rehman et al. 2020; Sapta et al. 2021; Shamim et al. 2019). For example, (Cohen 2000) indicated that job satisfaction intervenes positively between organizational involvement and commitment. This is confirmed by what was expressed by (Ali et al. 2018; Wu et al. 2017), in which workers who receive management training feel satisfied and deliver more efficient organizational performance. In the same way, employees will feel motivated, mainly, when they find an important meaning in their job, and consequently, their job involvement will determine their performance (Diefendorff et al. 2002).

However, job involvement could vary according to gender (Han and Yoo 2007). These authors found that employees showed more or less egalitarian gender role attitudes and that they were more involved in their families than in their work, and men had higher levels of job involvement. Similarly, (Zhang 2013) found that men had a stronger and more positive relationship than women between job involvement and organizational citizenship behaviour. Other studies have identified, on the contrary, that gender is not a determinant of job involvement (Ebrahimi 2021; Kim et al. 2018).

2.2. Job Involvement and Adoption of I4.0 Technologies

I4.0 is an adoption of technology (Dalenogare et al. 2018; Frank et al. 2019) where its potential finds better flexibility in manufacturing systems through ICTs, making production processes centralized and become decentralized and autonomous (Abubakar et al. 2019). According to (Vereycken et al. 2021), the job involvement of employees is associated with I4.0, regardless of the type of technology used, the size of the company, or the country of origin. Therefore, I4.0 could predict manufacturing results and boost communication between people, machines, and resources (Dassisti et al. 2018; Baena et al. 2017) and improve the relationship between customers (Ayala et al. 2017; Bortolini et al. 2017; Dalenogare et al. 2018; Jeschke et al. 2017). However, workers may also reject these technologies, perceiving that they replace their daily tasks (Lee et al. 2018).

The findings found by (Stachová et al. 2019) highlight that I4.0, particularly automation that interferes with multiple processes and professions, gradually changes the education and skill requirements of employees. All this, in addition, promotes that the involvement of employees, together with organizational change, has a positive relationship with the desire to work, as well as with the perceived organizational support and operational support of employees (Chun and Jo 2015). In this sense, it will be the workers who strengthen and promote I4.0 technologies, helping companies create new businesses (Luque-Vega et al. 2019).

On the other hand, it is known that the proportion of women working in the information and communication technology (ICT) sector is decreasing (Kirlidog et al. 2009; Veith and Costea 2019). ICT has been considered a male profession, both in industry and in academia (Krchová and Höesová 2021; Kirlidog et al. 2009; Güney-Frahm 2018). However, studies such as that of (Sardar et al. 2019) have found that these tools positively help women and that they can use them effectively to become successful entrepreneurs. (Mueller et al. 2018) found that Canadian women have better basic ICT skills than men, although they are less likely to be employed in ICT occupations.

2.3. Adoption of I4.0 Technologies and Job Performance

I4.0 uses various technological resources, such as ICT and intelligent assistance systems, that facilitate work and make it more flexible (Ras et al. 2017). Aguado et al. (2019) found that these technologies are related to certain elements that measure job performance such as productivity, absenteeism, and professional development potential. In the study by (Nantee and Sureeyatanapas 2021), it was identified that there is a better performance of workers when there is an effective implementation of technologies. I4.0, therefore, can improve industry performance (Ali and Aboelmaged 2021; Bettiol et al. 2021). In addition, (Narayanamurthy and Tortorella 2021) identified that the new ways of working (for example, home office, job insecurity, and virtual connection) due to the COVID-19 pandemic also affect employee performance. These I4.0 technologies are positively related to worker productivity (Polak-Sopinska et al. 2020).

2.4. Adoption of I4.0 Technologies, Job Involvement and Job Performance

I4.0 integrates machines and operators through network connections and information management, which organize the means of production differently, generating smart factories (Bortolini et al. 2017; Roldán et al. 2019). Digitalization, for its part, leads to paths of industrial, commercial, and value servitization (Coreynen et al. 2017).

Manufacturing companies have begun to integrate a series of emerging technologies into their processes, which are changing how products are designed, manufactured, and consumed (Wollschlaeger et al. 2017), and the architecture of microservices in the development of innovative industrial applications (Siqueira and Davis 2021). Moreover, according to (Rahman et al. 2020), I4.0 has an important role in promoting and improving the performance of service companies. (Nafchi and Mohelská 2021) identified that employment growth in the high-tech service sector has an upward trend from the use of I4.0. However, for (Cunha et al. 2022), the implementation of I4.0 still does not match the productivity and efficiency of workers.

Despite the contributions in these investigations, this study identified two gaps related to job involvement and the adoption of Industry 4.0 technologies that affect the job performance of millennials:

The first gap is the influence of job involvement on job performance. Although the behaviour of the employees may depend on emotions, which if positive, would increase their involvement with the company and improve their job performance (Bhutta et al. 2021; Albuquerque et al. 2021; Johari and Yahya 2016; Rehman et al. 2020; Saputra and Hutajulu 2020), millennials are a generational cohort that has a most challenging professional development (Moreno et al. 2022). They are people who have an open and frequent communication with their supervisors, so they are loyal to them but not to the organization (Alexander and Sysko 2012; Hebles et al. 2022; Moreno et al. 2022; Myers and Sadaghiani 2010).

Additionally, millennials are difficult to interact with and are authoritative but service-focused (Deal et al. 2010; Myers and Sadaghiani 2010). When their jobs do not meet their expectations, they feel discouraged and leave their jobs (Alexander and Sysko 2012; Deal et al. 2010; Myers and Sadaghiani 2010; Naim and Lenka 2018). In this way, the positive relationship between involvement and job performance can be ambiguous and confusing because it could be affected by certain factors, such as: years of experience of millennials in the company, level of education, gender, and the business sector in which they meet. In addition, they are workers who present certain characteristics of interest to companies, because they belong to a diverse multicultural environment (Deal et al. 2010; Moreno et al. 2022; Myers and Sadaghiani 2010). Only 26% of them are looking for a fair and loyal job and 25% want integrity, honesty, and trust (Deloitte Touche Tohmatsu Limited 2019).

The second gap deals with the adoption of Industry 4.0 technologies and allowed measuring the relationship between job involvement and job performance. (Tortorella et al. 2018) proposed one of the first studies that evaluated the relationship of job involvement with Industry 4.0 and job performance, in which it was identified that the involvement of workers is related to the improvement of operational performance, which, although it is a relevant indication, its results are not entirely conclusive, since they do not present sufficient evidence on human resources. Empirical evidence is still lacking on the way in which companies adopt these technologies and how they are related to the involvement and job performance of their employees (Dalenogare et al. 2018; Frank et al. 2019).

2.5. Hypothesis Development

2.5.1. Job Involvement and Job Performance

Job performance according to (Oppenauer and Van De Voorde 2016) depends on skills practices, motivation, job design opportunities, and emotional exhaustion of employees, depending on work overload and job responsibility. Furthermore, (Blau 1986), and (Jayawardana et al. 2013) stated that job involvement can increase if employees have greater decision-making authority at work, while (Johari and Yahya 2016) identified that job involvement influences performance when workers incorporate their skills into their tasks. (Lawler and Hall 1970) pointed out that when employees feel involved in a job that satisfies their work needs, this feeling encourages them to make greater efforts, and this increases their work performance, which is confirmed by the findings of (Park et al. 2019) when they identify it as something very important in their lives. For this reason, the following are proposed:

H1. *Job involvement (INV) has a relationship with or positive influence on job performance (PRF).*

H1.1. *Job involvement (INV) between men and women is related to or positively influences job performance (PRF).*

2.5.2. Job Involvement and Adoption of Industry 4.0 Technologies

Job involvement allows employees to become more and more committed to the organization, thus, there will be a cognitive improvement, which will be reflected in the satisfaction of their work activities (Diefendorff et al. 2002; Emery and Barker 2007). In this sense, the use of I4.0 technologies is part of that individual commitment, which helps companies expand their markets and incorporate innovations (Coreynen et al. 2017). Thus, I4.0 technologies, in addition to reducing manufacturing times, help customers with the delivery of specialized products (Ayala et al. 2017; Bortolini et al. 2017; Dalenogare et al. 2018; Jeschke et al. 2017) where workers will act based on their behavioural and subjective beliefs (Ajzen 2012). For this reason, the following are suggested:

H2. *Job involvement (INV) has a relationship with or positively influences the adoption of I4.0 technologies (IND).*

H2.1. *Job involvement (INV) between men and women has a relationship with or positively influences the adoption of I4.0 technologies (IND).*

2.5.3. Adoption of I4.0 Technologies and Job Performance

I4.0 technologies create more complex work environments that require a greater effort from workers, who must improve their technical skills to perform better (Narayanamurthy and Tortorella 2021; Imran and Kantola 2018). Additionally, (Khampirat 2021) found that regardless of gender, self-esteem and self-regulated learning mediate the impact of these technologies. Similarly, (Nedelko 2021) identified that gender, the position of employees in the organization, and the size of the organization are not substantial in the use of management tools for I4.0. Furthermore, (Cunha et al. 2022; Babatunde 2020) explained that the application of I4.0 does not have an impact on gender. The following are proposed:

H3. *The adoption of I4.0 technologies (IND) has a relationship with or positive influence on job performance (PRF).*

H3.1. *The adoption of I4.0 technologies (IND) among men and women has a relationship with or positive influence on job performance (PRF).*

2.5.4. Adoption of I4.0 Technologies, Job Involvement and Job Performance

Other contributions have established that the active participation of workers in the continuous improvement process generates an increase in performance and productivity as key elements of the I4.0 approach (Moica et al. 2019). The study by (Tortorella et al. 2018) demonstrated that worker involvement has a positive effect on the relationship between I4.0 adoption and improved operational performance. In addition, employees who are highly involved in their work will put in extra effort to achieve organizational goals (Park et al. 2019; Bhutta et al. 2021). Meanwhile, they would be more likely to participate in productive work activities, resulting in an improvement in the level of work performance (Saputra and Hutajulu 2020). For this reason, the following are proposed:

H4. *The adoption of I4.0 technologies (IND) has a mediating effect between job involvement (INV) and job performance (PRF).*

H4.1. *The adoption of I4.0 technologies (IND) among men and women has a mediating effect between job involvement (INV) and job performance (PRF).*

2.6. Control Variables

The following control variable is included in the research model to estimate the relationships between IND, PRF, and IND: (a) level of education and (b) years of work experience. The selection is based on the previous discussion and the existing empirical evidence on the relationship between these variables in business management and the applicability of I4.0.

(Nedelko 2021) stated that a higher level of education leads to a significantly higher use of basic skills in the performance of workers. In addition, workplace learning has gradually replaced training and education (Rassameethes et al. 2021), although organizations that rely on increased activity in education and development are more open to cooperation with other companies (Stachová et al. 2019).

On the other hand, according to (Reinhardt et al. 2020), the work experience of employees is indifferent to the knowledge of the I4.0 they have. Likewise, the introduction of new technologies can cause a decrease in the perceived quality of the work experience, and training significantly mitigates this effect in organizational environments that are relatively less technical (Marcaletti et al. 2022). The distinction between education level and years of work experience allows us to determine if there is a substantial difference between INV, PRF, and IND that has important implications for the derived findings and future research designs.

Figure 1 represents the theoretical research model, which relates job involvement with job performance through the adoption of I4.0 technologies and proposes the level of education and years of work activity as control variables.

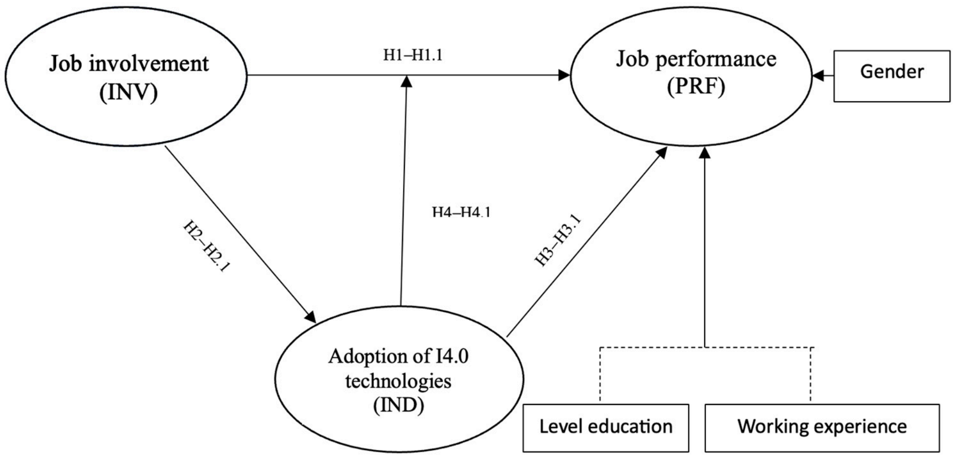

Figure 1. Theoretical research model.

3. Methodology

A quantitative investigation with descriptive purpose was carried out through a structural equation model (SEM) with the Unweighted Least Squares (ULS) procedure because the SEM technique requires a strategy for the treatment and identification of latent factors or variables and their corresponding items or observable variables (Ullman 2006; Hair et al. 2014). Control variables were identified for a better SEM analysis, and a multigroup analysis classified by gender was applied.

3.1. Population and Sample

Through convenience sampling, millennial employees of large manufacturing and service companies were selected, which were certified as a Great Place to Work, that is, they concentrate at least 30% of millennial employees. Thus, 5250 millennials worked at these companies, and 241 valid responses were received, representing a 90% confidence level with a 5.2% error range. Millennials were chosen because they are the ones who are taking over the workforce of companies, and even though they have skills for the use of technologies (Deal et al. 2010; Myers and Sadaghiani 2010; Alexander and Sysko 2012; Hebles et al. 2022; Moreno et al. 2022; Deka 2018), are not prepared to take on the challenges that Industry 4.0 entails (Deloitte Touche Tohmatsu Limited 2019).

This study was carried out in Canada because this country (a) brings together a high number of large companies with millennial employees (Knoema 2017); (b) it is the second largest in the world with a market value between 113,418 and 1.619 million dollars; and

(c) its innovation index is 50.80 (Global Innovation Index 2022). The research was carried out in the city of Toronto. The total sample was 241, of which 58.92% (142) correspond to young people between the ages of 22 and 29, and 41.08% (99) belong to the ages between 30 and 39.

3.2. Instrumentation

The questionnaire measures were based on the recommendations of the literature review. The questionnaire consisted of demographic scales related to gender, education level, time spent in the company, industry, income, and job title. To measure the I4.0 (IND), the questionnaire was created by (Frank et al. 2019), who proposed five factors with 44 items: (a) Technological bases (4); (b) Smart manufacturing (18); (c) Smart work (7); (d) Smart value chain (3); and (e) Smart products and services (12). Job involvement (INV) was based on (Lodahl and Kejnar 1965)'s questionnaire redefined by (Reeve and Smith 2001), made up of two factors of nine items (1, 3, 6, 7, 10, 11, 14, 15, and 18). Finally, for job performance (PRF), (Pearce and Porter 1986) 's questionnaire was used with the adaptation of (Park et al. 2018), structured in four factors with four items. All the variables were designed on a five-point Likert scale (1 = totally disagree and 5 = totally agree).

3.3. Data Collection

All employees were informed of the nature of the research and asked for their voluntary participation. Each participant signed a record accepting the criteria related to the measurement instrument. If at any time, upon reading said consent, any of the members wished to withdraw from the study, they were available to do so. Each participant was explained, in the same terms, about what Industry 4.0 and its technologies are, and those were described in the questionnaire and were applicable to their workplace. The instrument was applied through online surveys through the virtual platforms of the companies, according to the availability and requirements of the human resources department. Data collection was carried out from August 2021 to March 2022, when the home office was in full swing due to the COVID-19 pandemic. Data was collected on large companies that included both manufacturing and service companies that were located in the city of Toronto. For the analysis of the data collected, the statistical package SPSS and Amos v26 were used.

4. Results

The quality of the data was verified, managing to unify some similar responses in the categorical variables. An exploratory data analysis was carried out, where it was found that there were no typing errors and there were no missing values. The descriptive statistics of each scale were calculated, and normality was validated with the Mardia multivariate test, which determined that the data had a univariate non-normal behaviour (>1.96). The kurtosis coefficient was 447 (>70). In addition, the C.R (composite reliability) was 44 (>5.91).

4.1. Bivariate Results by Age Groups and Gender

Bivariate tables classified according to age groups and gender were built, using the Chi-square test, to identify the possible dependence between these variables. Table 1 describes these variables analysed according to age groups. It can be seen that the youngest employees (under 30 years of age) are bachelors, representing 95.1%, while those from 30 to 39 years old presented approximately one-third of the master's level and only 9.1% had a doctorate. This implies that age influences educational level ($p = 0.000 < 0.05$). Regarding the annual income, an influence of the two age groups was also detected. The oldest (30–39 years old) showed a higher annual income (CAD 100,000 or more) with a percentage of 11.1%, while the group from 22 to 29 years old showed an even higher income (between CAD 30,000 and CAD 100,000), which represented the 81.0% ($p = 0.000$).

Table 1. Description of company information by age group.

		Age			
		22–29		30–39	
		Count	%	Count	%
Level of Education	Bachelor	135	95.1%	60	60.6%
	Master	7	4.9%	30	30.3%
	PhD	0	0.0%	9	9.1%
Annual Income	CAD 110,000–more	0	0.0%	11	11.1%
	CAD 30,000–CAD 70,000	115	81.0%	23	23.2%
	CAD 70,001–CAD 110,000	27	19.0%	65	65.7%
Industry sector	Automotive	33	23.2%	15	15.2%
	Banking	48	33.8%	32	32.3%
	CPG	23	16.2%	14	14.1%
	Paper and Cellulose	22	15.5%	21	21.2%
	Pharmaceutical	16	11.3%	17	17.2%
Current role or function	Analyst or Technician	47	33.1%	17	17.2%
	Manager or Director	1	0.7%	28	28.3%
	Other	91	64.1%	21	21.2%
	Supervisor or Coordinator	3	2.1%	33	33.3%

Contrary to what was previously found, the industrial sector did not show significant statistical differences, considering that, in both age groups, the highest percentages were found in the banking sector (33.8–32.2%). In mass consumption companies (CPG), similar percentages were also found in both groups (16.2% in the youngest and 14.1% in those aged 30–39 with $p = 0.323 > 0.05$); therefore, it can be affirmed that age does not influence the industrial sector to which they are dedicated.

On the other hand, the role played by the respondents did mark differences according to age groups. For example, in the oldest, the positions of supervisors or coordinators (33.3%) and directors (28.3%) stood out. On the contrary, the majority of people between 22 and 29 years old (64.1%) belonged to other positions ($p = 0.000$).

According to gender, as evidenced in Table 2, the number of women was 111 (40.05%), compared to 125 (51.86%) men, which means that gender does not influence educational level (women = 82.9% and men = 78.4%) or annual income ($p = 0.528$). Most of the participants had a high school education level ($p = 0.575 > 0.05$), and regardless of gender, many of them had an income between CAD 30,000 and CAD 100,000 (women = 57.7% and men = 56.8%).

On the other hand, gender influenced the sector where they work. Although in some sectors there is no difference (banks = 33.3–34.4, automobiles = 19.8–17.6, and pharmaceuticals = 14.4–12.8), in other sectors, differences were found (CPG, with a majority of women, 22.5%, compared to 9.6% of men, and in the pulp and paper industry where the majority is men, 25.6%, compared to 9.9% of women, $p = 0.001 < 0.05$).

Finally, gender does not influence the role or function performed by employees, such as manager or director (10.8–12.8) and supervisors (14.4–15.2). Differences were found in other roles, including analyst (20.7–32.8) and others (54.1–39.2). In the Chi-square test, the p value was 0.227.

Table 2. Description of company information according to gender groups.

		Gender					
		Female		Male		Prefer Not to Say	
		Count	%	Count	%	Count	%
Level of Education	Bachelor	92	82.9%	98	78.4%	5	100.0%
	Master	14	12.6%	23	18.4%	0	0.0%
	PhD	5	4.5%	4	3.2%	0	0.0%
Annual Income	CAD 110,000–more	5	4.5%	5	4.0%	1	20.0%
	CAD 30,000–CAD 70,000	64	57.7%	71	56.8%	3	60.0%
	CAD 70,001–CAD 110,000	42	37.8%	49	39.2%	1	20.0%
Industry sector	Automotive	22	19.8%	22	17.6%	4	80.0%
	Banking	37	33.3%	43	34.4%	0	0.0%
	CPG	25	22.5%	12	9.6%	0	0.0%
	Paper and Cellulose	11	9.9%	32	25.6%	0	0.0%
	Pharmaceutical	16	14.4%	16	12.8%	1	20.0%
Current role or function	Analyst or Technician	23	20.7%	41	32.8%	0	0.0%
	Manager or Director	12	10.8%	16	12.8%	1	20.0%
	Other	60	54.1%	49	39.2%	3	60.0%
	Supervisor or Coordinator	16	14.4%	19	15.2%	1	20.0%

4.2. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA)

Although questionnaires already validated in the literature were used, it was considered convenient and useful to divide the total sample of 241 participants into two: (a) approximately 40%, which is equivalent to 99 surveys, and with them, carry out an EFA using the SPSS version 26 program; and (b) with said results, apply them to the remaining sample of 142 surveys, performing a Confirmatory Factor Analysis (CFA), thus guaranteeing the validity and reliability of the scales.

In the EFA, the main axes extraction method and the Promax rotation procedure (Hair et al. 2010; Byrne 2010; Hoyle 2015) were considered in order to determine the pattern matrix and, with it, identify the different factors. The criterion applied was the eigenvalue greater than the unit to determine the number of factors. The reliability in the EFA was analysed using Cronbach's Alpha, assuming that the reliability is acceptable when it is greater than 0.70 (Hair et al. 2010; Powell 1992).

Thus, PRF has a KMO of 0.747 with a Barlett's sphericity value of 0.00, finding only one factor, with Cronbach's alpha of 0.777 considered adequate. Regarding INV, the KMO was 0.888 with a Bartlett value of 0.00, finding only one factor, with Cronbach's alpha of 0.516 not being adequate; therefore, considering that items INV5, 7, and 9 presented a negative corrected total correlation of elements, these items were eliminated, achieving an increase in alpha to 0.882. Regarding IND, there were 44 items and an initial approach of five factors; however, the EFA showed some items or statements with values greater than unity; therefore, these statements were eliminated, repeating the process eight times, considering the decision not to allow values that contributed to two factors, where the final result showed a total of 30 items, a KMO of 0.935, and a Bartlett's sphericity value of 0.00.

The three new dimensions related to the adoption of I4.0 technologies were the following: (a) Smart manufacturing and working (SMART_Manu_Work), which is related to twenty-two investigative competencies; (b) Base technologies (Base_TECH) related to four investigative competencies; and (c) Smart products and services (Smart_PROD_SERV) with four competencies.

With what was detected in the EFA, it is concluded that the factor that measures IND has three dimensions, and therefore, a second-order model is configured, as can be seen in Figure 2.

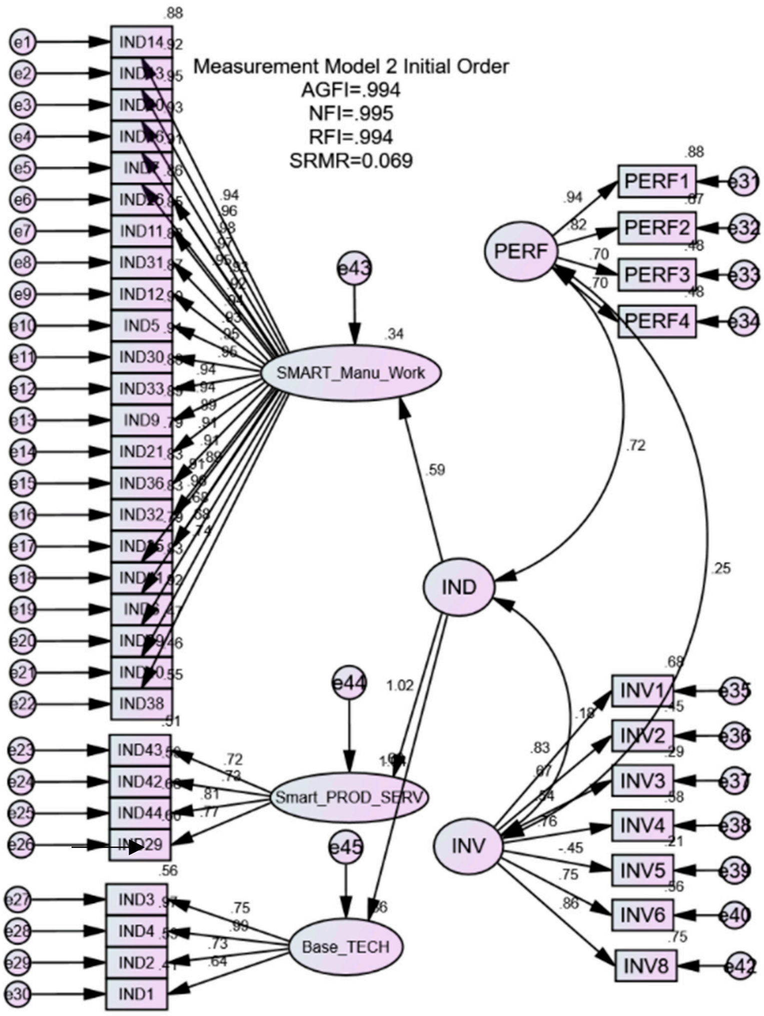

Figure 2. Initial second-order measurement model.

With this model, the psychometric indicators were calculated by executing the plugin on reliability and validity implemented in the AMOS v26 program, as shown in Table 3. It can be seen that CR complies in all constructs, PRF (0.867), INV (0.842), and IND (0.750), with values greater than 0.70. Regarding the convergent validity measured with the AVE, it was found that this is also fulfilled in the various factors, PRF (0.623), INV (0.521), and IND (0.507), with a minimum value of 0.5.

Table 3. Psychometric indicators measurement model second initial order.

Dimensions	CR	AVE	PRF	INV	IND
PRF	0.867	0.623	0.790		
INV	0.842	0.521	0.227 *	0.722	
IND	0.750	0.507	0.812 ***	0.181 †	0.712

† $p < 0.100$, * $p < 0.050$, *** $p < 0.001$.

According to (Henseler et al. 2015), the discriminant validity, which is the extent to which a construct is empirically distinct from other constructs in the structural model, proposed the traditional metric and suggested that each construct's AVE should be compared to the squared inter-construct correlation of that same construct and all other reflectively measured constructs in the structural model. The shared variance for all model constructs should not be larger than their AVEs.

Although recent research points out that this metric is not suitable for discriminant validity assessment, (Henseler et al. 2015) shows that (Fornell and Larcker 1981)'s criterion does not perform well, particularly when the indicator loadings on a construct differ only slightly.

As a replacement, (Henseler et al. 2015) proposed the Heterotrait–Monotrait (HTMT) ratio. By using this technique, whose results are displayed in Table 4, it was possible to demonstrate the factors met the discriminant validity, given that the values of the diagonal are less than 0.900 (Henseler et al. 2015). The matrix shows adequate values with respect to discriminant validity, where the results are low in the crossovers of the different factors.

Table 4. HTMT matrix.

	PRF	**INV**	**IND**
PRF	–		
INV	0.301	–	
IND	0.553	0.101	–

Through the ULS, it was possible to determine a good adjustment: SRMR = 0.069 (<0.08), AGFI (0.994), NFI (0.995), and RFI (0.994) (all > 0.95). The modification indices were calculated, and it was decided to eliminate item IND29, since it was related to various items of other factors. The final graph is shown in Figure 3.

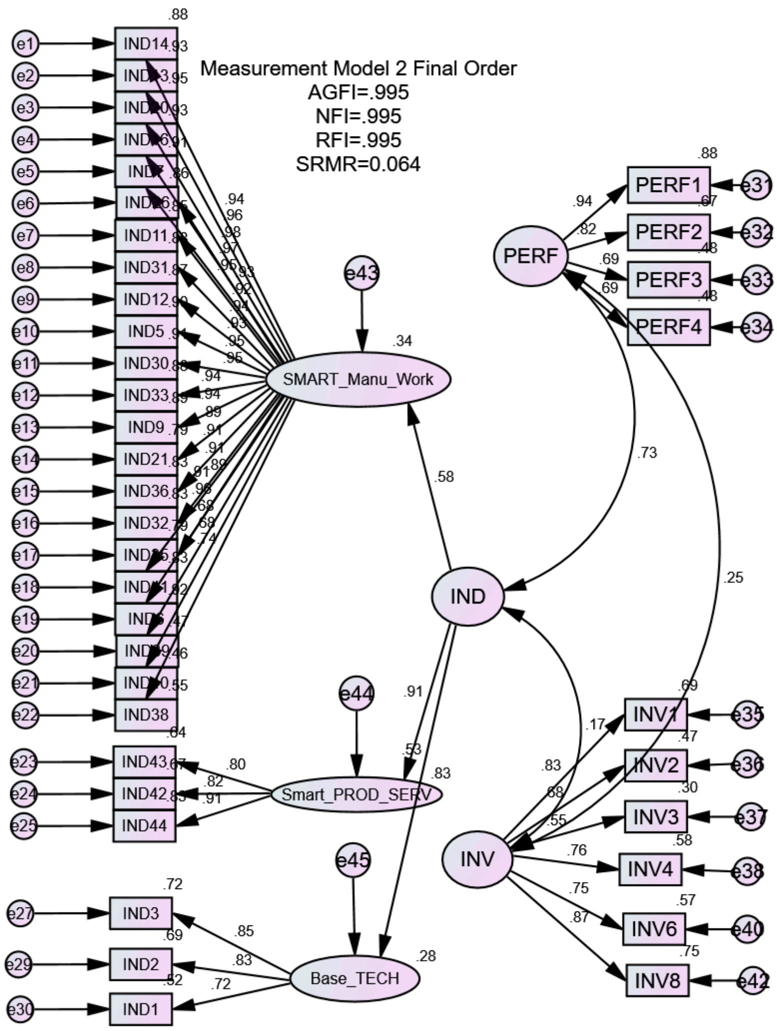

Figure 3. Final second-order measurement model.

The fit indices were the following: SRMR = 0.064 (<0.08), GFI (0.995), NFI (0.995), and RFI (0.995) (all > 0.95). In Table 5, the standardized coefficients are placed, noting that none of them exceeds the threshold of one. The same situation was found with the R^2: INDC (0.365), INDB (0.825) and INDA (0.338). IND4 (0.988) and INV5 (−0.457) were eliminated for causing possible Heywood cases.

Table 5. Standardized coefficients final second order measurement model.

			Estimate				Estimate
BASE_TECH	<--	IND	0.604	IND12	<--	SMART_Manu_Work	0.933
SMART_PROD_SERV	<--	IND	0.909	IND5	<--	SMART_Manu_Work	0.950
SMART_MANU_WORK	<--	IND	0.581	IND30	<--	SMART_Manu_Work	0.952
IND14	<--	SMART_Manu_Work	0.939	IND33	<--	SMART_Manu_Work	0.938
IND13	<--	SMART_Manu_Work	0.962	IND9	<--	SMART_Manu_Work	0.943
IND20	<--	SMART_Manu_Work	0.977	IND21	<--	SMART_Manu_Work	0.891
IND16	<--	SMART_Manu_Work	0.967	IND36	<--	SMART_Manu_Work	0.912
IND7	<--	SMART_Manu_Work	0.951	IND32	<--	SMART_Manu_Work	0.912
IND26	<--	SMART_Manu_Work	0.929	IND35	<--	SMART_Manu_Work	0.887
IND11	<--	SMART_Manu_Work	0.923	IND31	<--	SMART_Manu_Work	0.940
IND41	<--	SMART_MANU_WORK	0.911	IND43	<--	SMART_PROD_SERV	0.801
IND6	<--	SMART_MANU_WORK	0.960	IND42	<--	SMART_PROD_SERV	0.817
IND39	<--	SMART_MANU_WORK	0.683	IND44	<--	SMART_PROD_SERV	0.910
IND40	<--	SMART_MANU_WORK	0.676	IND3	<--	BASE_TECH	0.754
IND38	<--	SMART_MANU_WORK	0.738	IND4	<--	BASE_TECH	0.988
INV1	<--	INV	0.828	IND2	<--	BASE_TECH	0.727
INV2	<--	INV	0.673	IND1	<--	BASE_TECH	0.631
INV3	<--	INV	0.538	PRF1	<--	PERF	0.939
INV4	<--	INV	0.760	PRF2	<--	PERF	0.820
INV5	<--	INV	−0.457	PRF3	<--	PERF	0.694
INV6	<--	INV	0.748	PRF4	<--	PERF	0.694
INV8	<--	INV	0.860				

4.3. SEM Model—Structural Equations

Figure 4 shows the SEM with acceptable indicators: SRMR < 0.08 (0.064). NFI, RFI, and AGFI >0.95 (0.995).

Through the bootstrapping procedure shown in Table 6, statistically significant relationships were found between IND and Base_TECH ($p = 0.001 < 0.05$), IND and Smart_PROD_SERV ($p = 0.000 < 0.05$), and IDN and SMART_Manu_Work ($p = 0.009 < 0.05$). In addition, IND positively influenced PRF ($p = 0.001 < 0.05$). In the relationships INV with IND ($p = 0.302$) and in INV with PRF ($p = 0.157$), no statistical significance was found.

Table 6. Standardized coefficients and their significance with bootstrapping.

Parameter			Estimate	Lower	Upper	*p*
IND	<---	INV	0.170	−0.083	0.348	0.302
Base_TECH	<---	IND	0.530	0.352	0.709	0.001
Smart_PROD_SERV	<---	IND	0.912	0.784	1.000	0.000
SMART_Manu_Work	<---	IND	0.580	0.430	0.693	0.009
PRF	<---	IND	0.706	0.576	0.844	0.001
PRF	<---	INV	0.133	−0.017	0.281	0.157

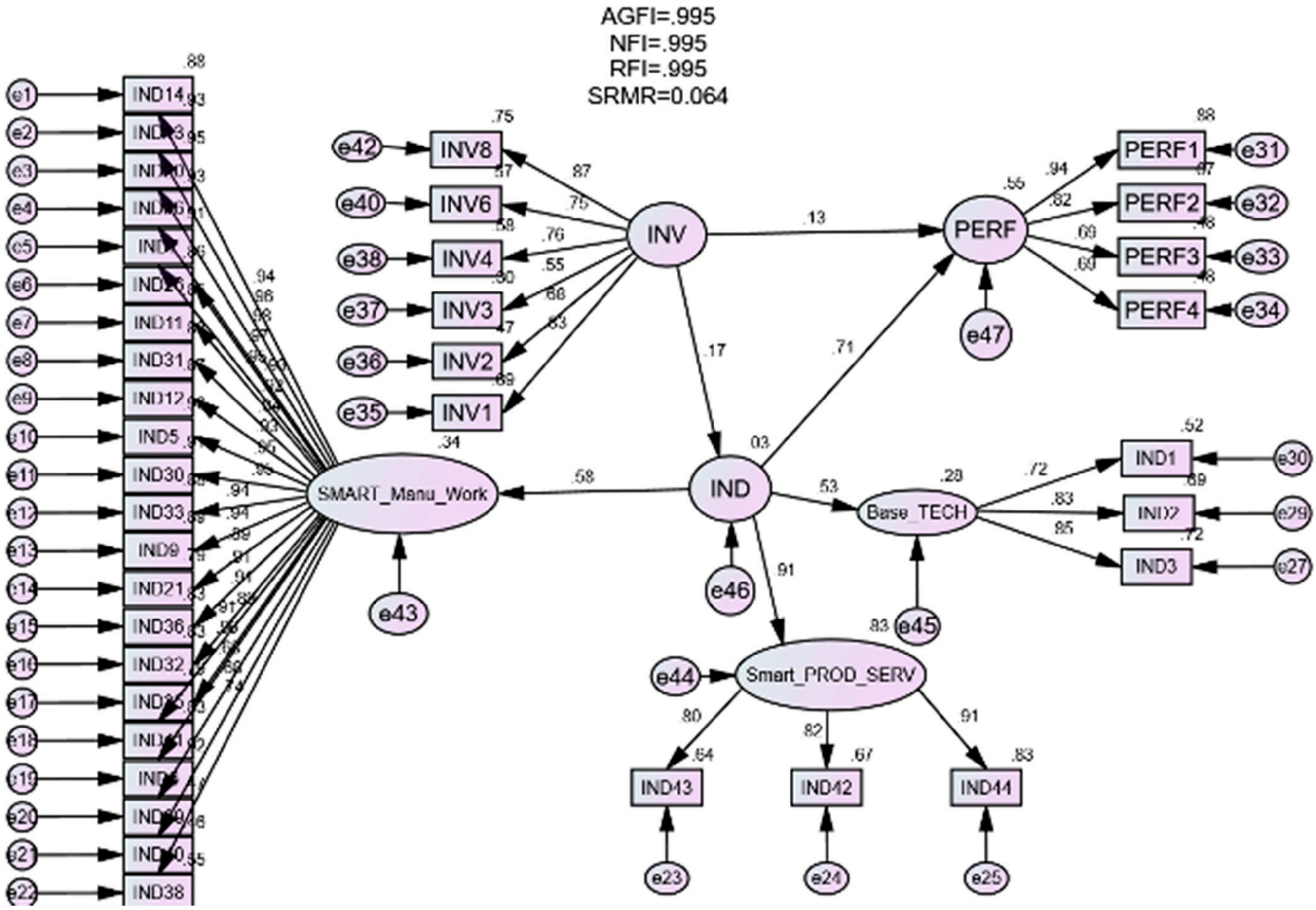

Figure 4. Final second-order SEM model.

4.4. Validation of Direct Hypotheses

Table 7 shows the results of the estimators and the p value for the respective validation of hypotheses.

Table 7. Hypothesis verification.

Hypothesis	Estimate	p	Conclusion
H_1: INV has a relationship with or positively influences PRF.	0.133	$p = 0.157$	No supported
H_2: INV has a relationship with or positively influences IND.	0.170	$p = 0.302$	No supported
H_3: IND has a relationship with or positively influences PRF.	0.706	$p = 0.001$	Supported
H_4: IND $\rightarrow$ SMART_Manu_Work IND $\rightarrow$ Smart_PROD_SERV IND $\rightarrow$ Base_TECH	0.580 0.912 0.530	$p = 0.009$ $p = 0.000$ $p = 0.001$	Supported

Regarding the direct relationship, Table 8 presents the results of the multigroup analysis where the non-standardized coefficients for both men and women, the difference between the coefficients, and the p value of the difference are observed. Considering the relevant relationships of this study, it is observed that the contribution of I4.0 technologies to job performance is not different according to gender, where a difference was detected in INV with PRF, since this relationship was significant only for men.

Table 8. Gender differences in direct effects.

Hypothesis	Female Beta	Male Beta	Difference in Betas	*p*-Value for Difference	Conclusion
$H_{1.1}$: INV between men and women has a relationship or positively influences PRF.	−0.043	0.188 †	−0.231	0.184	Supported male.
$H_{2.1}$: INV between men and women has a relationship or positively influences IND.	0.308 †	0.034	0.274	0.175	Supported female.
$H_{3.1}$: IND between men and women has a relationship or positively influences PRF.	0.936 ***	0.720 ***	0.216	0.751	There were no differences.
$H_{4.1}$: IND → Base_TECH	0.576 ***	0.664 ***	−0.087	0.13	Supported
$H_{4.1}$: IND → Smart_PROD_SERV	0.708 ***	0.958 ***	−0.25	0.022	Supported
$H_{4\cdot1}$: IND → SMART_Manu_Work	0.443 ***	0.658 ***	−0.215	0.251	Supported

† $p < 0.100$, *** $p < 0.001$.

4.5. Validation of Mediation Hypothesis

To validate the mediation hypotheses, the bootstrapping method (1000 samples) was used using the ULS procedure, finding (a) direct, indirect, and total effects; (b) their significance levels; and (c) 95% confidence intervals (MacKinnon et al. 2007; Preacher et al. 2011). It is important to highlight that the process was carried out jointly between companies in the service and manufacturing sectors, where the comparative results are presented in Table 9. It can be seen that only IND significantly influenced PRF, while INV was not statistically significant with PRF and with IND. Regarding the mediation of INF between INV and PRF, there was no mediating effect (p = 0.310). However, this situation changed when the companies are only manufacturing. The indirect effect of INV passing through IND to PRF (p = 0.025) was statistically significant, with a standardized coefficient = 0.141 and a 95% CI (0.041–0.326). There were differences, too, in direct effects when industry types were combined. There was no effect between INV and IND, while for manufacturing companies, a moderate effect was detected at 90%, because its p-value was 0.081, between 0.05 and 0.10. In the total effects, manufacturing industries showed some degree of effect, while, counting service companies, the INV–IND relationship did not show any relationship.

Table 9. Bootstrapping, mediation validation Industries 4.0, total effects, and according to manufacturing companies.

Relations	Standardized Coefficients	Significance Test	I.C		Conclusion
Manufacturing					
Direct effects			Lower limit	Upper limit	
INV→PRF	0.184	0.137	−0.020	0.342	There is no effect
INV→IND	0.259	0.081	0.018	0.451	The effect at 90%
IND→PRF	0.534	0.004	0.219	0.802	The effect at 95%
Indirect effects					
H_4: INV→IND→PRF	0.141	0.025	0.041	0.326	Significant mediating effect
Total effects					
INV→PRF	0.325	0.016	0.135	0.471	The effect at 95%
INV→IND	0.259	0.081	0.018	0.451	The effect at 90%
IND→PRF	0.543	0.004	0.219	0.802	The effect at 95%

Table 9. *Cont.*

Relations	Standardized Coefficients	Significance Test	I.C		Conclusion
		Manufacturing and services			
Direct effects			Lower limit	Upper limit	
INV→PRF	0.133	0.164	−0.020	0.279	There is no effect
INV→IND	0.170	0.355	−0.122	0.338	There is no effect
IND→PRF	0.706	0.002	0.553	0.823	The effect at 95%
Indirect effects					
H_4: INV→IND→PRF	0.120	0.310	−0.077	0.246	No mediating effect
Total effects					
INV→PRF	0.253	0.002	0.129	0.377	The effect at 95%
INV→IND	0.170	0.355	−0.122	0.338	There is no effect
IND→PRF	0.706	0.002	0.553	0.823	The effect at 95%

4.6. The Model with Control Variables

It was decided to use the variables educational level and years in the company as control variables, in order to minimize their confounding effect. Figure 5 presents the results of the model with acceptable adjustments.

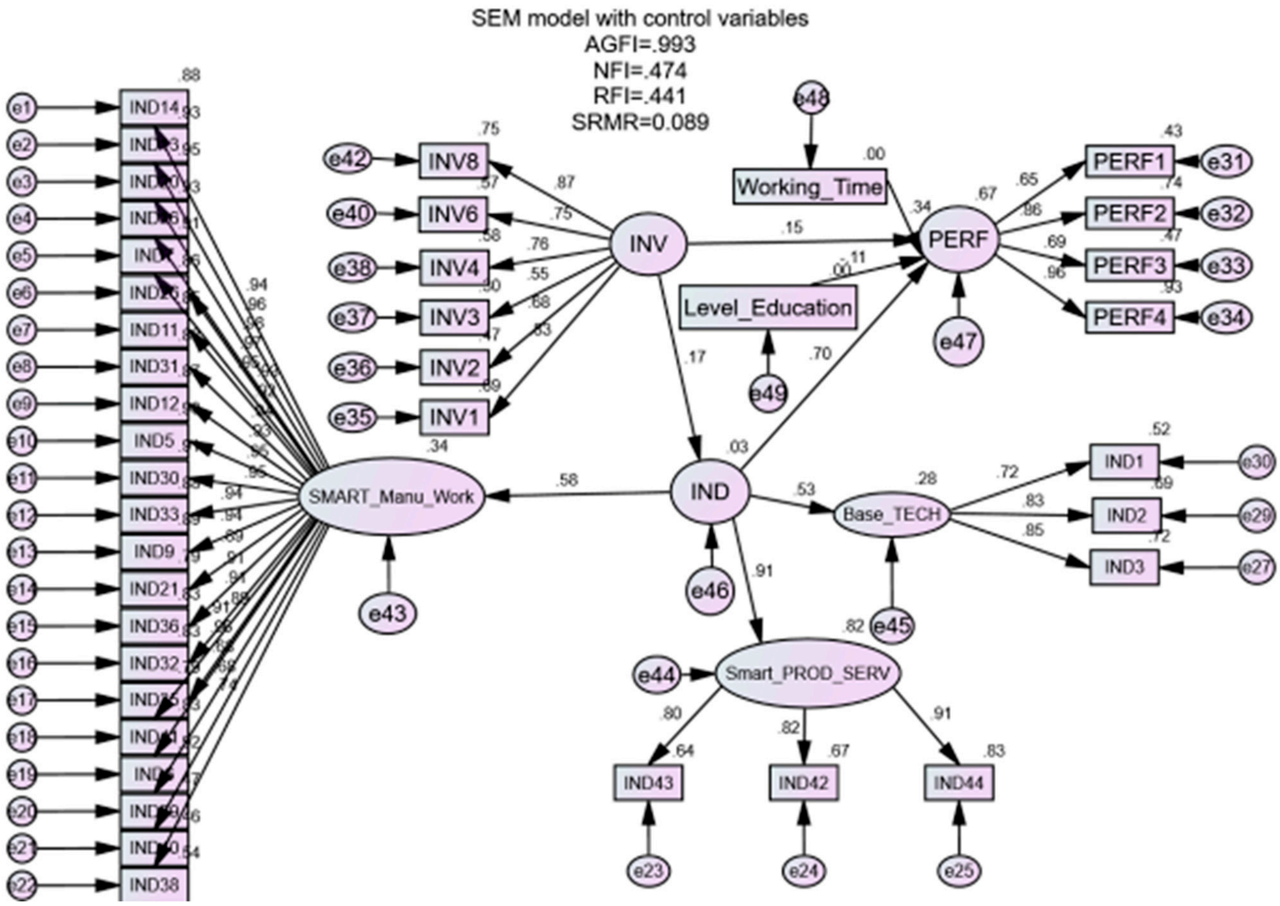

Figure 5. SEM model with control variables.

In Table 10, it is observed that educational level is not a confounding factor to explain the PRF, since its value of statistical significance measured with the value p is greater than 0.05 (0.258). On the contrary, the working time in the company does influence the explanation of the PRF. since its p value was 0.002.

Table 10. Non-standardized coefficients and their significance with bootstrapping.

Hypothesis	Estimate	Lower	Upper	p	Conclusion
PRF <--- working experience	−0.109	−0.268	0.039	$p = 0.258$	No supported
PRF <--- level education	0.343	0.230	0.445	$p = 0.002$	Supported

5. Discussion

This research responds to recent calls that highlight the need to consider how millennials are involved at work and face their job performance when I4.0 technologies intervene. With this in mind, this study incorporated the Theory of Planned Behaviour and examined the relationship between INV, PRF, and IND in millennial employees working in large Canadian companies. In addition, following the most recent literature, this research incorporates the level of education and the years of work experience as control variables, in addition to determining differences in the behaviour of employees, classified by gender. Therefore, the results of this study extend the existing literature in several ways. The findings partially support other works regarding INV and PRF (Bhutta et al. 2021; Rehman et al. 2020; Sapta et al. 2021; Shamim et al. 2019). The mediating role of IND that is included in these conclusions has not been studied in other investigations.

H1: The results were partially accepted (Estimate = 0.133 and p value = 0.157), which establishes that the INV is positively related to the PRF of millennials. Although, no significant relationships were observed between the INV and the PRF jointly between men and women. In the case of men (H1.1), INV had positive relationships to PRF (Male Beta = 0.188). Therefore, in line with other findings (Han and Yoo 2007; Zhang 2013), this study reveals that each time men become involved with the company, their PRF increases, that is, the more involved they are, the better their PRF. In this way, these employees will be willing to improve their performance and excel in their activities.

On the contrary, in the case of women (H1.1), INV did not have a positive relationship with PRF (Female Beta = −0.043). The research results highlight the crucial role of INV and PRF independently. This study determines that although millennial women base their behaviour on individual beliefs and subjective norms, this behaviour is not restrictive to being involved with the organization, and therefore, it is not a determinant of their PRF. Thus, the job performance of millennial women is not related to the degree of INV. With these findings, it is verified that the relationship between INV and PRF is established mainly by demographic characteristics such as gender rather than by the commitment, work environment, or motivation of the employees (Michie et al. 2002; Ćulibrk et al. 2018; Vroom 1962).

H2: This study establishes that there is no significant difference between men and women (Estimate = 0.170, p value = 0.302), that is, that the INV does not positively influence IND. In the case of women (H2.1), INV had a positive relationship with IND (Female Beta = 0.308, $p < 0.10$). This implies that even though in Canada, the proportion of women in ICT is lower than the proportion in other countries, the higher the INV of women, the higher the reception of I4.0 technologies in any business sector where they are found. Following (Mueller et al. 2018) who stated that Canadian women have better basic ICT skills than men and (WEF 2018) which determines that I4.0 presents a greater risk for jobs held by women, the findings of this study establish that I4.0 plays a crucial role in how women develop their work. It is then argued that the higher the INV, the more determined women will be to make an extra effort to use I4.0 and achieve their employment goals.

On the other hand, in the case of men (H2.1), INV had no positive relationship with IND (Male Beta = 0.034). This finding is interesting in this research, since, having been carried out in a developed economy, its socioeconomic context does not pose barriers to the implementation of I4.0. Therefore, regardless of the challenges of I4.0, men will be involved in their work, which will incentivize better PRF. In addition, despite the fact that I4.0 is known to provide its workers with new cognitive skills (Polak-Sopinska et al. 2020; Imran and Kantola 2018), organizations have not yet emphasized the training of their millennial employees to better execute work with new technologies.

H3: This research supports previous studies (Aguado et al. 2019) and justifies the importance of IND and PRF (Estimate = 0.706, p value = 0.001) regardless of gender (H3.1) (Female Beta = 0.936 and Male Beta = 0.720, $p < 0.001$). It suggests that millennial employees can increase their performance by fostering I4.0 (Abubakar et al. 2019; Diez-Olivan et al. 2018; Posada et al. 2015; Stachová et al. 2019), regardless of the business sector in which they operate. These results, in contrast to the previous literature that establishes that millennials are not yet ready to face the challenges that I4.0 promotes (Deloitte Touche Tohmatsu Limited 2019), invite organizations to reinforce I4.0 technologies.

Therefore, this study highlights that companies should emphasize both (a) base technologies (internet of things, cloud, and big data); (b) smart manufacturing and working (automatic identification of non-conformities in production, artificial intelligence for predictive diagnostics in equipment, real-time digital integration of manufacturing with customers and distributors, artificial intelligence for production planning and control, regulatory control of processes, real-time digital integration of manufacturing with suppliers, virtual commissioning, additive manufacturing, real-time digital integration with other company units and partners, etc); and (c) smart products and services (remote digital services, face-to-face technical services, and digital customer equipment monitoring services). In particular, this study shows that smart product and service technologies are more significant for men, while basic technologies and smart manufacturing and working do not differ in gender preferences. Meanwhile, in line with other authors (Tortorella et al. 2018; Gupta 2020), these findings encourage employees who reinforce I4.0 practices during continuous improvement activities to achieve a higher level of PRF when adopting IND.

H4: This study supports H4. For manufacturing companies, IND has a positive relationship with SMART_Manu_Work (Estimate = 0.580, p value = 0.009), IND has a positive relationship with SMART_Prod_Serv (Estimate = 0.912, p value = 0.000), and IND has a positive relationship with Base Tech (Estimate = 0.530, p value = 0.001). H4.1 has a positive relationship despite gender, with a $p < 0.001$. In fact, in recent years, I4.0 has gained relevance in this sector. The findings show that IND mediates the relationship between INV and PRF. Therefore, it is established that the employees of manufacturing companies that are involved at work, when they adopt I4.0 technologies, improve their work performance. It can be affirmed that these companies have a better development of I4.0, and therefore, they are better at managing their R&D processes and their human resources (Stachová et al. 2019). This is because in these companies, there is a very employee-oriented management philosophy, which explains the work performance of its workers through the use of I4.0. Therefore, these results show that manufacturing companies would be providing innovative and high-quality products.

When utility companies are included, this study establishes that IND does not mediate the relationship between INV and PRF; however, direct, and total effects are shown between IND and PRF and between INV and PRF. This means that, regardless of the use of I4.0 in companies, when millennials become involved at work, their performance increases. In addition, as (Nafchi and Mohelská 2021) suggested, when employees use I4.0, their performance also increases. However, this study shows a need to promote I4.0 in service companies to improve both the INV and the PRF of their employees. For this reason, it is necessary to develop motivation and training programs to satisfy the needs for prestige and autonomy of the employees, since, in addition, those who feel more involved will have a greater sense of duty to the company. As revealed by (Barkat and Beh 2018), intellectual capital is a source of competitive advantage, because it contributes to the creation of value.

Although the COVID-19 pandemic generated drastic changes in work environments and many workers felt comfortable working from home (Narayanamurthy and Tortorella 2021), it is possible that this is increasingly affecting the INV in these companies. As such (Johari and Yahya 2016), identified the importance that workers give to tasks and the feedback they receive increases their performance. In addition, Canada is one of the largest economies in the world and is oriented toward the market with a high cultural vision. Its companies must reinforce the typical roles in their work environments and influence the social actions of their members.

Finally, it was found that, after controlling the variables of the level of education and years of work experience, the latter had an impact on INV, PRF, and IND. In this way, the study validates that the greater the experience of the employees, the more likely they are to use I4.0. In addition, the results show a lack of presence of a younger workforce in management positions, as well as a lack of knowledge of I4.0 among the youngest millennials. In fact, millennials who have identified with management positions may not have complete knowledge transfer. Despite this, level of education is not relevant between INV, PRF, and IND. Although it was found that age is a determining factor for Canadian companies and they concentrate a greater number of millennial employees, only 5% of them have a higher educational level, which is not a determinant of their income, since millennials between 22 and 29 years old receive higher incomes than those between 30 and 39 years of age.

Regarding gender, this study found that level of education and salary were not different between men and women. In this way, although the companies do not have a gender distinction in their employees, the older ones are in management positions, despite the fact that the younger ones receive higher incomes. Furthermore, the industrial sector in which they are found is indifferent to the activities they carry out and the positions they hold.

6. Conclusions

This research analyses the mediating role of IND in the relationship between INV and PRF in millennial employees of large Canadian companies. This study identified the mediating effect of IND in manufacturing firms but not in service firms. This study reveals that although INV is stronger in men when it impacts PRF and that INV is even more significant in women when it impacts IND. IND is more relevant to PRF in both men and women. This means that, regardless of the millennials' gender, the use of INDs substantially improves the PRF. Therefore, given the current and projected shortage of ICT professionals, women represent a large, as yet untapped pool of talent. In addition, it was evidenced that the years of work experience were substantial in the relationships between INV, PRF, and IND. This study highlights the relevance of I4.0 and proposes extending the workforce to new roles that improve productivity and lead to the creation of new roles in companies.

7. Implications

7.1. Theoretical Implications

This research is an effort to expand the knowledge base of previous studies using the Theory of Planned Behaviour, now being tested in Canadian millennial workers. In general, this study provides evidence by explaining the variations between INV and PRF from IND when different behaviours of employees are involved based on gender. It is found that men have higher INV and PRF, while women who feel more involved with the company are more IND, but it is not a determinant of their PRF. The theoretical contributions of this study suggest that I4.0 strengthens the IND of millennial employees, mainly in manufacturing companies, who can in turn significantly improve the PRF of millennials. Additionally, as companies continue to focus on implementing efficient ways of conducting business, there will be increased interest in incorporating new technologies.

7.2. Managerial Implications

The practical contributions assume that in the socioeconomic context and from the COVID-19 pandemic, additional barriers are raised for the implementation of I4.0 technologies, especially with regard to work experience in the company and differences by gender. Even in this context, the INV and the PRF are essential for the permanence of companies through a committed workforce. This research provides companies with arguments for managers to emphasize that their current continuous improvement approaches will need to be human-centred and consistent with new I4.0 technologies. In turn, managers who reinforce INV practice during continuous improvement activities might achieve a higher level of PRF by adopting IND than those who neglect the importance of these organizational actions.

8. Limitations and Directions for Further Research

This research complements previous work, and its findings advance the body of knowledge on I4.0 in organizations. However, it has some limitations that should be taken with care when generalizing the results. Firstly, the data collection was carried out through online surveys of millennial employees of different hierarchical levels, which despite being the most effective and reliable way through which information on the organization's processes can be obtained and despite its relevance and ease of use, it is likely susceptible to participant bias. Secondly, the study applied convenience sampling for the researchers, due to the difficulty of access to companies that use I4.0 technologies, and because it is a technique suggested in similar studies; however, the interpretation of the results must be limited to the Canadian study population and companies. It is suggested to use random sampling for future studies.

Future research could replicate this study by examining other regions, countries, company sizes, job titles, or cultural backgrounds. In addition, as this study only included millennial employees in the analysis, other research could study the behaviour of other generational groups to compare them with millennials and corroborate the results of this research and, if possible, measure the evolution over time using a longitudinal study. Finally, future research can include, from the point of view of theories such as Job Demands-Resource, Societal Cognitive, Task-Technology Fit or the Technology Acceptance Model, the implications of adopting Artificial Intelligence, Internet of Things (IoT), Organizational Culture, Development Skills and Training Programs, Motivation and Work Commitment, in the mediating role of the adoption of industry 4.0 technologies between job involvement and job performance.

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Appendix A

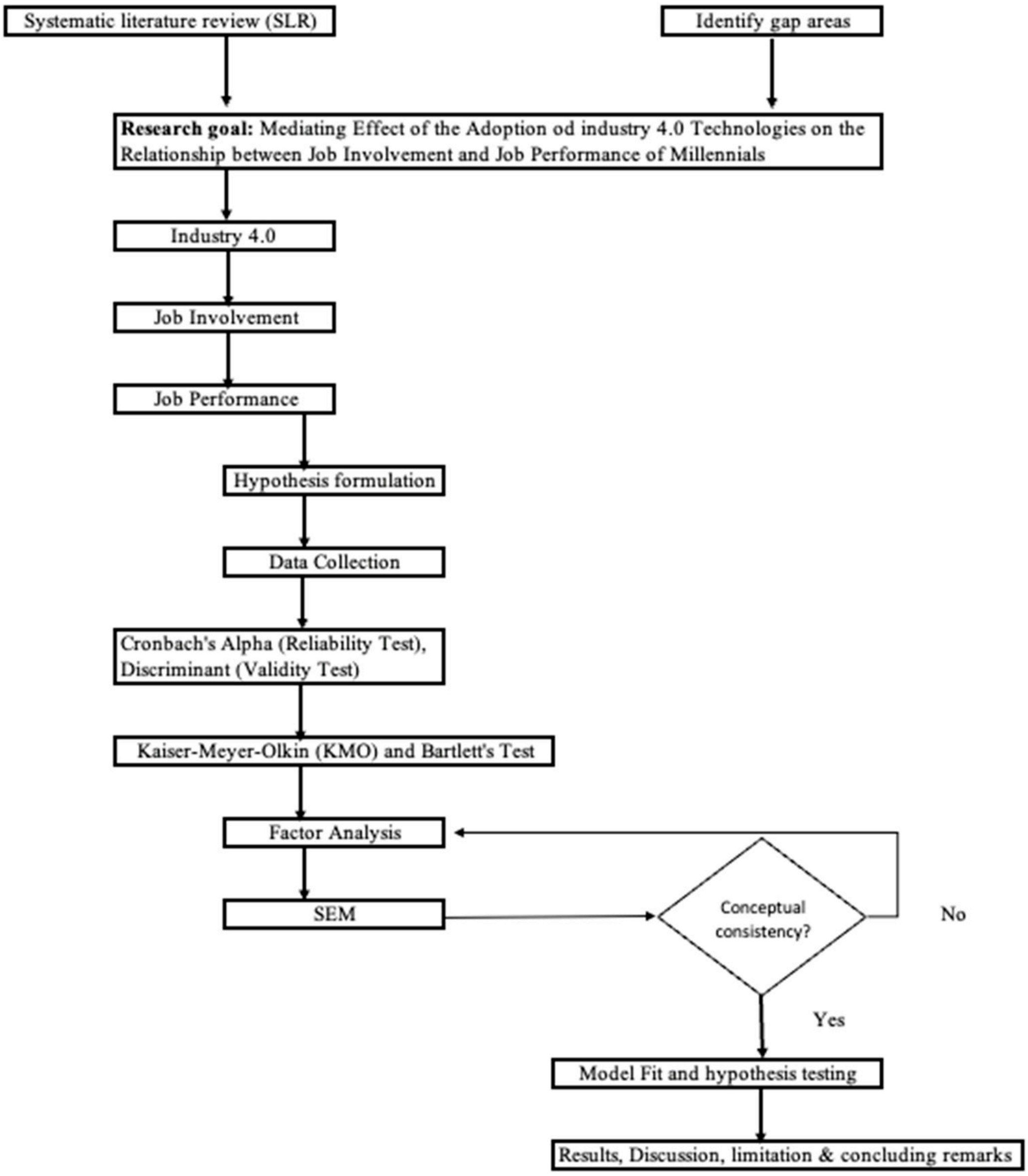

Figure A1. Research methodology flowchart.

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