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TOWARDS A MODEL OF THE NEXUS BETWEEN TECHNOLOGIES, JOB SATISFACTION, ORGANIZATIONAL COMMITMENT, AND PERFORMANCE FOR PROJECT-DRIVEN ORGANIZATIONS IN SOUTH AFRICA

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Abstract

The purpose of this study was to develop a model of the relationship between the use of digital technologies (DTs), employee job satisfaction (EJS), employee organization commitment (EOC), and employee job performance (EJP). A quantitative research design was adopted, and a closed-ended questionnaire survey was used to collect data from four project-driven engineering organizations. 148 valid responses were obtained. The partial least squares structural equation modeling was used to analyze the quantitative data. The results showed that the use of DTs significantly influenced EJS, EOC, and EJP. EJS substantially affected EOC and EJP. However, EOC trivially impacted EJP. EJS complementarily mediated the relationship between the use of DTs and EJP and between the use of DTs and EOC. EOC fully mediated this relationship between the use of DTS and EJP and between EJS and EJP. The research presents a unique nexus model for successful digital transformation initiatives for engineering organizations.

Keywords

Digital Technologies, Job Performance, Organizational Commitment, Job Satisfaction, Project-Driven Engineering Organizations

Introduction

The project-driven engineering organizations in South Africa are pursuing digital transformation initiatives. This is because digital transformation ensues novel value-adding tasks (Gong and Ribiere 2021; Verhoef et al. 2021) and new business models (Datti and Kuppusamy 2023; Horváth and Szabó 2019; Savić 2020). Fittingly, digital transformation programs are essential for organizations' survival and long-term sustainable success (Bozintan et al. 2023; Evans and Price 2020; Margiono 2020; Shehadeh et al. 2023). DTs play a key role in digital transformation as they affect all aspects of the organization's life; ultimately, these DTs result in radical changes (Barrutia and Echebarria 2021; Mergel et al. 2019; Schot and Steinmueller 2018). Moreover, organizational resources are fundamental to achieving digital transformation objectives (Gong and Ribiere 2021). The implication is that an integrative approach is required when adopting and using DTs (Barrutia and Echebarria 2021; Mergel et al. 2019). Therefore, organizations must simultaneously focus on adopting and using DTs, organizational behavior, structure, and processes (Hartl and Hess 2017; Kraus et al. 2022; Oludapo et al. 2024; Tuukkanen et al. 2022).

While the adoption and use of DTs results in numerous benefits (Bakon et al. 2020; Jayaprakash and Pillai 2022), high failure rates have been reported (Bakon et al. 2020; Jayaprakash and Pillai 2022; Lee et al. 2020; Ramesh 2019; Sanchez-Segura et al. 2024; Tabrizi et al. 2019). Organizational culture (OC) is the chief contributor to these high failure rates (Figueroa-Flores et al. 2020; Ramesh 2019; Tabrizi et al. 2019; Trushkina et al. 2020; Zumstein et al. 2022). This is logical, as OC affects all aspects of organizational life (Ciampi et al. 2020; Dahlbom et al. 2020). OC informs how organizational members do things, think, and feel (Ciampi et al. 2020; Dahlbom et al. 2020; Hisa et al. 2022; Schein and Schein 2017). Hence, OC must be transformed to align with the use of DTs to increase the success rates of digital transformation initiatives (Ciampi et al. 2020; Dahlbom et al. 2020; Nagy et al. 2020; Rosak-Szyrocka et al. 2021; Terra et al. 2021).

A conducive OC is also fundamental to positively shaping employees' attitudes and behaviors (Denison et al. 2004; Schein and Schein 2017). Employees are strategic assets, directly affecting organizational effectiveness (Sinding and Waldstrom 2014; Steyn and Schmikl 2013). So, there has been an increasing focus on employees to positively impact organizational outcomes (Baqir et al. 2020; Ciampi et al. 2020; Fallahnejad et al. 2023; Hassan et al. 2023; Irsyadi 2023; Kundi et al. 2021; Setianto and Andreas 2023; Rawindaran et al. 2023). However, human resources (HR) practices must also be congruent with OC and strategies for sustainable competitive edge and success (Narang and Singh 2012; Steyn and Schmikl 2013; Uen et al. 2023). When OC and HR practices are aligned to create a conducive environment for employees, employees feel valued, positively impacting their attitudes and behaviors (Sinding and Waldstrom 2014).

On the one hand, employees' attitudes comprise EJS and EOC; on the other hand, employees' behaviors entail EJP (Hassan et al. 2023; Sivaraman 2020; Sinding and Waldstrom 2014). Significantly, DTs must be synchronized with employees' attitudes and behaviors to guarantee the success of digital transformation schemes (Çini et al. 2023; Michna and Kmieciak 2020; Sharma 2015; Sivaraman 2020). Therefore, digital transformation must incorporate employee transformation (Oludapo et al. 2024; Tapia-Andino and Barcellos-Paula 2023); particularly, digital transformation must be employee-focused (Sharma 2015; Sivaraman 2020; Thite 2018). This implies that an integrative approach that focuses on the technical aspects of digital transformation and organizational behavior is required. Few studies (Chhabria and Yadav 2023; Çini et al. 2023; Sivaraman 2020; Tapia-Andino et al. 2023) have examined the relationship between DTs and some aspects of employees' attitudes and/or behaviors. These studies point to the pivotal role of DTs for employees. However, no study has been identified that has established the nexus between the use of DTs, EJS, EOC, and EJP.

While the relationship between EJS, EOC, and EJP has been extensively studied, how emerging disruptive DTs affect employees' attitudes and behaviors requires more research. This is expected as digital transformation is burgeoning, so it is not fully grasped, especially in developing countries (Bozintan et al. 2023; Kraus et al. 2022; Sanchez-Segura et al. 2024; Shehadeh et al. 2023). Thus, the primary objective of this research study is to apprehend the nexus between the use of DTs, EJS, EOC, and EJP and to develop a model for use by project-driven engineering organizations in South Africa. This study contributes to the knowledge by developing a nexus model for project-driven engineering organizations in South Africa to benefit from digital transformation initiatives. To be precise, this study underlines the need for DTs to be an employee-centric key in guaranteeing organizational success. The examination of how DTs relate to employees' attitudes and behaviors aids in achieving the study's purpose. Section 2 of the study turns to a literature review. Section 3 is about hypotheses and conceptual model development. Section 4 is the research methodology. Section 5 focuses on the study's results, and Section 6 discusses the results. Section 7 concludes the study.

Literature Review

Digital technologies

Emerging disruptive DTs are critical in sustaining organizational success and competitive advantage. Some of these DTs are the internet of things (IoT), big data (BD), cloud computing (CC), and artificial intelligence (AI). The IoT is an advanced unified internet that warrants the fusion of physical objects and cyberspace (Burhan et al. 2018; Tom, 2023). Devices like radio frequency identification tags, smartphones, actuators, sensors, software, and other technologies are used to integrate physical objects and the internet (Burhan et al. 2018; Tom, 2023). Communication technologies are also essential to enable data exchange between physical things and the internet (Burhan et al. 2018; Khan and Kaidi, 2023; Kong et al. 2022;

Tom, 2023). Further, computing technologies, such as edge and fog computing, are essential for the success of IoT (Al-Alshaqi et al. 2020; Khan and Kaidi, 2023; Kong et al. 2022; Oprea and Bâra 2023; Ren et al. 2019).

IoT generates massive volumes of data, which must be processed and analyzed (Kusuma and Viswanath 2018). BD is used to process and analyze this IoT-generated massive data (El Hilali et al. 2021; Fosso Wamba et al. 2020; Mishra et al. 2022; Ramos et al. 2022; Sabharwal and Miah 2022; Supriya and Chattu 2021). This generated data is foundational for an organization's decision-making; specifically, it is transformed into valuable data (Mishra et al. 2022; Ramos et al. 2022; Sabharwal and Miah 2022; Supriya and Chattu 2021; Vranopoulos et al. 2022). As part of BD, analytics technologies are used to transform raw big data into valuable data (Attaran et al., 2018; Bag et al. 2021; Fosso Wamba et al. 2020).

However, CC is required to enable big data storage, instantaneous exploration, and big data administration (Latifian 2022; Vijayasekaran and Duraipandian 2022). Hence, CC is critical for successfully applying IoT, BD, and analytics (Khan and Kaidi 2023; Plageras et al. 2017; Vijayasekaran and Duraipandian 2022). IoT generates an enormous amount of data, which is then transported and stored in CC, and then this stored big data is analyzed through analytical techniques and tools (Khan and Kaidi 2023). AI is necessary to guarantee further benefits from IoT, BD, and CC, as it makes data valuable for organizations (Alaimo and Kallinikos 2020). Therefore, combining these DTs is key for a data-driven approach and, ultimately, for improved organizational performance and sustainable competitive advantage.

Employee Job Satisfaction

Job satisfaction (JS) is one of the essential employees' attitudinal aspects as it affects their performance. When employees feel happy about their jobs, their performance is positively impacted. JS is "a pleasurable or positive emotional state resulting from the appraisal of one's job or job experiences" (Locke 1976). This definition suggests that emotions are foundational for job satisfaction (Locke 1976). Differently put, JS is an emotional response to a job (Locke 1976; Sinding and Waldstrom 2014). An individual's emotional state and mental condition affect him/her, the team, and organizational outcomes (Abdullah and Wan 2013). While EJS comprises affective JS and cognitive JS (Dugguh and Dennis 2014; Huang et al. 2017), the study's interest is in affective JS. Affective JS "reflects employee feelings toward the job, such as liking and hatred" (Huang et al. 2017). It is, therefore, crucial for organizations to guarantee that their employees are happy about their jobs.

Employee Organizational Commitment

EOC is another attitudinal aspect that impacts organizational success. When employees feel valued, they become committed to the organization. While EOC comprises affective commitment, continuance, and normative commitment (Hassan et al. 2023; Potipiroon and Ford 2017; Sinding and Waldstrom 2014; Sudha et al. 2023), this research focuses on affective commitment. "Affective commitment is a psychological bond with the organization, including loyalty to and identification with the organization (i.e., pride in the organization, internalization of its goals, and acceptance of its core values)" (Lambert et al. 2017). There is harmony between the employee and the organization regarding goals and values; therefore, the employee has a deep emotional bond with the organization (Potipiroon and Ford 2017). Thus, an organization must focus on employees' affective commitment due to its benefits (Kundi et al. 2021; Lambert et al. 2017; Potipiroon and Ford 2017). Affective commitment strongly leads to high employee performance (Kundi et al. 2021; Potipiroon and Ford 2017; Sudha et al. 2023) and, ultimately, to sustained organizational success (Sudha et al. 2023).

Employee Job Performance

An organization cannot meet its objectives and goals if employees perform poorly in their tasks. Therefore, one critical concern for human resources is effectively managing employees by intentionally focusing on their job performance (Choi et al. 2019; Fallahnejad et al. 2023; Irsyadi, 2023; Sudha et al. 2023). EJP affects the team's performance and, ultimately, organizational effectiveness (Kundi et al. 2021; Setianto and Andreas 2023; Sinding and Waldstrom 2014). EJP is "the total expected value to the organisation of the discrete behavioural episodes that an individual carries out over a standard period" (Sudha et al. 2023). While EJP comprises contextual and task performance (Choi et al. 2019; Ding and Liu 2022; Sudha et al. 2023; Uraon and Gupta 2021), this study focuses on task performance. Task performance "is the effectiveness with which job incumbents perform activities that contribute to an organization's technical core either directly by implementing a part of its technological process or indirectly by providing it with

needed materials or services" (Uraon and Gupta 2021). It is an employee's expected behavior based on the job description to accomplish his/her duties (Ding and Liu 2022; Nam and Park 2019; Shoss et al. 2012).

Hypotheses and Conceptual Model Developments

The Relationship between the Use of DTs and EJP

Employees are indebted to DTs to optimally perform their tasks (Alshammary and Hilmi 2024). Particularly, the use of DTs is pivotal for EJP. Fittingly, research underlines the important role of the use of DTs on EJP (Aguado et al. 2019; Alshammary and Hilmi 2024; Çini et al. 2023; Schmitt, 2024; Tapia-Andino et al. 2023). Therefore, organizations must adopt and use appropriate DTs to positively impact EJP (Tapia-Andino et al. 2023). This implies that during the planning stages, correct DTs are selected based on employees' inputs to guarantee that they will positively impact employees' tasks. Moreover, employees must be trained to understand and correctly use DTs deployed by the organization. The result is increased EJP. It is, therefore, hypothesized that,

H1: The use of DTs directly and positively affects EJP.

The Relationship between the Use of DTs and EJS

The use of DTs has a direct impact on employees. Therefore, research has resolved that digital transformation initiatives must concurrently focus on adopting and using DTs and human capital (Oludapo et al. 2024; Tapia-Andino et al. 2023). Organization's plans to adopt and use DTs must embed organizational behavior to guarantee success (Hartl and Hess 2017; Kraus et al. 2022; Oludapo et al. 2024; Tuukkanen et al. 2022). Hence, employee-centricity is needed as part of digital transformation (Sharma 2015; Sivaraman 2020; Thite 2018). Fittingly, some studies (Alshammary and Hilmi 2024; Brougham and Haar 2024) suggest that DTs directly impact EJS. This effect of DTs can either be positive or negative, underlining the need for optimal use of DTs for enhanced EJS (Alshammary and Hilmi 2024; Brougham and Haar 2024; Miglioretti et al. 2021; Molino et al. 2020; Schmitt 2024). When optimally used, DTs positively impact EJS (Alshammary and Hilmi 2024; Brougham and Haar 2024; Molino et al. 2020; Schmitt 2024). There is a need to train and support employees in the correct ways to use DTs for their well-being and, ultimately, EJS (Alshammary and Hilmi 2024; Miglioretti et al. 2021; Molino et al. 2020; Schmitt 2024). Therefore, the hypothesis is that:

H2: The use of DTs directly and positively impacts EJS.

The Relationship between the Use of DTs and EOC

The preceding discussion is relevant to the relationship between the use of DTs and EOC, as it is another attitudinal aspect (Wang et al. 2020). ICT use is suggested to affect employees' jobs and their experiences (Wang et al. 2020). Particularly, the use of DTs has been found to impact EOC (Chhabria and Yadav 2023; Wang et al. 2020). Nonetheless, excessive use of DTs has been found to have a negative effect on EOC (Hwang and Cha 2018; Kumar et al. 2013; Marchiori et al. 2020). This underlines the need for appropriate use of DTs to guarantee improved EOC. Also, DTs, specifically cloud computing and deep learning, have been found to affect EOC (Priya et al. 2022). It is, therefore, hypothesized that:

H3: The use of DTs directly and positively impacts EOC.

The Relationship between EJS and EOC

EJS and EOC have been found to be directly related (Ahsan and Khalid 2024; Marchiori et al. 2020; Nelwan et al. 2024; Ngoc et al. 2024; Noor et al. 2024). Studies resolved that when employees are happy about their jobs, they are more committed to the organization (Ahsan and Khalid 2024; Fu 2014; Fu and Deshpande 2014; Marchiori et al. 2020). However, it has also been concluded that EOC affects EJS (Li et al. 2020; Ngoc et al. 2024). Evidently, the relationship between EJS and EOC is complex. This study focuses on the impact of EJS on EOC. It is, therefore, hypothesized that:

H4: EJS is directly and positively related to EOC.

The Relationship between EJS and EJP

EJS has been found to be related to EJP (Dhamija et al. 2019; Ekmekcioglu and Nabawanuka 2023; Inoyatova and Isakov 2022; Ngoc et al. 2024; Rojikinnor et al. 2022). EJS influences EJP (Dhamija et al. 2019; Ekmekcioglu and Nabawanuka 2023; Inoyatova and Isakov 2022; Rojikinnor et al. 2022). This implies that when employees are satisfied with their jobs, their job performances increase (Ekmekcioglu and Nabawanuka 2023; Jalagat 2016; Vermeeren et al. 2014). Nonetheless, the relationship is complex, as some studies indicate that EJP directly affects EJS (Dugguh and Dennis 2014; Jalagat 2016; Rojikinnor et al. 2022). Therefore, the results are generally inconclusive (Anghelache 2014; Dugguh and Dennis 2014; Jalagat 2016). However, the general indication is that EJS influences EJP (Dugguh and Dennis 2014). The hypothesis is, therefore, that:

H5: EJS directly and positively impacts EJP.

The Relationship between EOC and EJP

EOC has been found to be related to EJP (Indrayani et al. 2024; Jaber et al. 2024; Thao et al. 2024; Wang et al. 2020). Specifically, EOC directly and significantly impacts EJP (Indrayani et al. 2024; Jaber et al. 2024; Kundi et al. 2021; Sudha et al. 2023; Thao et al. 2024). This implies that the more committed employees are, the higher their job performance. Nonetheless, there might be a negative relationship between EOC and EJP (Lambert et al. 2017; Sinding and Waldstrom 2014). Employees might feel trapped in the organization, hence its negative effect. Also, employees might pursue unethical behaviors due to their commitment. Additionally, underperforming employees might commit to staying longer at the organization. Moreover, EOC has also been found to have an insignificant effect on EJP (Wolor et al. 2022). Therefore, the empirical results suggest a contradictory influence of EOC on EJP. However, it has been resolved that affective commitment positively impacts EJP (Potipiroon and Ford 2017; Kundi et al. 2021; Sudha et al. 2023). It is, therefore, hypothesized that:

H6: EOC has a direct and positive impact on EJP.

The Mediation Roles of EJS and EOC

There has recently been a growing interest in the mediation function of a variable between two variables (Hair et al. 2022). "A change in the exogenous construct results in a change of the mediator construct, which, in turn, changes the endogenous construct" (Hair et al. 2022). It has been concluded that EJS mediates the relationship between DTs and EOC (Chhabria and Yadav 2023). Also, it has been resolved that EOC mediates the relationship between DTs and EJP (Li et al. 2021). Further, EOC has been found to mediate the relationship between EJS and organizational performance (Firdaus et al. 2022). Additionally, EJS mediates the relationship between the use of DTs and EOC. This is particularly true due to the complex relationship between EJS and EOC (Vieira et al. 2023). Therefore, it is hypothesized that:

H7: EJS mediates the relationship between the use of DTs and EJP.

H8: EOC mediates the relationship between the use of DTs and EJP.

H9: EJS mediates the relationship between the use of DTs and EOC.

H10: EOC mediates the relationship between EJS and EJP.

Therefore, Figure 1 below is the conceptual model of the nexus between the use of DTs, EJS, EOC, and EJP. This conceptual model was then finalized based on quantitative data collected from four project-driven engineering organizations in South Africa, as further elaborated in the next section.

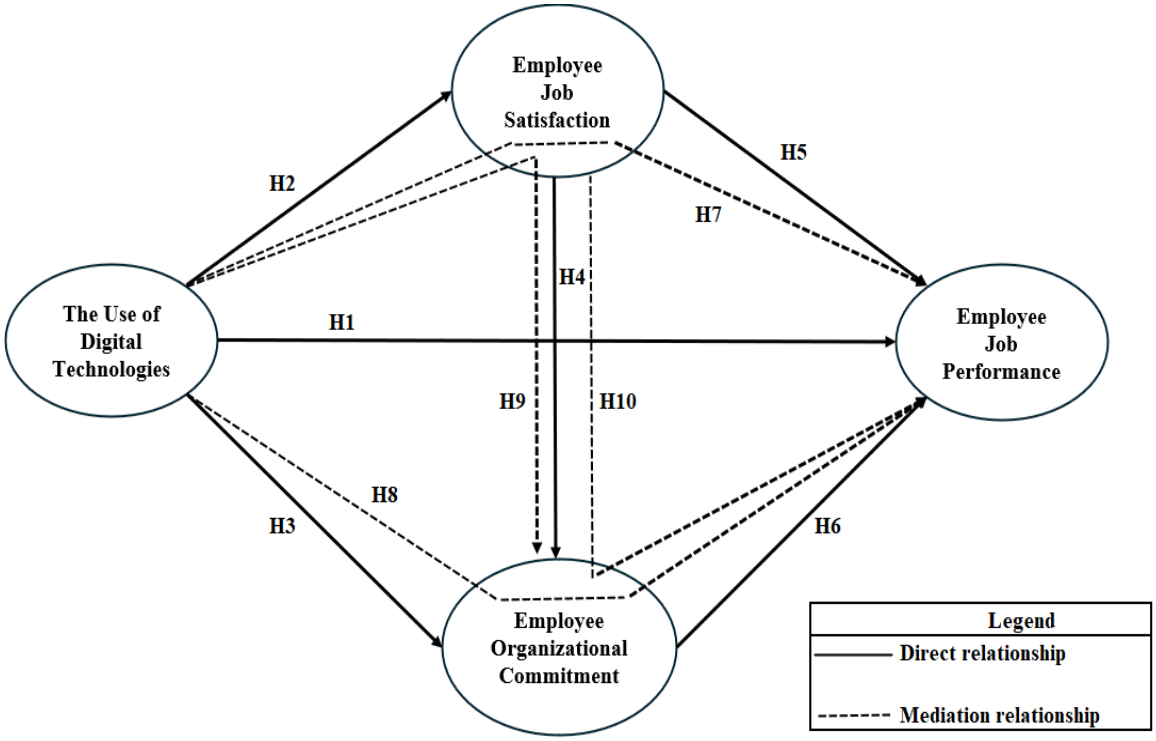

Fig. 1. A conceptual model of the nexus between the use of DTs, EJS, EOC, and EJP.

Research Methodology

Research Method

A quantitative research method design, which is aligned with the positivism paradigm (Remenyi et al. 2010; van Aardt and Quesada 2021; Watkins 2016), was adopted. The positivism paradigm was particularly suitable as the interest was to test hypotheses to generalize the results (Remenyi et al. 2010; Watkins 2016). A cross-sectional survey was used to collect quantitative data from the four organizations. Moreover, questionnaires were used to collect quantitative data. The questions were closed-ended, as it was quicker for participants to complete and suitable for quantitative research design (du Toit 2021; Remenyi et al. 2010). Online survey tools, Microsoft Forms for energy company employees and Google Forms for employees of the water utility and two logistics organizations were used.

The data-capturing instruments comprised demographic and multiple-choice questions. The main constructs' statements were primarily adapted from previously validated instruments. Few statements were developed from existing literature to warrant content validity. The researchers discussed and reviewed all statements to eliminate any errors. This review guaranteed that the statements were properly drafted and that all key themes for the four constructs (use of DTs, EJS, EOC, and EJP) were covered adequately. The items were structured on a five-point Likert scale: strongly disagree, disagree, undecided, agree, strongly agree. While strongly disagree was scored 1, strongly agree was scored 5.

The study area was four project-driven engineering organizations in South Africa. These organizations were an energy utility, a water utility, and two logistics companies. They have been using DTs for several years. They were distinct from each other as they operated in different industries and had different executive management and board of directors. Therefore, while they were all project-driven engineering organizations, their cultures were distinct, which was vital in generalizing the findings. Additionally, the energy company and one of the logistics companies are made up of different businesses (or divisions), with different executive management and board of directors responsible for the different businesses and reports to the holdings company. Hence, the different divisions were distinct from each other.

The four organizations employed several employees, who were the study's population. Two of the four organizations had over one thousand employees, and the other two had over thirty thousand employees. The interest of this study was to generalize the findings to this population. Nonetheless, considering the large number of employees from the four organizations, collecting data from the whole

population was impossible. Therefore, a representative sample from the whole population was required to generalize the findings (Creswell and Creswell 2023; Faasen 2021; Remenyi et al. 2010). Regarding the sample frame, the study included permanent employees who were users of DTs and had at least one year of experience in the organization. These employees included professionals (such as technicians, engineers, IT technical personnel, engineering and IT specialists), managers, and senior managers for sample representativeness to guarantee the accuracy of results..

Since the study fell under the positivistic view, probability sampling was adopted to select representative samples (Remenyi et al. 2010). Cluster sampling was chosen to guarantee that all four organizations and the three groups of employees were represented in the sample. Additionally, it was necessary to determine the minimum sample size. There are divergent views regarding the minimum sample size for partial least squares structural equation modeling (PLS-SEM) to test the hypotheses (Hair et al. 2022; Kock and Hadaya 2018; Memon et al. 2020; Mooi et al. 2018). Some studies claim that small sample sizes are acceptable, while others advocate for larger samples. However, PLS-SEM requires a minimum sample size for the accuracy of the results (Hair et al. 2019; Hair et al. 2022).

While there are different ways to calculate the minimum sample size for PLS-SEM (Hair et al. 2022; Kock and Hadaya 2018), this study used power analysis, which has recently been recommended (Creswell and Creswell 2023; Hair et al. 2022; Memon et al. 2020; Mooi et al. 2018; Ringle et al. 2018; Ringle et al. 2023; Serdar et al. 2021; Uttley 2019). G*Power statistical package was used to calculate sample size. The results suggested a minimum sample size of 77. In other words, a total of 77 responses had to be obtained from the combined responses of the four participating organizations. 148 valid responses were obtained, hence meeting the minimum sample size. Participation in the questionnaire survey was voluntary, and therefore, participants were informed that they were free to withdraw from participation at any time. Therefore, by continuing with participation in the survey, the participants gave consent to participate in the study. The reason for this consent was that written consent, that is, approval to conduct the study from the four participating organizations, had already been given to the researchers before the data collection commenced. Table 1 shows the frequency distribution of the four organizations.

Organization	Frequency	Percentage
Energy Company	111	75%
Water Company	19	12.8%
Logistics Company 1	5	3.4%
Logistics Company 2	13	8.8%
Total	**148**	**100%**

Table 1. Frequency distribution of the four organizations.

Data Analysis

As already stated, PLS-SEM was used to analyze the quantitative data collected from the four organizations. Structural equation modeling (SEM) is a group of statistical techniques (Henseler et al. 2016) that began appearing in social sciences in the 1970s (Hair et al. 2022; Kock and Hadaya 2018). It was first applied in marketing research in the 1980s (Hair et al. 2011). There are two main types of SEM: covariance-based SEM (CB-SEM) and variance-based SEM (PLS-SEM; Dash and Paul 2021; Hair et al. 2022; Purwanto and Sudargini 2021). While CB-SEM has been predominant, PLS-SEM has recently been increasingly used in various fields (Hair et al. 2022; Sarstedt and Cheah 2019).

This study employed PLS-SEM as it was mainly exploratory; the conceptual model has not been used before (Behl 2022; Hair et al. 2019). Further, the study was complex as it incorporated mediator variables, making PLS-SEM an appropriate method (Hair et al. 2022; Hair et al. 2019). Moreover, knowledge about the relationship between the use of DTs, EJS, EOC, and EJP was in the early stages, making PLS-SEM suitable for the study (Hair et al. 2022; Hair et al. 2019; Mishra et al. 2022). SmartPLS 4 software package was used to test the research study's hypotheses.

Validity and Reliability

Validity and reliability are two critical quality criteria used to judge the collected data for quantitative research (Creswell and Creswell 2023; van Aardt and Hirschsohn 2021). Validity is concerned with whether the instruments accurately gauge what they were designed to measure (Creswell and Creswell 2023; Hirschsohn 2021). Reliability is concerned with the extent to which the findings are repeatable (Creswell and Creswell 2023; van Aardt and Hirschsohn 2021). An unreliable construct cannot be valid in

terms of the relationship between validity and reliability (Hair et al. 2022; Sarstedt and Mooi 2019). Meaning that the construct must be reliable before it can be valid. While multiple items were used to increase the accuracy of the constructs, measurement errors remained, requiring quality assessment (Hair et al. 2022).

The quality assessment focused on convergent validity, internal consistency reliability, and discriminant validity (Hair et al. 2022). Convergent validity includes outer indicator loadings, indicator reliability, and average variance extracted (AVE; Hair et al. 2022). The rule of thumb for indicator outer loadings is 0.7 and above to be deemed acceptable (Ab Hamid et al. 2017; Hair et al. 2022), but values between 0.5 and 0.7 are also acceptable (Hair et al. 2022). When the indicator value is 0.4 and below, the indicator is removed (Ab Hamid et al. 2017; Hair et al. 2022), while indicators with values between 0.4 and 0.7 need to be evaluated and be considered for removal if they do not compromise validity and reliability (Ab Hamid et al. 2017; Hair et al. 2022). In this study, one indicator (IME1) was below 0.4. The AVE must be 0.5 and above (Hair et al. 2022). After removing three indicators (DCS3, IME3, IME4) on the use of DTs, the AVE was above the threshold. Figure 2 shows the results of outer loadings and AVE.

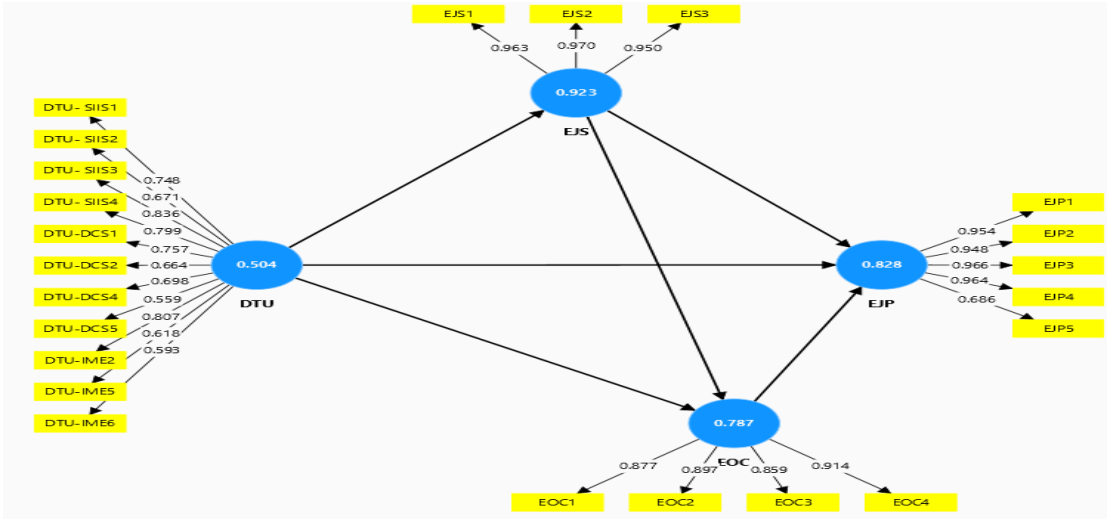

Fig. 2. Results of outer loadings and AVE

Additionally, the reliability was evaluated using internal consistency reliability (Hair et al. 2022). Internal consistency reliability was tested using Cronbach's alpha, composite reliability (ρ_A), and composite reliability (ρ_c; Hair et al. 2022). The threshold value should be above 0.6 for a construct to be deemed reliable (Hair et al. 2022). Cronbach's alpha is a conservative test with lower reliability values, while the composite reliability (ρ_c) is liberal (Hair et al. 2022). The actual reliability is between Cronbach's alpha and composite reliability (ρc), which is the composite reliability (ρ_A; Hair et al. 2022). As shown in Table 2, all the results met the threshold.

Construct	**Cronbach's alpha**	ρ_A	ρ_c
Digital Technologies' Use	0.901	0.922	0.917
Employee Job Satisfaction	0.958	0.961	0.973
Employee Organizational Commitment	0.910	0.913	0.936
Employee Job Performance	0.945	0.965	0.960

Table 2. Results of internal consistency reliability for the study's constructs (Own).

Moreover, the study examined discriminant validity. It was assessed using the heterotrait Monotrait (HTMT) ratio (Ab Hamid et al. 2017; Hair et al. 2022). HTMT is a stringent measure of discriminant validity, guaranteeing no multicollinearity (Ab Hamid et al. 2017; Hair et al. 2022). Two thresholds are used for HTMT; if constructs are conceptually similar, 0.9 is the threshold, and if they are distinct, 0.85 is the threshold (Hair et al. 2022; Henseler et al. 2015; Roemer et al. 2021). However, other researchers, such as Altinay et al. (2023), Gold et al. (2001), Lacap and Alfonso (2022) and Teo et al. (2008), argue for a 0.90 threshold. The decision to use 0.85 or 0.90 relies on the conservativeness of the researcher (Henseler et al. 2015; Roemer et al. 2021). This study adopted 0.90, and as shown in Table 3,

the HTMT values were within the required threshold.

	DTU	EJP	EJS	EOC
Digital Technologies' Use (DTU)				
Employee Job Performance (EJP)	**0.674**			
Employee Job Satisfaction (EJS)	0.574	**0.733**		
Employee Organizational Commitment (EOC)	0.567	0.563	**0.816**	

Table 3. Results of HTMT values

Results

The PLS-SEM algorithm requires that before hypotheses testing, an assessment of collinearity is conducted (Hair et al. 2022). High collinearity in a model negatively impacts the results (Hair et al. 2022). The variance inflation factor (VIF) assesses collinearity in a model (Hair et al. 2022; Johnston et al. 2018; Kock 2015). The conservative VIF threshold value of 5 (Hair et al., 2022) was adopted. As indicated in Table 4, all VIF values were below 3, suggesting no collinearity risk (Hair et al. 2022). Moreover, the values below 3 suggest that there is no common method bias (Kock 2015; Kock 2021).

Constructs	**VIF**
DTU -> EJP	1.506
DTU -> EJS	1.000
DTU -> EOC	1.460
EJS -> EJP	2.629
EJS -> EOC	1.460
EOC -> EJP	2.477

Table 4. Results of VIF values of the inner model

Then, the study progressed to hypotheses testing, using a path coefficient and probability (*p*) value of 0.05 (Hair et al. 2022). When the path coefficient (or total effect) value is closer to zero (0), it indicates an insignificant relationship (Hair et al. 2022). On the other hand, when the path coefficient (or total effect) value is closer to 1 (+/-), it depicts a positive or negative significant relationship (Hair et al. 2022). A *p*-value above 0.05 indicated insignificant relationships between the two constructs (Hair et al. 2022). Table 5 shows the results of path coefficients of the PLS path model. Also, Figure 3 shows the results of path coefficients and *p* values. Table 6 depicts the results of the total effects of the PLS path model.

Constructs Relationships	**Path Coefficients**	**t Values**	**ρ Values**	**95% Confidence Interval**	**Significance (ρ < 0.05)?**
DTU -> EJP	0.407	6.259	0.000	[0.277, 0.530]	Yes
DTU -> EJS	0.561	8.584	0.000	[0.407, 0.671]	Yes
DTU -> EOC	0.137	1.986	0.047	[0.006, 0.275]	Yes
EJS -> EJP	0.575	7.216	0.000	[0.417, 0.730]	Yes
EJS -> EOC	0.687	11.572	0.000	[0.557, 0.788]	Yes
EOC -> EJP	-0.128	1.579	0.114	[-0.291, 0.029]	No

Table 5. Path coefficients results of the PLS path model.

Constructs Relationships	**Total Effects**	**t Values**	**ρ Values**	**95% Confidence Interval**	**Significance (ρ < 0.05)?**
DTU -> EJP	0.663	12.428	0.000	[0.534, 0.749]	Yes
DTU -> EJS	0.561	8.584	0.000	[0.407, 0.671]	Yes
DTU -> EOC	0.522	7.559	0.000	[0.362, 0.638]	Yes
EJS -> EJP	0.487	6.640	0.000	[0.338, 0.622]	Yes
EJS -> EOC	0.687	11.572	0.000	[0.557, 0.788]	Yes
EOC -> EJP	-0.128	1.579	0.114	[-0.291, 0.029]	No

Table 6. Total effects results of the PLS path model.

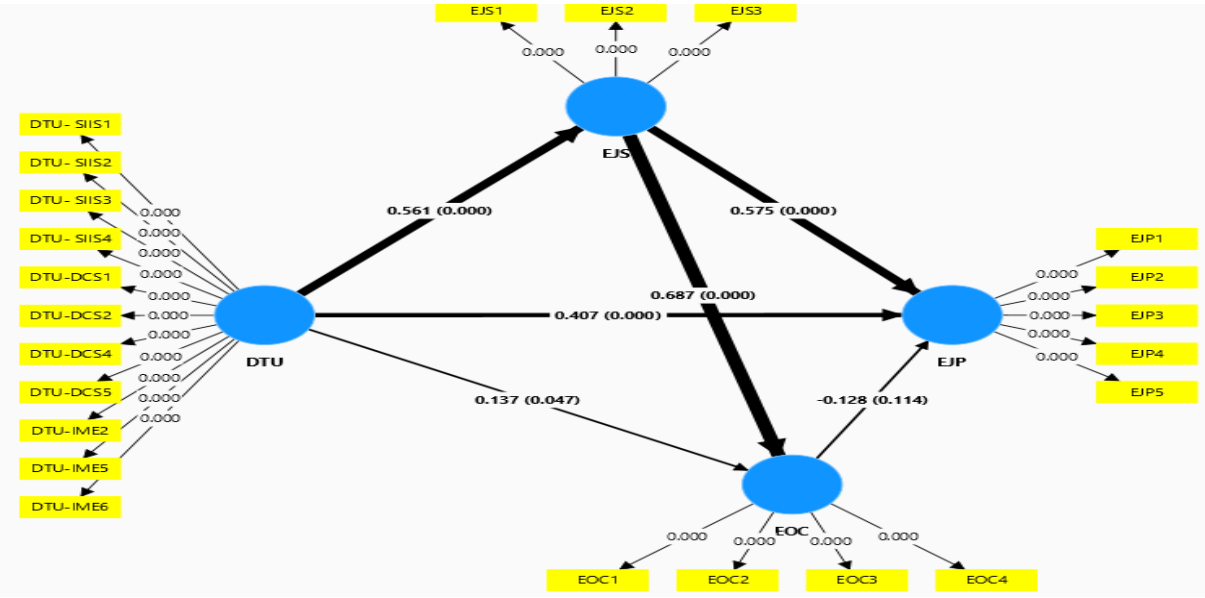

Fig. 3. Results of path coefficients and *p* values.

Additionally, the study evaluated the model's explanatory power to determine whether the results fit the in-sample data, using the coefficient of determination (R-square) and f- square effect size (Hair et al. 2022). The R-square measures the exogenous construct's total effect on the endogenous variable (Hair et al. 2022; Shmueli et al. 2016). The R-square values of 0.75, 0.50, and 0.25 are large, medium, and trivial, respectively (Hair et al. 2022; Shmueli et al. 2016). When f-square value is 0.02, 0.15 and 0.35 implies small, moderate, and extensive effect sizes, respectively (Hair et al. 2022). Figure 4 depicts the R-square (adjusted) values (0.600 for EJP, 0.310 for EJS, and 0.591 for EOC) and f- square.

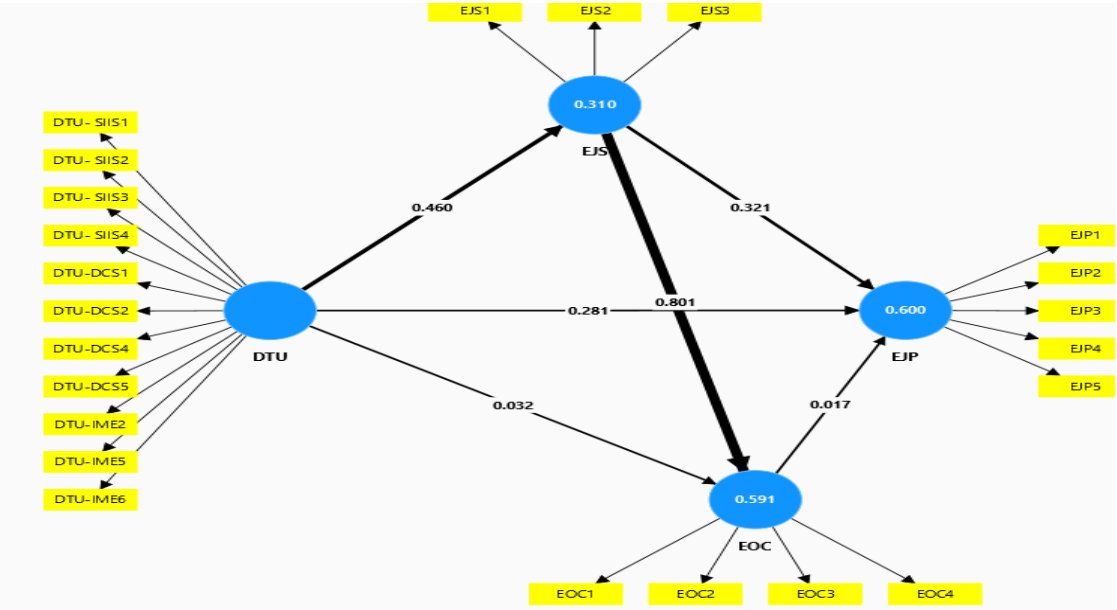

Fig. 4. Results of adjusted R-squared and *f*-squared values.

Lastly, the study assessed the mediation effects of EJS and EOC. Mediation is categorized into two broad types: non-mediation and mediation (Hair et al. 2022). The non-mediation type is divided into direct-only mediation and no effect (Hair et al. 2022). The directly-only implies that a direct relationship is significant, but no mediation exists (Hair et al. 2022). The second category of mediation has three types: complementary, competitive, and indirect-only (full mediation; Hair et al. 2022). Complementary mediation is when all relationships (direct and indirect) are significant and positive (Hair et al. 2022).

Competitive mediation is when all relationships (direct and indirect) are significant and are not all positive (Hair et al. 2022). The full mediation is when the direct relationship is significant, but the indirect relationship is insignificant (Hair et al. 2022). Table 7 shows the results of the complementary mediation of EJS. Table 8 indicates the results of the full mediation of EOC.

Constructs Relationships	Direct Effect	95% Confidence Interval of Direct Effect	Significance (ρ<0.05)?	Indirect Effect via EJS	95% Confidence Interval of Indirect Effect	Significance (ρ<0.05)?
DTU -> EJP	0.407	[0.277, 0.530]	Yes	0.323	[0.232, 0.429]	Yes
DTU -> EOC	0.137	[0.006, 0.275]	Yes	0.386	[0.283, 0.487]	Yes

Table 7. Results of the mediation roles of EJS.

Constructs Relationships	Direct Effect	95% Confidence Interval of Direct Effect	Significance (ρ<0.05)?	Indirect Effect via EOC	95% Confidence Interval of Indirect Effect	Significance (ρ<0.05)?
DTU -> EJP	0.407	[0.277, 0.530]	Yes	-0.018	[-0.063, 0.002]	No
EJS -> EJP	0.575	[0.417, 0.730]	Yes	-0,088	[-0.207, 0.017]	No

Table 8. Results of the mediation roles of EOC.

Discussion

The Relationship between the Use of DTs and EJP

The hypothesis that there is a direct and positive relationship between the use of DTs and EJS was supported. The path coefficient was 0.407, and the *p*-value was 0.000. The total effect was 0.663, and the *p*-value was 0.000. Therefore, both the path coefficient and total effects suggested a significant effect of the use of DTs on EJP. The adjusted R-square value was 0.600, which suggested a moderate effect, and the *f*-square value was 0.281, indicating a medium effect of the use of DTs on EJP. Therefore, the use of DTs has a significant and relevant impact on EJP. Similarly, the literature has resolved that the use of DTs significantly impacts EJP (Aguado et al. 2019; Alshammary and Hilmi 2024; Çini et al. 2023; Schmitt 2024; Tapia-Andino and Barcellos-Paula 2023). When organizations adopt emerging disruptive DTs, it is critical to consider how these DTs impact EJP. Organizations cannot decide to adopt and use DTs without first understanding the needs of employees and how these DTs would impact their performance. Therefore, organizations must adopt appropriate performance tools to assess how the use of DTs impacts EJP. Appropriate actions must be taken when the use of DTs does not positively influence EJP..

The Relationship between the Use of DTs and EJS

The hypothesis that there is a direct and positive relationship between the use of DTs and EJS was supported. The path coefficient was 0.561, and the *p*-value was 0.000. The total effect was 0.561, and the *p*-value was 0.000. Therefore, both the path coefficient and total effects suggested a significant effect of the use of DTs on EJS. The adjusted R-square value was 0.310, which suggested a small effect, and the *f*-square value was 0.460, indicating a large effect of the use of DTs on EJS. Thus, the use of DTs has a significant and relevant impact on EJS.

Likewise, the literature suggests that the use of DTs impacts EJS (Alshammary and Hilmi 2024; Brougham and Haar 2024; Miglioretti et al. 2021; Molino et al. 2020; Schmitt 2024). However, this impact can either be positive or negative. The implication of this positive and negative effect of the use of DTS on EJS requires optimal use of DTs to enhance EJS (Alshammary and Hilmi 2024; Brougham and Haar 2024; Miglioretti et al. 2021; Molino et al. 2020; Schmitt 2024). During strategic development, organizations must determine how the use of DTs would affect employees' well-being. Moreover, appropriate strategies must be implemented to guarantee the positive effect of the use of DTs on employees. These strategies must include training and support of employees on the use of DTs. Ultimately, the adoption and use of DTs must be employee-centered (Hartl and Hess 2017; Kraus et al. 2022; Oludapo et al. 2024; Sharma 2015; Sivaraman 2020; Tapia-Andino and Barcellos-Paula 2023; Thite 2018; Tuukkanen et al. 2022).

The Relationship between the Use of DTs and EOC

The hypothesis that there is a direct and positive relationship between the use of DTs and EOC was supported. The path coefficient was 0.137, and the *p*-value was 0.047. The total effect was 0.522, and the *p*-value was 0.000. Therefore, the path coefficient and total effects suggested a significant effect of the use of DTs on EOC. The adjusted R-square value was 0.591, which suggested a moderate effect, and the *f*-square value was 0.032, indicating a small effect of the use of DTs on EOC. Hence, the use of DTs has a significant and relevant impact on EOC.

Also, the literature has underlined the significant impact of the use of DTs on EOC (Chhabria and Yadav 2023; Hwang and Cha 2018; Kumar et al. 2013; Marchiori et al. 2020; Priya et al. 2022; Wang et al. 2020). DTs affect employees' jobs and their experiences. These experiences can either be positive or negative. Organizations must, therefore, guarantee the appropriate use of DTs for employees to commit to the organization. Thus, organizations must implement appropriate strategies that align the use of DTs with employees' attitudes. Specifically, employees must feel valued by the organization for effective commitment. Moreover, organizations must train and support employees on the appropriate use of DTs. It is when the adoption and use of DTs are employee-focused (Hartl and Hess 2017; Kraus et al. 2022; Oludapo et al. 2024; Sharma 2015; Sivaraman 2020; Tapia-Andino and Barcellos-Paula 2023; Thite 2018; Tuukkanen et al. 2022) that would guarantee a positive effect on employees.

The Relationship between EJS and EOC

The hypothesis that there is a direct and positive relationship between EJS and EOC was supported. The path coefficient was 0.687, and the *p*-value was 0.000. The total effect was 0.687, and the *p*-value was 0.000. Therefore, the path coefficient and total effects suggested a significant effect of EJS on EOC. The adjusted R-square value was 0.591, which suggested a moderate effect, and the *f*-square value was 0.801, indicating a large effect of EJS on EOC. Hence, EJS has a significant and relevant impact on EOC.

The literature on the relationship between EJS and EOC also suggested positive effects (Ahsan and Khalid 2024; Fu 2014; Fu and Deshpande 2014; Marchiori et al. 2020; Nelwan et al. 2024; Ngoc et al. 2024; Noor et al. 2024). Employees who are happy about their jobs are more committed to the organization (Ahsan and Khalid 2024; Fu 2014; Fu and Deshpande 2014; Marchiori et al. 2020; Nelwan et al. 2024). Thus, considering the substantial effect of EJS on EOC in this study, organizations must pay careful attention to EJS so that employees can commit to the organization. So, appropriate strategies are required to shape employees' attitudes positively.

The Relationship between EJS and EJP

The hypothesis that there is a direct and positive relationship between EJS and EJP was supported. The path coefficient was 0.575, and the *p*-value was 0.000. The total effect was 0.487, and the *p*-value was 0.000. Therefore, the path coefficient and total effects suggested a significant effect of EJS on EJP. The adjusted R-square value was 0.600, which suggested a moderate effect, and the *f*-square value was 0.321, indicating the moderate effect of EJS on EJP. Thus, EJS has a significant and relevant impact on EJP.

Research also has accentuated the essential role of EJS on EJP (Abdullah and Wan 2013; Anghelache 2014; Dhamija et al. 2019; Ekmekcioglu and Nabawanuka 2023; Indrayani et al. 2024; Inoyatova and Isakov 2022; Kim and De Dear 2013; Munir and Rahman 2016; Ngoc et al. 2024; Rojikinnor et al. 2022). This means that when employees feel happy about their jobs, their job performances improve (Ekmekcioglu and Nabawanuka 2023; Jalagat 2016; Vermeeren et al. 2014). These findings suggest that organizations must carefully consider EJS to guarantee improved EJP. So, appropriate strategies must be developed and implemented to ensure EJS. Organizations must focus on strategies that positively affect employees' well-being.

The Relationship between EOC and EJP

The hypothesis that there is a direct and positive relationship between EOC and EJP was not supported. Specifically, while the two variables had a direct relationship, the relationship was negative and insignificant. The path coefficient was -0.128, and the *p*-value was 0.114. The total effect was -0.128, and the *p*-value was 0.114. Therefore, the path coefficient and total effects suggested an insignificant effect of EOC on EJP. The adjusted R-square value was 0.600, which suggested a moderate effect, and the *f* square value was 0.017, indicating the small effect of EOC on EJP. Hence, EOC has an insignificant effect on EJP.

The literature suggested a relationship between EOC and EJP (Indrayani et al. 2024; Jaber et al. 2024; Thao et al. 2024; Wang et al. 2020). On one hand, EOC significantly impacts EJP (Indrayani et al. 2024; Jaber et al. 2024; Kundi et al. 2021; Potipiroon and Ford 2017; Sudha et al. 2023; Thao et al. 2024); on the other hand, EOC negatively impacts EJP (Lambert et al. 2017; Sinding and Waldstrom 2014). Therefore, results from the literature are contradictory. This study indicated a negative and direct insignificant impact of EOC on EJP. So, the study's results align with the literature that suggested a negative relationship between EOC and EJP. Moreover, the study results align with another research (Wolor et al. 2022), which resolved that EOC had an insignificant influence on EJP. Nevertheless, while EOC has an insignificant influence on EJP, it is still crucial due to its mediation function.

The Mediation Role of EJS

The hypothesis that EJS mediates the relationship between the use of DTs and EJP was supported. The direct effect of the use of DTs on EJP was significant. Moreover, the indirect effect was significant. Therefore, EJS provided complementary mediation on the relationship between the use of DTs and EJP. Similarly, EJS provided complementary mediation on the relationship between the use of DTs and EOC. This was because the direct and indirect effects were significant.

Similarly, literature has suggested that EJS mediates the relationship between DTs and EOC (Chhabria and Yadav 2023). Broady, EJS has been found to accomplish a mediation function (Tang et al. 2019). Therefore, while scant research suggested the mediation role of EJS, this study's findings further underline the importance of EJS. This means that any changes in the use of DTs affect EJS, which ultimately affects EOC and EJP, respectively. Particularly, since the mediation type of EJS was complementary, this underlines its foundational role in the nexus between the use of DTs, EJP, EOC, and EJP. Therefore, organizations must develop and implement appropriate strategies to warrant harmony between the use of DTs, EJS, EOC, and EJP.

The Mediation Role of EOC

The hypothesis that EOC mediates the relationship between the use of DTs and EJP was supported. The direct effect of the use of DTs on EJP was significant. However, the indirect effect was insignificant. Therefore, EOC provided an indirect-only full mediation on the relationship between the use of DTs and EJP. Similarly, EOC provided an indirect-only full mediation on the relationship between EJS and EJP. This was because the direct effect was significant, while the indirect effect was insignificant.

Equally, Li et al. (2021) indicated the mediation role of EOC on the relationship between DTs and EJP. Moreover, EOC has been found to accomplish a mediation function (Tang et al. 2019). Therefore, while no extensive research has been found that indicates the mediation role of EOC, this study's findings further underline the importance of EOC. This means that any changes in the use of DTs and EJS affect EOC, ultimately affecting EJP. While the direct relationship between EOC and EJP was insignificant in this study, the mediation role of EOC implies its crucial role in the nexus between the use of DTs, EJS, EOC, and EJP. Therefore, organizations must develop and implement appropriate strategies to warrant harmony between the use of DTs, EJS, EOC, and EJP. The overall findings require an integrative-balanced approach to guarantee the success of digital transformation initiatives.

Conclusion

The main purpose of this research was to understand the nexus between the use of DTs, EJS, EOC, and EJP and to develop a model for use by project-driven engineering organizations in South Africa. This main objective was achieved by investigating the direct and indirect relationships between the use of DTs, EJS, EOC, and EJP. Data analysis suggested a relationship between the use of DTs, EJS, EOC, and EJP. In other words, a nexus model was established between the use of DTs, EJS, EOC, and EJP. The use of DTs had a direct and positive effect on EJS, EOC, and EJP. While EJS directly and positively impacted ECO and EJP. However, EOC had a direct and negative insignificant relationship with EJP. Moreover, EJS performed a complementary mediation role in the relationship between the use of DTs and EJP and between the use of DTs and EOC. Meanwhile, EOC provided an indirect-only mediation on the relationship between the use of DTs and EJP and between EJS and EJP. Overall, these findings accentuate the need for DTs to align with employees to warrant success and achieve organizational objectives and goals.

Therefore, research must pay careful attention to the relationship between the use of DTs, EJS, EOC, and EJP, considering their significant direct and indirect relationships. Organizations must develop and implement appropriate strategies that guarantee alignment between DTs, EJS, EOC, and EJP to ensure the success of digital transformation programs. This underlines the need for employee-centered digital transformation initiatives. When employees are aligned with the adopted DTs, organizations will benefit positively from the use of DTs. While previous research has suggested the nexus, this study made an important contribution to the literature as it established a nexus between the use of DTs, EJS, EOC, and EJP. The study implies that policymakers must ensure that the adoption and use of DTs are employee-focused. This means that using DTs would affect employees' attitudes and behaviors, which must be embedded in digital transformation strategies for organizations to benefit from emerging disruptive DTs. This study was limited to only four project-driven engineering organizations within the public sector, which is a limitation. Therefore, it must be extended to other similar organizations within the private and public sectors to further assess the relevance of results to project-driven engineering organizations

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