**The Role of Task-Technology Fit In Determining Digital Transformation Fit: Moderating Effect of Job Signaling and IFRS Compliance**

**Abstract**

The purpose of the study is to investigate how task characteristics and technology characteristics impact task-technology fit and also explores the influence of task-technology fit on digital transformation fit examining the moderating effects of job signaling and International Financial Reporting Standards (IFRS) compliance in shaping these relationships. The study employed partial least squares structural equation modeling to assess both the direct and moderating effects, drawing data from a sample of 250 employees across diverse firms in Bangladesh. The study also utilized the IPMA (Importance-Performance Map Analysis) approach to identify key areas of significance and performance, thereby offering a comprehensive understanding of critical factors influencing digital transformation fit. The findings revealed a significant positive impact of technology characteristics on task-technology fit but task characteristics exhibit no significant effect on task-technology fit. The study also showed that task-technology fit has a positive impact on digital transformation fit and the moderating effects of job signaling and IFRS compliance are not statistically significant. The IPMA analysis demonstrated that job signaling a critical factor and organizations should take full advantage of it for enhancing digital transformation fit. Using a sophisticated theoretical framework, this study advances theoretical understanding in the area of digital transformation and provides valuable insight for businesses looking to make strategic decisions regarding their digital transformation fit.

**Keywords:** Task-Technology Fit, Digital Transformation Fit, Job Signaling and IFRS

**JEL Code:** M15, M41

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**Ethics:** Ethics has been followed in all spheres of this research, from data collection to reporting.

1. **INTRODUCTION**

Digital transformation fit refers to the alignment between an organization's resources and capabilities with the requirements of digital transformation initiatives. It involves ensuring that the organization has the necessary skills and capabilities to leverage digital technologies effectively (Al Ameri et al., 2022). The concept of digital transformation fit can be approached from different dimensions, including internal and external resource fit, as well as internal and external capability fit (Liu et al., 2011). Digital transformation can enable the execution of circular economy regulations and the adoption of circular business models, but also posing possible hazards and unforeseen repercussions (Barteková & Börkey, 2022). In the context of industrial companies, digital retrofitting is a strategy to enable digital transformation by integrating legacy systems into the digital transformation process (Tantscher & Mayer, 2022). Overall, digital transformation fit involves integrating digital techniques, competencies, and processes across all stages and functions of an organization to meet dynamic business and market requirements (Shalini & Devi, 2022). In practically every industry, digital transformation has been shown to be a unique strategic choice that may influence the development, value, and delivery of projects and products (Schindlwick, 2021). It enables organizations to quickly adjust, make wiser choices, and boost competitiveness in the digital age (Carroll et al., 2023). It involves creating new business methods or modifying existing ones to meet dynamic market requirements using digital technologies (Shalini & Devi, 2022). In a market where competition is fierce and ever-changing, many businesses are turning to digital transformation (DT) as a new strategy to obtain a competitive edge (X. Zhang et al., 2022).

Task-Technology Fit (TTF), which has been extensively used in various contexts, evaluates the link between technology and the tasks it supports (Spies et al., 2020). This suggests that when an information system has a good fit to the actions at hand, improvements to performance and utilization of the system can be realized (Furneaux, 2012). However, the concept of TTF remains limited in both theoretical validity and practical applicability (Gebauer & Ginsburg, 2009). Despite this, it has been demonstrated that TTF improves the efficiency of information systems. (Cane & McCarthy, 2009). TTF is influenced by the alignment of task characteristics and technology characteristics (Gebauer & Ginsburg, 2009). Task characteristics refer to the specific attributes or qualities of a task that can influence its outcomes or success (Shih & Chang, 2013). Technology characteristics are those particular features or aspects that set a technology opposed to other (Lawton, 2009). These characteristics can include factors such as the complexity, functionality, performance, and adaptability of the technology. A range of studies have explored the relationship between task and technology characteristics. Zhang et al., (2011)and Gaardboe et al., (2017) both propose models for this fit, with Zhang focusing on mobile work and Gaardboe on business intelligence. Serrano & Karahanna, (2016) highlight how the capabilities of technology and the user interact to compensate for each other when doing a particular task. Vörös et al., (2021) further delves into the impact of task characteristics on the correlation between task outcome and time-on-task in digital problem-solving. Task characteristics such as task identity, task relevance, task autonomy, task complexity, task interdependence, task non-routineness, diversity of abilities and feedback have been found to have a direct relationship with task fit in organizations (Zhu et al., 2021). These characteristics influence the compatibility between tasks and the use of technology or business intelligence (BI) within an organization (Gaadboe et al., 2017). Task-technology fit is significantly and favorably impacted by both technological characteristics and task characteristics (Ratna et al., 2018). This fit is crucial for team performance, with initial fit predicting performance but teams innovating and adapting over time (Fuller & Dennis, 2009). From the standpoint of Bangladesh, it is unclear how task characteristics and technology characteristics affect task-technology fit.

In the subject of information systems, TTF has been thoroughly researched and has been found to have positive effects on individuals' perceptions, intentions, behaviors, and performance related to technology use (Etinger, 2023). When utilizing digital technology to assist work, the combinations of activities, tools, and usage habits can either help achieve good consequences or cause negative ones (Mikalef et al., 2019). Technological factors promote the success of SMEs' digital transformations (X. Zhang et al., 2022). However, specifically, the impact of task-technology fit on digital transformation fit is not clear in the literature.

Job signaling is a process in labor markets where Potential workers use their academic credentials to tell companies about their productivity. This information is valuable to both parties, as it indicates job skills and productivity for the employer and enhances the possibility that the individual may find work at a higher wage (Jeong, 2019). In job signaling model, competition among employers and workers plays a crucial role. Stronger competition among employers intensifies competition between workers, leading to increased investment in costly education by workers (Ge & Haller, 2018). IFRS compliance refers to the adherence of companies to the International Financial Reporting Standards (IFRS) in their financial reporting (Kabwe et al., 2021). These standards provide guidelines on how events and activities related to accounting should be represented in the financial statements in order to preserve the financial industry's credibility and transparency. IFRS compliance requires significant changes in organizational information systems (Peslak, 2012). However, the potential moderating effect of job signaling and IFRS compliance is not clear in context of digital transformation fit.

Digital transformation in Bangladesh has been a significant focus across various sectors (Islam, 2023). The emergence of a digital culture in Bangladesh, while offering benefits such as time and cost savings, also presents challenges, as noted by Hussain, (2015). The absence of research on digital transformation from a business perspective is a gap in Bangladesh (Hausberg et al., 2019). In the context of Bangladesh, it is significant to conduct comprehensive study on digital transformation fit.

To address the gap regarding digital transformation fit in the literature, this study aims to comprehensively examine the impact of task characteristics and technology characteristics on task-technology fit as well as the influence task-technology fit on digital transformation fit within the context of Bangladesh, with a specific focus on exploring the moderating effects of job signaling and IFRS compliance.

The study provides a great deal to the theoretical understanding of digital transformation and information systems. By highlighting the critical roles that task characteristics, job signaling, task-technology fit, and technology characteristics play in the success of digital transformation initiatives, it enhances current frameworks. Notably, it advocates for putting flexible and aligned technologies initially and promotes a technological determinism approach by highlighting the impact of technology characteristics on task-technology fit. The results also challenge long-held beliefs about the nature of tasks, pointing to the need for theoretical models to be expanded to account for the complexity of task-related elements in organizational transformation. In order to improve task-technology fit, companies are urged to strategically invest in technology, giving flexibility and employee training first priority. The study emphasizes the importance of job signaling, arguing that making employees aware of the aims of the digital transformation may increase motivation and engagement, which in turn can lead to a more effective and meaningful digital transformation that is in line with organizational goals.

The use of Signaling Theory (Connelly et al., 2011), Compliance Theory (Mitchell, 2014), and Task-Technology Fit Theory (Goodhue & Thompson, 1995) in this study adds to a strong theoretical foundation for understanding Digital Transformation (DT) fit. The study examines how well technology characteristics and task characteristics align, with a focus on the significance of technological aspects, using the framework of task-technology fit theory. By emphasizing the function of job signaling in promoting congruence with digital transformation objectives, Signaling Theory contributes depth and illuminates the communication elements of organizational change. Furthermore, Compliance Theory presents a regulatory viewpoint and provides insights into how IFRS Compliance moderates the relationship between Task-Technology Fit and Digital Transformation Fit. This comprehensive theoretical framework contributes to our knowledge of the dynamics of digital transformation and makes it easier to explore all the different aspects that affect how well digital initiatives are implemented in organizational settings.

This is the study's organizational framework. The literature review and the formulation of hypotheses are covered in Section 2, which comes after Section 1. After that, the research method is presented in Section 3. The analysis of the data and the findings' presentation are covered in Section 4. Section 5 contains a discussion of the findings. Sections 6 and 7 discuss the implications, limitations, and recommendations for further study. Section 8 provides the last coverage of the conclusion.

1. **LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT**

**2.1 Task characteristics and Task-Technology Fit**

The concept of Task-Technology Fit (TTF) has been widely researched in the field of information systems (IS) over the past few decades (Furneaux, 2012). TTF is the measure of how well a technology facilitates the tasks that people or organizations carry out (Tripathi & Jigeesh, 2015). One of the key determinants of TTF is task characteristics, such as task equivocality, task dependency, quality, location, authorization, compatibility, production timeliness, system dependability, and simplicity of use (Goodhue & Thompson, 1995). Goodhue & Thompson, (1995) proposed that TTF is influenced by three factors: task characteristics, technology characteristics, and individual differences. The study found that task characteristics in the context of mobile banking have a favorable and considerable impact on task technology fit (Mishra, 2023). Gupta et al., (2023) also reported the same result. Another study showed that the suitability of task technology fit is not significantly impacted by task characteristics (Putri et al., 2022). According to Ratna et al., (2018), TTF is significantly and favorably influenced by task characteristics; in the context of hotels, this means that greater task characteristics cause stronger task-technology fit. In engineering students studying in the Philippines during the COVID-19 epidemic, task characteristics exhibited a favorable effect on task-technology fit (Navarro et al., 2021). Venkatesh & Davis, (1996) found that the perceived ease of use of a technology, which is another important factor influencing TTF, was positively correlated with task characteristics. The following hypothesis can be made in light of the literature review:

H1: There is a significant effect of Task Characteristics (TC) on Task-Technology Fit.

**2.2 Technology characteristics and Task-Technology Fit**

Indirect signs of technology's impact on flexibility include response times, business process owners' and technology maintenance organizations' communication styles, and how change requests are managed (Nelson & Ghods, 1998). Nelson et al., (1997) provide a process for evaluating and investigating the adaptability of new technology. Businesses need to provide generally marketable technologies in order to remain as specialized traders. Hicks & Hegde, (2005) make the following assumptions about such technology using Arora, Fosfuri, and Gambardella's markets-for-technology framework. The results found that there is a positive but insignificant effect of technology characteristics on task-technology fit (Gupta et al., 2023; Mishra, 2023). Putri et al., (2022) revealed that technology characteristics have a significant effect on the suitability of the task-technology fit. Another research suggested that in the context of hotels, technology characteristics have a considerable and favorable impact on task-technology fit, i.e., greater technology characteristics contribute to improved TTF (Ratna et al., 2018). Following the justifications, the following hypothesis is suggested:

H2: There is a significant effect of Technology Characteristics on Task-Technology Fit.

**2.3 Task-Technology Fit and Digital Transformation Fit**

Digital transformation fit, on the other hand, is a concept that relates to the fit between digital technologies and the tasks they are intended to support (Rai & Selnes, 2019). It involves understanding how digital technologies, such as digital media and big data analytics (BDA), align with and enhance task performance and business value (Jeyaraj, 2022). While TTF has primarily focused on traditional IT, recent research has extended the concept to include digital technologies like BDA and digital media (Al-Rahmi et al., 2023; Howard & Hair, 2023). The degree to which a technology is integrated with a collection of related activities necessary to achieve the behavior's objective when the technology is employed is referred to as task-technology fit (Rai & Selnes, 2019). Omotayo & Haliru, (2020) determined the factors influencing students' usage of digital libraries by examining the task-technology fit of these resources in three Nigerian universities. The study showed that the independent factors (The outcome, computer self-efficacy, task-technology fit, and technological characteristics) and usage of digital libraries were shown to have a significant association and a somewhat favorable correlation. According to TTF theory, digital technologies have a greater chance of having a beneficial effect when the functions they offer match the tasks that people need to do (Mikalef et al., 2019). Since its introduction, the idea has been expanded upon in a number of ways. The most recent research has acknowledged that the way people use these technologies have a major influence on the performance of technology utilization, in addition to the design and training protocols around adoption and dissemination (Aljukhadar et al., 2014). Based on the literature, the given hypothesis is suggested:

H3: There is a significant effect of Task-Technology Fit on Digital Transformation Fit.

**2.4 Job signaling as moderator**

Despite ensuring the task-technology fit, some variables may influence the ultimate DT fit. One of them is job signaling. Bobsin et al., (2015) and Shi et al., (2023) both highlight the importance of individual-task-technology fit in the context of digital transformation. Shi et al., (2023) introduces the concept of digital job crafting, which can enhance this fit and improve job performance. Bobsin et al., (2015) found that managerial work determinants, such as experience and frequency of IT use, can influence the perception of task-technology fit. Alyoubi & Yamin, (2019) extends this by showing that task-technology fit has a major influence on job performance and employee desire to embrace technology. Mikalef et al., (2019) further explores the role of task-technology fit in manufacturing, emphasizing the need for alignment between technology and human factors. This transformation has created both opportunities and challenges for workers, with the emergence of new job opportunities and diverse forms of employment (Doan & Nguyen, 2023). In the context of digital transformation, leadership competencies such as collaboration, strategic thinking, and customer orientation are crucial, with technical skills playing a secondary role (Gilli et al., 2023).

H4: There is a significant moderating effect of job signaling between Digital Transformation Fit and Task-Technology Fit.

**2.5 IFRS compliance as moderator**

Most of the economies of the world have already adopted the IFRS for their reporting system (Daske et al., 2008). Accounting reporting is becoming increasingly digital due to the development of modern information systems and technologies (Spilnyk et al., 2020). Accounting technique and practice have undergone major changes as a result of the usage of contactless identification, blockchain technology, and the internet (A. A. et al., 2022). Many businesses now require digital transformation, when before it was voluntary. This has created a number of issues, including poor performance improvement and inadequate transformational durability (Shi et al., 2023). Horton et al., (2013) and Jones & Finley, (2011) show why IFRS compliance has advantages, including improved information quality and reduced financial reporting diversity. ERP installation project performance may be enhanced by a company's application of effective IT governance (Tsai et al., 2015). In with the literature, the following hypothesis is suggested:

H5: There is a significant moderating of IFRS Compliance between Digital Transformation Fit and Task-Technology Fit is significant.



**Figure 1: Conceptual framework**

1. **RESEARCH METHODOLOGY**

**3.1 Ethical Approval**

The Center for Modern Information Management, Huazhong University of Science and Technology, Wuhan, China, granted ethical approval (No: CMIN2020B003) for this work.

**3.2 Survey Instrument**

To make the survey items more suited for the study, they were somewhat adjusted from earlier research. The survey questionnaire is divided into two sections, specifically: demographic details and items construction information (Quality- **five items**, Location- **four items**, Authorization- **one item**, Compatibility-**three items**, Production Timeliness**-two items**, Systems Reliability- **two items**, Ease of Use/Training- **four items**, Relationship with users- **three items**, Task Equivocality- **three items**, Task Interdependence- **two items** , Task-Technology Fit**- two items**, Job Signaling- **five items**, IFRS compliance- **three items**, Digital Transformation Fit- **two items**). Using a back-translation approach, the English version of the questionnaire was transformed into Bengali to guarantee equal message (Brislin, 1970). Two specialists in business informatics are thoroughly reviewing and approving the Bengali version of the survey. A seven-point Likert scale was used to rate the items, with 1 denoting strongly disagree and 7 denoting strongly agree. The pretest findings demonstrated that there were no problems with the Bengali questionnaire's phrasing or understandability and it was successfully completed.

**3.3 Participants and Procedure**

The professionals working for **different organizations in Bangladesh** were the population unit considered in this study. A variety of demographics (e.g., education, age) were represented in the sample. The research population, or professionals in business enterprises, was taken into consideration while determining the sample size. Nonetheless, a total of 250 respondents from offline and online sources were employed in this study. Only one response from a single respondent was permitted in order to guard against any sampling bias.

Both online and offline channels were used to gather survey data. The survey was conducted in two steps, the first of which involved giving consent to participate and outlining the purpose of the study. We employed convenience sampling techniques to guarantee the ideal sample size, even though random sampling is the best way to obtain data. First, the website was shared on a number of social networking sites (Facebook, LinkedIn, etc.). Subsequent examination revealed that the sample response was inadequate to yield significant insights, and it remained uncertain if the research was voluntary. As a result, we made the decision to send 600 business professionals questionnaires. To gather data, ten knowledgeable, competent, impartial, and independent interviewers with at least three years of surveying expertise were hired. There were 254 answers in all, from sources that are both offline and online. Based on Mahalanobis distance, due to guarantee correct information to identify influential spots, the dataset was scrutinized and carefully examined (J. F. Hair et al., 2010). Consequently, the suggested integrated research model was assessed using 250 valid replies.

**3.4 Analyzing Procedures**

To evaluate the validity and reliability of the instruments, we used SmartPLS-4 to perform Structural Equation Modeling (SEM). SEM studies were then carried out to investigate the suggested theories. A tried-and-true technique in management research for predicting complex cause-and-effect connection models is PLS path modeling (Gudergan et al., 2008). For PLS-SEM analysis, complex models with plenty of variables, indicators, and structural connections work effectively (Hair et al., 2016). When developing and testing theories at an early stage, PLS-SEM is particularly useful since it makes it easier to examine the interactions and components in complex structural models (Hair et al., 2016). In light of the little-known relationship between task-technology fit and digital transformation fit, this is especially relevant. Because it doesn't make any assumptions about the distribution of the data and can function effectively with smaller sample numbers, PLS-SEM has several advantages (Hair et al., 2016). Having a sample size that is at least 10 times the number of arrows pointing to a specific construct is advised when using PLS-SEM (Hair et al., 2016). In our study, there are fourteen arrows pointing at the constructions, and the sample size is 250, which is significantly more than what is recommended.

Recently, IPMA has been used in together with PLS-SEM, providing researchers with a way to analyze their data and extract more accurate and nuanced conclusions. According to Ringle & Sarstedt, (2016), this technique takes into account the average values of latent variable scores as well as the estimations of path coefficients concurrently. We have been able to supplement traditional PLS-SEM results with insightful information that may help direct managerial choices due to the collaborative evaluation of the importance and performance of these variables (Hair et al., 2018).

The IPMA's final output is a graph in which each attribute's performance is shown on the y-axis and its relevance is shown on the x-axis. To be more precise, the performance latent variable is the outcome of rescaling the average scores of each attribute on a scale from 0 to 100, where 100 represents the highest performance level and 0 the lowest. A vertical line that represents the mean significance value and a horizontal line that indicates the mean performance value are added to the map to improve interpretability and split it into four quadrants. As a result, every feature is placed in a particular quadrant that is defined by a certain mix of performance (low or high) and importance (high or low) levels (Hair et al., 2018).

**3.5 Demographic Information**

Majority of the respondents are male (90.4%), while only 9.6% are female. Nearly 50% of those surveyed fall under the age group of 30-40 years (48.4%), followed by 40+ years (30.4%), 18-30 years (19.2%), and below 18 years (2%). Majority of the respondents have a Master's degree (73.6%), followed by other (12.4%), Bachelor's degree (8.8%), and PhD (5.2%). IT Expert is the most common profession among the respondents (33.2%), followed by Accountant (20.4%), Manager (13.2%), and Financial Officer (12.4%). None is the most common answer (59.2%), followed by CA (13.6%), other (11.6%), CCMA (4.4%), and others.

**Table 1: Demographic Attributes**

|  |  |  |  |
| --- | --- | --- | --- |
| **Attributes** | **Criteria** | **Frequency** | **Percentage** |
| Gender | Male | 226 | 90.4 |
| Female | 24 | 9.6 |
| Education level | PhD | 13 | 5.2 |
| Master | 184 | 73.6 |
| Bachelor | 22 | 8.8 |
| Other | 31 | 12.4 |
| Profession | Accountant | 51 | 20.4 |
| Marketer | 30 | 12 |
| Manager | 33 | 13.2 |
| Financial Officer | 31 | 12.4 |
| IT expert | 83 | 33.2 |
| Economist | 7 | 2.8 |
| Statistician | 5 | 2 |
| Other | 10 | 4 |
| Professional degree | CA | 34 | 13.6 |
| CCMA | 11 | 4.4 |
| ACCA | 3 | 1.2 |
| CIMA | 2 | 0.8 |
| SUN certificate | 5 | 2 |
| Google Certificate | 7 | 2.8 |
| Java Certificate | 7 | 2.8 |
| Data Analyst Certificate | 4 | 1.6 |
| Other | 29 | 11.6 |
| None | 148 | 59.2 |
| Age | 40+ | 76 | 30.4 |
| 30-40 years | 121 | 48.4 |
| 18-30 years | 48 | 19.2 |
| Below 18 years | 5 | 2 |
| Firm industry |  |  | Various |

1. **DATA ANALYSIS AND RESULTS**

**4.1 Normality Test**

Utilizing the skewness-kurtosis method, we have determined each variable's univariate normality (Hair et al., 2010). The acceptable range for the normalcy of univariate distributions is achieved by all skewness values, as indicated in Appendix A, being between -2 and + 2, and all kurtosis values, between -7 and + 7 (Abdollahi et al., 2015).

**4.2 Common Method Bias (CMB)**

We have to exclude the possibility that CMB may have compromised the validity of our results because all of our assessment scales were self-reported. Using all fourteen constructs, Harman's single-factor has been employed to make guarantee the data obtained are free of CMB (Podsakoff et al., 2003). One factor was created by combining the fourteen constructions. The examination found that, compared to the recommended threshold of 50%, the single component only explained 30.19% of the variation (Podsakoff et al., 2003), suggesting that this study did not provide any CMB evidence.

**4.3 Evaluating measurement model**

To determine the validity and reliability of the constructs, the measurement model was evaluated. First of all, every item in the model has factor loadings (see Appendix A) with values higher than the minimal acceptable value of 0.50 (Hair et al., 2010). In social science studies, researchers often find smaller outer loadings (<0.70), even though factor loading of 0.7 is desirable (Vinzi et al., 2010). Rather than just removing indications at random, the impact of removing the item on convergent validity, content, and composite reliability will be investigated. Items having outer loadings between 0.40 and 0.70 typically are only removable if doing so increases the average variance extracted (AVE) or composite reliability above the range that is recommended (Hair et al., 2016). Because the construct values in the current study were already over the suggested level, the removal of the item (TTF2=0.655) would not have significantly increased the composite reliability and AVE. Additionally, analysis of the present's confidence range for the loadings showed that none of the outside loadings for the items included a zero. As a result, no study item was excluded from additional examination. A measure of multi-collinearity between the metrics is the VIF. Elevated variance indices may suggest that the measurements are same or redundant. Every VIF measurement in the research (see Appendix 1) is below the suggested threshold 5 (Hair et al., 2016).

To evaluate reliability, Cronbach's alpha, rho\_a, and composite reliability were employed (see Table 2); figures for both Cronbach's alpha and composite reliability are above the suggested threshold of 0.700 (Wasko & Faraj, 2005). According to Sarstedt et al., (2021), the rho\_a number obtained fell between Cronbach's alpha and composite dependability. It was also found to be over 0.70, suggesting strong reliability (Henseler et al., 2016). Given that the AVE was greater than 0.500, convergent validity was found reasonable. Two methods are used to confirm the discriminant validity, which measures how much one construct differs from the other experimentally. One way is by Fornell & Larcker, (1981), where the square root of the AVE is greater than the correlation's diagonal inter-construc (see Table 3). Henseler et al., (2015) propose the Heterotrait–Monotrait ratio of correlation (HTMT), which is the most recent method for evaluating discriminant validity. As seen in Table 4, the values between the constructs are less than 0.9, indicating a more liberal approach. Discriminant validity is thus proven.

**Table 2: Reliability and validity analysis**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Cronbach's Alpha | rho\_A | Composite Reliability | Average Variance Extracted |
| Digital Transformation Fit | 0.894 | 0.920 | 0.949 | 0.904 |
| IFRS Compliance | 0.807 | 0.927 | 0.884 | 0.718 |
| Job Signaling | 0.864 | 0.873 | 0.902 | 0.648 |
| Task Characteristics | 0.938 | 0.957 | 0.944 | 0.569 |
| Task-Technology Fit | 0.752 | 0.947 | 0.776 | 0.561 |
| Technology Characteristics | 0.758 | 0.833 | 0.839 | 0.510 |

**Table 3: Fornell-Larcker Criterion**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Construct | DTF | IFRSC | JS | TC | TTF | TEC |
| DTF | 0.951 |  |  |  |  |  |
| IFRSC | -0.051 | 0.847 |  |  |  |  |
| JS | 0.608 | -0.069 | 0.805 |  |  |  |
| TC | 0.006 | -0.002 | -0.017 | 0.608 |  |  |
| TTF | 0.475 | -0.058 | 0.585 | -0.045 | 0.749 |  |
| TEC | 0.617 | -0.031 | 0.499 | 0.041 | 0.372 | 0.707 |

Abbreviations: Digital Transformation Fit (DTF); IFRS Compliance (IFRSC); Job Signaling (JS); Task Characteristics (TC); Task-Technology Fit (TTF); Technology Characteristics (TEC)

**Table 4: Heterotrait-Monotrait ratio (HTMT)**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Construct | DTF | | IFRSC | | JS | | TC | | TTF | |
| DTF | |  |  | |  | |  | |  | |
| IFRSC | | 0.055 |  | |  | |  | |  | |
| JS | | 0.675 | 0.097 | |  | |  | |  | |
| TC | | 0.073 | 0.077 | | 0.113 | |  | |  | |
| TTF | | 0.553 | 0.16 | | 0.689 | | 0.135 | |  | |
| TEC | | 0.744 | 0.118 | | 0.606 | | 0.138 | | 0.682 | |

Abbreviations: Digital Transformation Fit (DTF); IFRS Compliance (IFRSC); Job Signaling (JS); Task Characteristics (TC); Task-Technology Fit (TTF)

**4.4 Structural Model**

The structural model reflects the pathways that the research framework suggests. The significance of paths, R2, and Q2 are used to evaluate structural models (see Table 6). R2 value for the dependent variable (Briones Penalver et al., 2018) indicates the strength of each structural path and indicates how strong the model is; the value of R2 should be more than or equal to 0.1 (Falk & Miller, 1992). All R2 values are more than 0.1, as indicated by the data in Table 6. Thus, it is demonstrated that the predictive capability. Q2 also proves that the endogenous constructs have predictive relevance. In the event that the Q2 exceeds zero, the model has predictive relevance. Table 6 displays the results, which indicate that the constructs' predictions are significant. The standardized root mean square residual was also used to evaluate the model fit. In order to prevent model misspecification, SRMR values should typically range from 0.08 to 0.10 (Hu & Bentler, 1998). Our model's SRMR score of 0.081 indicates a good fit (see Table 6).

The study performed an assessment of the goodness of fit and tested hypotheses to determine the significance of the relationship (see Table 5). The first hypothesis (H1) tests whether Task Characteristics has a significant impact on Task-Technology Fit. However, the results showed that Task Characteristics do not have a significant impact on Task-Technology Fit (β = -0.060, t = 1.100, p = 0.272). So, H1 was not supported. On the other hand, the second hypothesis (H2) also tests whether Technology Characteristics has a significant impact on Task-Technology Fit, and the results showed that it has significant impact (β = 0.374, t = 6.395, p < .000), thus supporting H2. The finding showed that Technology Characteristics has a significant impact on Task-Technology Fit (β = 0.374, t = 6.395, p < .000) supporting H2. The results showed that Task-Technology Fit has a significant impact of on Digital Transformation Fit (β = 0.179, t = 2.485, p = .013), supporting H3.

The study generated 95% confidence intervals through 5,000 resamples, which are presented in Table 5. If the confidence interval is different from zero, it indicates a significant relationship. The results of the hypotheses testing are summarized in Table 5.

**Table 5: Path Analysis**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Hypothesis** | **β** | **T**  **Statistics** | **P Values** | **Confidence Interval** | | **Supported** |
| **2.5%** | **97.5%** |
| H1: Task Characteristics -> Task-Technology Fit | -0.060 | 1.100 | 0.272 | -0.164 | 0.049 | No |
| H2: Technology Characteristics -> Task-Technology Fit | 0.374 | 6.395 | 0.000 | 0.252 | 0.478 | Yes |
| H3: Task-Technology Fit -> Digital Transformation Fit | 0.179 | 2.485 | 0.013 | 0.043 | 0.318 | Yes |
| H4: TTF\*JS -> Digital Transformation Fit | 0.032 | 0.598 | 0.550 | -0.068 | 0.137 | No |
| H5: TTF\*IFRSC -> Digital Transformation Fit | 0.079 | 1.132 | 0.258 | 0.230 | 0.093 | No |

Abbreviations: IFRS Compliance (IFRSC); Job Signaling (JS); Task-Technology Fit (TTF)

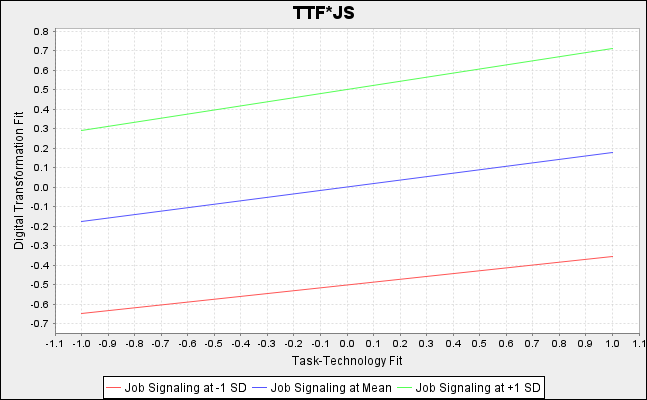
**Table 6: Assessment of structural model**

|  |  |  |
| --- | --- | --- |
| **Construct** | **R-Square** | **Q-Square** |
| Task-Technology Fit | 0.142 | 0.055 |
| Digital Transformation Fit | 0.398 | 0.338 |
| **Estimated model** |  |  |
| SRMR (<.10) 0.081 |  |  |

**Figure 2: Path Analysis**

**4.5 Moderating Effects**

To examine the moderating effects of Job Signaling and IFRS Compliance, this research used the product-indicator method (Chin, 1998) through PLS-SEM. This method involves multiplying the items of the endogenous factors and the moderator factor by two sets of items each. By doing so, the multiplied items represent the component of latent interaction (Henseler & Fassott, 2010). The study also revealed that JS (β = 0.032, t = .598, p= 0.550) and IFRSC (β = 0.079, t = 1.132, p= 0.258) have no statistically significant moderating effect between Task-Technology Fit and Digital Transformation Fit (see Table 5, Figure 3,4). So, H4 and H5 were not supported.



**Figure 3: Slope Analysis for Moderator (TTF\*JS)**

**Chart, line chart

Description automatically generated**

**Figure 4: Slope Analysis for Moderator (TTF\*IFRS)**

**4.6 Importance-Performance Map Analysis (IPMA)**

Through the use of the Importance-Performance Map Analysis (IPMA) approach, this study seeks to improve comprehension of the critical elements that lead to DTF success following a PLS-SEM model analysis. IPMA aims to discover the construct that may significantly affect the endogenous construct and has a lower average latent variable score.. The method used for IPMA measurement follows the approach outlined by Pisitsankkhakarn & Vassanadumrongdee, (2020). The results presented in Table 7 and Figure 5 demonstrate the effectiveness of DTF, which is influenced by factors such as IFRS Compliance, Job Signaling, Task Characteristics, Task-Technology Fit, and Technology Characteristics.

**Table 7: Importance-Performance Map Analysis for Digital Transformation Fit**

|  |  |  |
| --- | --- | --- |
| **Construct** | **Importance** | **Performance** |
| IFRS Compliance | 0.005 | 83.816 |
| Job Signaling | 0.494 | 68.766 |
| Task Characteristics | -0.011 | 65.648 |
| Task-Technology Fit | 0.181 | 58.852 |
| Technology Characteristics | 0.068 | 75.734 |

Looking at the results, we can see that Job Signaling is the most important construct for digital transformation fit, with a score of 0.494. However, the organization's performance on this construct is only 68.766, which is below average. Technology Characteristics also have relatively high importance (0.068) but the performance is high (75.734). On the other hand, Task Characteristics have negative importance (-0.011), indicating that they are not very important for the adoption of digital transformation. However, the organization is performing relatively well on this construct, with a score of 65.648. IFRS Compliance has very low importance (0.005), but the organization is performing exceptionally well on this construct, with a score of 83.816. Finally, Task-Technology Fit has moderate importance (0.181) and moderate performance (58.852), indicating that this construct may be an area for improvement.

Chart, scatter chart

Description automatically generated

**Figure 5: Important-performance map**

1. **DISCUSSION**

The study found that Task Characteristics do not significantly influence Task-Technology Fit. This suggests that specific task attributes may not be pivotal in determining the alignment between tasks and technology. The finding supports the study of Putri et al., (2022) who also found insignificant influence of Task Characteristics on Task-Technology Fit based on the study of academic information systems. The results of this study suggest that technology characteristics have a beneficial effect on task-technology fit. This implies that a technology's ability to meet the requirements of a given task is greatly influenced by its characteristics and properties. The result emphasizes how crucial technology-related elements are to improving the match between activities and the used technology. A deliberate focus on technological features can help organizations maximize task-technology alignment and promote effectiveness and efficiency. The results are in line with the work of Putri et al., (2022), Gupta et al., (2023) and Ratna et al., (2018) who also found same relation. The study found that Task-Technology Fit has a significant beneficial impact on Digital Transformation Fit. This suggests that there is a resultant improvement in the larger context of digital transformation outcome when tasks and technology are properly linked. The findings are support the relevant study of Aljukhadar et al., (2014) and Omotayo & Haliru, (2020).The conclusion highlights how crucial task-technology synergy is to the promotion and implementation of successful digital transformation efforts. Results from the analysis of the moderating effects of IFRS Compliance and Job Signaling in the association between Task-Technology Fit and Digital Transformation Fit were not statistically significant. The results suggest that these moderating factors' effects could not have a significant influence on how the connection is shaped overall. The research findings concerning the moderating effect of Job Signaling and IFRS Compliance contribute to the literature by clearing its insignificant moderating effects on Digital Transformation Fit.

The findings of IPMA approach provide fascinating new perspectives on the variables influencing how well an organization's digital transformation fits in. This study using IPMA as a first revealed that Job Signaling is a critical factor, indicating that it is essential for promoting alignment with goals of digital transformation fit. But the below-average performance raises questions and indicates that the company may not be taking full advantage of Job Signaling. Addressing this gap could greatly improve the organization's preparation for the shift to digital transformation. Technology characteristics that are associated with high performance indicate how well an organization has adapted its technical resources to the demands of the digital revolution. This shows that the strategic integration of technology has been done in a remarkable manner. There may be a mismatch between the perceived significance and the actual influence on the adoption of digital transformation, since task characteristics are surprisingly viewed as less important and have a negative importance-performance correlation. While the organization does a good job in this area, there is room for improvement in terms of task-related aspects' strategic inclusion and relevance. It is necessary to investigate the surprising positive link further in light of the contradiction of low relevance yet extraordinary achievement in IFRS Compliance. Gaining an understanding of the factors influencing this performance will help you better understand how to use compliance activities to achieve wider success in digital transformation.

Positioned with intermediate priority and performance, Task-Technology Fit indicates a balanced yet adjustable condition. Optimizing the fit of the digital transformation might potentially be achieved by improving the synergy between tasks and technology. To strengthen the organization's overall digital transformation fit, these findings based on IPMA approach give actionable options and urge a deliberate reconsideration of Task Characteristics, Job Signaling, and Task-Technology Fit.

1. **IMPLICATIONS**

**6.1 Theoretical implication**

The study's theoretical implications provide a substantial contribution to the body of knowledge on information systems and digital transformation. The results provide subtle insights and expand on the theoretical frameworks that are already in use in these domains. The study's theoretical implications offer important insights into how the dynamics of digital transformation integrate into organizational settings. The findings demonstrate how many elements interact and emphasize the importance of task characteristics, task-technology fit, job signaling, and technology characteristics in determining how well digital transformation projects are implemented.

In the domain of information systems, the technological determinism perspective is supported by the favorable effect of technology characteristics on task-technology fit. This emphasizes that the intrinsic properties of technology greatly influence how well it meets task requirements. The theoretical conclusion here is that technology with certain features that improve its flexibility and alignment with the activities at hand should be deliberately prioritized by companies. This emphasizes how crucial it is to include technological factors in theoretical models of digital transformation.

Furthermore, in the body of literature on digital transformation, the study's implications about the beneficial effects of task-technology fit on digital transformation fit has a role in the ideas that direct organizational development. According to theoretical ramifications, a purposeful concentration on maximizing the fit between tasks and technology is essential to the success of the digital transformation as a whole. By emphasizing the critical importance of task-technology synergy, this contributes to the expanding library of literature on digital transformation.

Our knowledge of moderating factors in digital transformation contexts is being furthered by the non-significant moderating effects of IFRS Compliance and Job Signaling on the link between Task-Technology Fit and Digital Transformation Fit. Theoretically, this means that the overall connection may not be significantly shaped by these particular moderating variables. Moreover, the paradoxical character of Task Characteristics—that is, its efficacy despite being deemed less important—challenges theoretical presumptions about the impact of certain task characteristics on digital transformation. Theoretically, this means that variables other than the traditional weights given to certain job characteristics may determine an organization's preparation for and success in the digital transition. It is necessary to broaden the scope of theories on digital transformation to include the complex nature of task-related components and their function in organizational change.

Finally, the theoretical implications of these findings aid in the improvement and enlargement of current theories regarding digital transformation.

**6.2 Practical implication**

For organizations attempting to optimize their suitability for digital transformation, the findings from the research have several practical implications. Organizations ought to prioritize technology-related aspects in order to enhance the coherence between their operations and the technology they employ. In order to fulfill the demands of the digital revolution, businesses must strategically integrate technology resources, as the study emphasizes the critical role that technological characteristics play in establishing task-technology fit.

For example, companies might spend money on technology that can adjust to various jobs and workflows. This might entail updating current software systems to better meet work needs or putting automation technologies into place to expedite repetitive processes. Ensuring that employees are properly taught and prepared to use new technologies is also essential, as this may enhance task-technology fit and the success of the digital transformation as a whole.

Furthermore, the research indicates that job signaling plays a crucial role in fostering congruence with the objectives of digital transformation. Employers may take advantage of this by explaining to staff employees the significance of digital transformation objectives and giving them the tools and assistance they need to meet these objectives. Employee motivation and engagement may increase as a result of knowing how their job fits into the organization's larger efforts to undergo digital transformation.

As a whole, the findings of this research advise firms to concentrate on enhancing the way tasks and technology work together, which may be done by maximizing how well the digital transformation fits into their business. Organizations may attain a more purposeful and efficient digital transformation that serves their objectives by giving priority to technology-related components, job signaling, and task characteristics. The capacity of an organization to remain competitive in the rapidly changing digital market can be aided by increased productivity, efficiency, and overall performance.

1. **LIMITATION AND FUTURE RESEARCH DIRECTIONS**

There are a number of limitations to the study that can motivate further investigation. Firstly, the study was carried out in Bangladesh, which restricts how broadly the findings can be applied. To confirm the results, the study should be repeated in other nations in future research. Second, an important aspect that may have been missed in the study was the effect that organizational culture and leadership had on the success fit of digital transformation. Thirdly, future research should incorporate other factors like the working environment and culture to increase the recommended model's explanatory ability. Finally, because of data restrictions, the study's sample size was quite limited. Larger sample sizes in future studies may yield more reliable findings. Overall, there is a need for further research to address these limitations and extend our understanding of digital transformation success.

1. **CONCLUSION**

The findings of the study highlighted a significant positive impact of technology characteristics on task-technology fit, while indicating that task characteristics do not exhibit a statistically significant effect on task-technology fit. The study showed that task-technology fit positively influences digital transformation fit. Furthermore, the moderating effect of job signaling and IFRS compliance on digital transformation fit is not statistically significant. These results further emphasize the importance of technology characteristics and the synergy between tasks and technology in achieving successful digital transformation outcomes. While job signaling is identified as a critical factor based on IPMA, the results suggest that there is room for improvement in this area. Organizations should optimize task-technology fit by considering task and technology characteristics to achieve maximum efficiency and effectiveness. These findings provide valuable insights for organizations seeking to enhance their digital transformation fit and succeed in the digital revolution.

**Appendix A: Weights and measures of the construct loading development outcomes**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Items | Outer Loading | T Statistics | P Value | Confidence Interval | | VIF | SD | Kurtosis | Skewness |
| 2.50% | 97.50% |
| Aut1 | 0.915 | 58.231 | 0.000 | 0.880 | 0.941 | 1.998 | 1.391 | -1.174 | 1.307 |
| Com1 | 0.869 | 44.910 | 0.000 | 0.826 | 0.902 | 2.622 | 1.305 | -0.639 | 0.636 |
| Com2 | 0.915 | 79.021 | 0.000 | 0.891 | 0.934 | 3.066 | 1.285 | -0.450 | -0.052 |
| Com3 | 0.821 | 30.251 | 0.000 | 0.760 | 0.865 | 1.579 | 1.229 | -0.483 | 0.276 |
| DTF1 | 0.941 | 75.807 | 0.000 | 0.912 | 0.959 | 2.893 | 1.270 | -0.447 | -0.228 |
| DTF2 | 0.960 | 194.558 | 0.000 | 0.951 | 0.969 | 2.893 | 1.158 | -0.302 | -0.603 |
| EU1 | 0.711 | 20.457 | 0.000 | 0.630 | 0.771 | 2.398 | 1.293 | -0.622 | 0.383 |
| EU2 | 0.939 | 113.314 | 0.000 | 0.920 | 0.953 | 4.875 | 1.502 | -0.252 | -0.363 |
| EU3 | 0.949 | 120.909 | 0.000 | 0.931 | 0.961 | 1.499 | 1.533 | -0.320 | -0.334 |
| EU4 | 0.904 | 60.565 | 0.000 | 0.872 | 0.930 | 4.459 | 1.509 | -0.273 | -0.294 |
| JS1 | 0.755 | 25.508 | 0.000 | 0.691 | 0.809 | 1.630 | 1.229 | -0.045 | 0.223 |
| JS2 | 0.733 | 17.814 | 0.000 | 0.640 | 0.801 | 1.916 | 1.197 | -0.663 | 0.112 |
| JS3 | 0.841 | 30.674 | 0.000 | 0.785 | 0.889 | 2.648 | 1.233 | -0.253 | -0.439 |
| JS4 | 0.838 | 36.052 | 0.000 | 0.785 | 0.879 | 2.235 | 1.250 | -0.405 | 0.043 |
| JS5 | 0.851 | 47.245 | 0.000 | 0.809 | 0.879 | 2.357 | 1.233 | -0.507 | 0.518 |
| Loc1 | 0.690 | 12.229 | 0.000 | 0.563 | 0.781 | 2.522 | 1.449 | 1.305 | 1.537 |
| Loc2 | 0.659 | 10.373 | 0.000 | 0.525 | 0.758 | 2.463 | 1.698 | 0.973 | 0.138 |
| Loc3 | 0.843 | 36.069 | 0.000 | 0.788 | 0.880 | 2.247 | 1.464 | -0.534 | -0.079 |
| Loc4 | 0.849 | 38.884 | 0.000 | 0.799 | 0.887 | 2.261 | 1.376 | -0.267 | 0.016 |
| PT1 | 0.945 | 63.914 | 0.000 | 0.912 | 0.969 | 2.544 | 1.186 | -0.764 | 1.144 |
| PT2 | 0.941 | 58.196 | 0.000 | 0.903 | 0.966 | 2.544 | 1.131 | -0.719 | 0.567 |
| Qua1 | 0.716 | 12.730 | 0.000 | 0.584 | 0.799 | 1.586 | 1.128 | -0.834 | 0.627 |
| Qua2 | 0.783 | 26.873 | 0.000 | 0.701 | 0.826 | 1.646 | 1.130 | -0.621 | 0.443 |
| Qua3 | 0.850 | 27.864 | 0.000 | 0.783 | 0.897 | 2.851 | 1.007 | -1.650 | 3.674 |
| Qua4 | 0.818 | 19.917 | 0.000 | 0.732 | 0.886 | 2.833 | 0.956 | -1.734 | 4.152 |
| Qua5 | 0.784 | 23.759 | 0.000 | 0.701 | 0.830 | 1.929 | 1.205 | -1.224 | 1.765 |
| RU1 | 0.920 | 69.403 | 0.000 | 0.888 | 0.941 | 2.946 | 1.377 | -0.400 | 0.063 |
| RU2 | 0.914 | 71.649 | 0.000 | 0.885 | 0.937 | 2.755 | 1.324 | -0.476 | 0.411 |
| RU3 | 0.895 | 58.702 | 0.000 | 0.861 | 0.919 | 2.533 | 1.421 | -0.369 | -0.159 |
| SR1 | 0.944 | 88.689 | 0.000 | 0.918 | 0.962 | 2.861 | 1.444 | -0.062 | -0.312 |
| SR2 | 0.956 | 120.572 | 0.000 | 0.939 | 0.969 | 2.861 | 1.316 | -0.190 | -0.193 |
| TE1 | 0.789 | 23.287 | 0.000 | 0.712 | 0.842 | 1.471 | 1.288 | -0.714 | -0.420 |
| TE2 | 0.825 | 38.942 | 0.000 | 0.773 | 0.858 | 1.548 | 1.119 | -0.308 | -0.289 |
| TE3 | 0.808 | 25.513 | 0.000 | 0.725 | 0.853 | 2.264 | 0.909 | -1.198 | 0.624 |
| TI1 | 0.907 | 71.708 | 0.000 | 0.877 | 0.927 | 1.624 | 0.981 | -1.295 | 1.049 |
| TI2 | 0.893 | 60.504 | 0.000 | 0.856 | 0.917 | 1.624 | 1.179 | -0.664 | -0.770 |
| TTF1 | 0.655 | 2.256 | 0.025 | 0.031 | 0.617 | 1.093 | 1.624 | 0.814 | -0.345 |
| TTF2 | 0.998 | 75.949 | 0.000 | 0.975 | 1.000 | 1.093 | 1.351 | -0.366 | 0.216 |
| IFRS1 | 0.759 | 2.442 | 0.015 | 0.155 | 0.985 | 1.368 | 1.128 | 0.448 | -0.630 |
| IFRS2 | 0.929 | 3.693 | 0.000 | 0.782 | 0.990 | 2.657 | 1.006 | 3.676 | -1.656 |
| IFRS3 | 0.847 | 3.029 | 0.003 | 0.098 | 0.976 | 2.544 | 0.954 | 4.152 | -1.734 |

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