FACTORS INFLUENCING EFFECTIVE MANAGEMENT OF STAKEHOLDERS IN IT 4IR PROJECTS IN SOUTH AFRICA

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KEYWORDS

Fourth Industrial Revolution (4IR), IT Projects, Project Stakeholder

ABSTRACT

In a technologically changing world, the roles and expectations of stakeholders are continuously evolving. It behooves project practitioners to understand and appreciate the dynamics of stakeholder management in this new world order. The study was conducted within the South African context to investigate the factors influencing stakeholder management and project performance. A quantitative approach was used, and inferential factor analysis statistics were applied to analyse responses from questionnaire distributed on-line using via the Lime Survey platform. Statistical analyses were performed using the SPSS ® Amos® Version 29. The aim of the research was to identify factors that influence IT project stakeholder management in the Fourth Industrial Revolution (4IR) in South Africa. "Communication and engagement practices," which focus on strategies and tools that facilitate effective stakeholder communication and involvement; and secondly, "Data-driven stakeholder engagement" which emphasises on the use of data and application of technology to enhance stakeholder engagement were identified as major factors impacting stakeholder management.

INTRODUCTION

As highlighted by Gemünden and Schoper (2015), transnationalism represents a social phenomenon that entails increasing interconnectedness among individuals, groups, and institutions in an emerging global context. Project managers must perpetually update their skills in response to an ever-changing environment (Whysall *et al.,* 2019). They must evolve alongside the organisation and take the lead in executing technology-related projects (Marnewick and Marnewick, 2021). The present suite of skills and competencies according to the Project Management Institute (PMI, 2017) and the International Project Management Association (IPMA, 2015), does not encompass the vital and essential progression in skills and competencies. Managing stakeholders plays a pivotal role in influencing the performance of complex projects (Beringer et al., 2018). The perspectives of stakeholders can differ significantly during information system (IS) projects, presenting a challenge in achieving universal satisfaction. Stakeholder perspectives are identified as the foremost concern for IS projects in general, suggesting an escalating complexity in managing stakeholder expectations and achieving overall satisfaction (Marnewick, C., Erasmus, W. & Joseph, N., 2017). This emphasis on stakeholder management is particularly pronounced in the top three considerations for the Overall, Agile, and Waterfall viewpoints, reflecting a trend prevalent in contemporary project success literature (Joseph & Marnewick 2014; Todorovic´ *et al.* 2015; Williams 2016).

METHODS

In this study, data collection was achieved using a questionnaire. The questionnaire was distributed online using the Lime Survey platform. Lime Survey was used as it enables easy distribution of the questionnaire. This was an effective way to collect responses from a sample for quantitative analysis purposes (Fink, 2009). Respondents were asked to give ratings to a series of questions on a provided Likert scale. The factors that were included in the questionnaire were gleaned from the literature (Adzmi, & Hassan, 2018; Eyiah-Botwe, et al., 2016; Marnewick & Marnewick, 2021). Snowball sampling was used. This is a non-probability sampling strategy implying that the findings cannot be generalised to the entire population because specific segments of the population may be overrepresented or underrepresented (Saunders et al. 2009). Due to the low uptake of AI technologies in South Africa (SA) (Munoriyarwa, 2023) the response rate was low. A filter question was used to sideline those respondents that were not directly involved in 4IR IT projects. There were 107 responses, of which 50 indicated that they were directly involved in IT projects using 4IR technology. The 50 responses were further analysed as discussed below.

RESULTS & DISCUSSIONS

Table 1: KMO and Bartlett's Test

Correlation Matrix[a]		
a. Determinant = .006		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.759
Bartlett's Test of Sphericity	Approx. Chi-Square	234.277
	df	36
	Sig.	<.001

Kaiser-Meyer-Olkin (KMO) Measure:
The KMO test assesses the adequacy or sufficiency of data for factor analysis. Values close to 1 indicate suitability for factor analysis. The value of 0.759 above indicates, thus, that the data is reasonably appropriate for factor analysis. The value is above the acceptable threshold of 0.7 (Shrestha, 2021.). In other words, the correlations between variables are adequate for factor analysis to be conducted on that data to derive meaningful factors. Bartlett's Test of Sphericity checks whether the correlation matrix is significantly different from an identity matrix (i.e., whether there are meaningful relationships between variables). The chi-square value (approx. 234.277) and the associated significance level (<0.001) indicate that these correlations were not due to chance. Therefore, as indicated by the values, the data were suitable for being subjected to factor analysis.

Table 2: Communalities

	Initial	Extraction
Regular communication with stakeholders	1.000	.773
Transparent communication with stakeholders	1.000	.653
Engaging stakeholders in the project planning process	1.000	.608
Engaging stakeholders in the decision-making process	1.000	.449
Proactive mitigation of risks related to stakeholder concerns.	1.000	.465
Leveraging data analytics for informed stakeholder engagement	1.000	.841
Leveraging data AI for informed stakeholder engagement	1.000	.910
Agile project management methodologies for flexibility in adapting to changing stakeholder needs	1.000	.471
Collaborative tools for efficient communication	1.000	.656
Extraction Method: Principal Component Analysis.		

From Table 2 above, “leveraging AI data for informed to stakeholder engagement has a value of 0.910, followed by “leveraging data analytics for informed stakeholder engagement” with their value of 0.841. These constituted the higher communalities, and the implication was that these factors explained the major portion of their variance. Next in line were the moderate values that implied that they are well represented by the extracted factors. These included “regular communication with stakeholders” with 0.773 and “transparent communication with stakeholders” with 0. 653.The variables with lower communalities included “engaging stakeholders in the decision-making process”, (0.449); “proactive mitigation of risks related to stakeholder concerns”, (0.465). The communalities helped in understanding how the variables fitted into the factor structure and helped in understanding how any variables might have needed further investigation.

Communalities represent the proportion of variance inherent in each variable or item that is explained by the extracted components. The initial communalities have values of one at the beginning, and this implies that the variables explain 100% of their own variance. The underlying assumption is that the variable is independent. Usually after performing factor analysis or extraction the communalities change. Generally, the extraction of communality shows the proportion of variance that is accounted for by the components. For instance, “leveraging AI data for informed stakeholder engagement” has a high extraction communality of 0.910 and this implies that this factor contributes significantly to one of the extracted components. On the other hand, “engaging stakeholders in the decision-making process” has a low extraction communality of 0.449 which means it has less contribution to the extracted factors. Practically speaking, variables with higher extraction communalities are more relevant to the components that had been identified and, conversely variables with lower communalities may not align strongly with any specific factor.

Table 3: Total Variance

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4.376	48.627	48.627	4.376	48.627	48.627	4.251
2	1.450	16.109	64.736	1.450	16.109	64.736	2.259
3	.959	10.653	75.389				
4	.732	8.128	83.517				
5	.436	4.846	88.363				
6	.398	4.421	92.784				
7	.338	3.759	96.544				
8	.172	1.906	98.450				
9	.140	1.550	100.000				

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

The eigenvalues show the amount of variance in the data explained by each principal component whilst the percentage of variance indicates the percentage of total variance that is explained by each component. The cumulative percentage shows the cumulative variance that is explained by each component. Extraction sums of squared loadings account for the variance explained by the components that were retained after the extraction process. The rotation of data redistributes variance across components and makes them more interpretable. The rotation sums of squared loadings are calculated to make the interpretation of components easier, and these values represent the variance explained by the rotated components.

Component 1 has an eigenvalue of 4.376 after the initial extraction. This component explains 48.627% of the overall variance and after rotation, it still retains a significant amount of variance, though it is slightly less at 4.251.

Component 2 has an eigenvalue of 1.450 and it explains an additional 16.109% of the variance. After rotation the contribution increases to 2.259, and this suggests that rotation made this component more prominent or more influential in explaining the variance.
Components 3 through 9 all have eigenvalues of less than one and this typically indicates that they explain less variance individually. The cumulative variance that is accounted for by Component 1 and Component 2 totals 64.736 and that is deemed sufficient in for analysis. The percentage means that they captured much of the data. The variance after rotation is still significant and this suggests that they are crucial for understanding the underlying structure of the data. Components with eigenvalues below one is not retained as they contribute much less to the explained variance.

Table 4: Pattern Matrix

Pattern Matrix[a]

	Component	
	EMFact1	EMFact2
Regular communication with stakeholders	.919	
Transparent communication with stakeholders	.829	
Engaging stakeholders in the project planning process	.790	
Collaborative tools for efficient communication	.738	
Agile project management methodologies for flexibility in adapting to changing stakeholder needs	.679	
Engaging stakeholders in the decision-making process	.653	
Proactive mitigation of risks related to stakeholder concerns.	.635	
Leveraging data AI for informed stakeholder engagement		.987
Leveraging data analytics for informed stakeholder engagement		.855

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization[a]
a. Rotation converged in 3 iterations.

Component Loadings (EMFact1 and EMFact2)

EMFact1 and EMFact2 are the rotated components. The loadings reflect the contribution of each variable to the component, and higher absolute values indicate a stronger relationship. Component EMFact1 has high loadings in variables such as "regular communication with stakeholders" which has a value of 0.919; transparent communication with stakeholders" with a value of 0.829 and "engaging stakeholders in the project planning process" which has a loading of 0.790. Thus, to sum it up EMFact1 appears to represent a factor related to stakeholder engagement and communication," focusing on direct human-centered approaches to managing stakeholder relationships. Component EMFact2 has high loading in variables that entail are firstly "leveraging data AI for informed stakeholder engagement" with (0.987); followed by "leveraging data analytics for informed stakeholder engagement" with 0.855. This component seems to focus on the "use of data and technology in stakeholder engagement". It is apparent that the variables load clearly and cleanly onto one factor thus indicating that the two components are different and represent distinct concepts. In summary the analysis has identified two distinct factors in the data, namely one focusing on communication and stakeholder engagement and the other centering on leveraging data technologies. These components were then used to interpret the structure of the dataset.

Table 5: Structure Matrix

	Component	
	1	2
Regular communication with stakeholders	.868	

Transparent communication with stakeholders	.805	
Collaborative tools for efficient communication	.794	.417
Engaging stakeholders in the project planning process	.779	
Agile project management methodologies for flexibility in adapting to changing stakeholder needs	.686	
Proactive mitigation of risks related to stakeholder concerns.	.673	.328
Engaging stakeholders in the decision-making process	.669	
Leveraging data AI for informed stakeholder engagement		.947
Leveraging data analytics for informed stakeholder engagement	.440	.906

Extraction Method: Principal Component Analysis: Rotation Method: Promax with Kaiser Normalization.

The structure matrix is an output of factor analysis especially when using oblique rotation methods such as ProMax. The pattern matrix shows the unique contribution of each variable to a factor, but the structure matrix takes this further and shows the correlations between them. The loadings in the above structure matrix reveal the correlation between each variable and the extracted components with higher absolute values indicating a stronger correlation with the component. It can be seen that “regular communication with stakeholders” (0.868) is strongly correlated with Component 1 as well as “transparent communication with stakeholders” (0.805) and “collaborative tools for efficient communication” (0.794), which also showed high correlations with the same Component 1, thus inferring that these are closely associated with the first component. “Engaging stakeholders in the project planning process” (0.779) also loads onto Component 1 and what thus reinforcing the interpretation that this component is reflecting “Stakeholder engagement and communication”. On the other hand, “leveraging data AI for informed stakeholder engagement” (0.947) shows a very strong correlation with Component 2 as does “leveraging data analytics for informed stakeholder engagement” (0.906) which has a high loading also on Component 2. This reinforces the conclusion that this component is focusing on “data-driven decision making”. However, “collaborative tools for efficient communication” (0.417) and “proactive mitigation of risk related to stakeholders’ concerns” (0.328) somewhat have moderate correlation with Component 2. They thus have an indirect linkage primarily to Component 1. Therefore, Collaborative tools for efficient communication have moderate loadings on both Component 1 and Component 2, suggesting that they contribute in various measures to both components. Constructs were identified by factor analysis. Fit statistics were utilised to assess these individual constructs of the proposed model. The graphical illustration in Figure 1 was obtained from SPSS AMOS Version 29. The figure represents a Confirmatory Factor Analysis (CFA) model for the latent variable "EMDim1," which was measured by the observed variables EM1, EM2, EM4, EM5, EM9, EM12, and EM13. While some indices suggest the model has a reasonable fit (Cmin/DF, p-value, GFI, PClose), others like NFI, CFI, and RMSEA suggest room for improvement. The model fit is moderate, with some potential areas that could be improved. The variable EM4 has the highest loading (1.00), meaning it is strongly associated with the latent variable EMDim1.

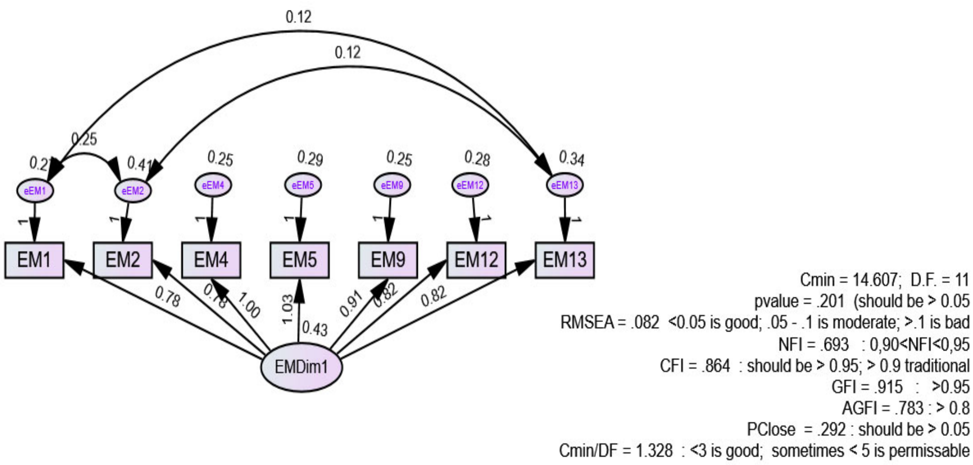

Figure 1: Confirmatory Factor Analysis (CFA) model

CONCLUSIONS

Component 1 is characterised by variables that emphasize regular transparent communication together with stakeholder involvement in planning and the use of other collaborative tools. Their high correlations imply that the aspects are strongly correlated and that they form a cohesive factor which can be summarised as explaining "traditional engagement-focused aspects of stakeholder management." Component 2 reflects a more technology-centric approach since it's dominated largely by "Using AI and data analytics for informed stakeholder engagement". In summary factor analysis has unveiled two separate components that are related to stakeholder engagement i.e., "Communication and engagement practices" which focus on strategies and tools that facilitate effective stakeholder communication and involvement; and secondly "data-driven stakeholder engagement," which emphasizes on the use of data and application of technology to enhance stakeholder engagement**.** This research is part of a greater study that looks at 4IR, IT project stakeholder management challenges in a developing economy such as SA. A model to manage the stakeholders will be the output of the study.

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