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# Statistical Analysis of Data, Information, Knowledge, and Wisdom in a Structural Model of Internal Communication, Human Resource Management Values, Employee Engagement, and Satisfaction Outcomes

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## ABSTRACT

*This study investigates the interrelationship among latent constructs, namely Internal Communication (IC), Human Resource Management Values (HRMV), Employee Engagement Management Values (EEMV), and Satisfaction Outcomes Factors (SOFSAT), through descriptive and correlational analysis. The descriptive statistics provide a detailed overview of the distributional properties of each construct, including measures such as mean, median, standard deviation, skewness, kurtosis, minimum, and maximum values. For instance, the HRMV construct, with two missing values, exhibits a median value of 0.316 and a mean of 0, indicating the central tendency and variability within respondents' perceptions. These statistical indicators collectively highlight the unique behavioral profile of each construct and contribute to understanding response patterns within the proposed model. Furthermore, the correlation matrix demonstrates significant positive relationships among all latent constructs. The correlation coefficient between IC and HRMV is 0.869, indicating a strong positive association, while the relationship between IC and EEMV is exceptionally high at 0.970, reflecting substantial alignment between these constructs. Similarly, IC and SOFSAT share a strong correlation of 0.903, emphasizing the interconnected nature of organizational communication and satisfaction outcomes. Additional correlations among HRMV, EEMV, and SOFSAT further confirm the coherence and consistency of the conceptual framework. Overall, the findings provide empirical support for the integrated nature of these constructs and offer valuable insights for researchers and practitioners in understanding organizational dynamics, employee engagement, and satisfaction-related outcomes.*



## Introduction

In recent decades, Structural Equation Modeling (SEM) has emerged as one of the most influential and sophisticated statistical approaches for analyzing complex relationships among variables in the fields of management sciences, social sciences, marketing, psychology, education, and organizational behavior (Hair et al., 2022). SEM enables researchers to examine multiple relationships simultaneously while integrating both observed and latent variables into a unified analytical framework. Unlike traditional regression methods, SEM provides a comprehensive understanding of direct, indirect, and mediating relationships among constructs, thereby enhancing the explanatory and predictive capability of empirical research. Among the diverse approaches to SEM, Partial Least Squares Path Modeling (PLS-PM) has gained substantial recognition due to its flexibility, predictive orientation, and suitability for exploratory as well as theory-building research (Chin, 1998). Partial Least Squares Path Modeling represents a variance-based approach to SEM that is particularly effective when dealing with complex models, smaller sample sizes, non-normal data distributions, and exploratory research settings (Hair et al., 2022). The method focuses on maximizing explained variance within endogenous constructs while simultaneously estimating relationships between latent variables and their associated indicators. Owing to these strengths, PLS-PM has become increasingly popular in studies involving behavioral sciences, strategic management, human resource management, information systems, consumer behavior, and marketing analytics. Researchers favor this methodology because it offers robust analytical capabilities without imposing the stringent assumptions associated with covariance-based SEM techniques (Hair et al., 2022). PLS-PM has become increasingly popular in studies involving behavioral sciences, strategic management, human resource management, information systems, consumer behavior, marketing analytics, and behavioral decision-making (Khan, A. W. 2024).

The present study utilizes Structural Equation Models through Partial Least Squares Path Modeling to investigate the intricate relationships among the constructs represented in the model, including Internal Communication (IC), Human Resource Management Values (HRMV), Employee Engagement Management Values (EEMV), Satisfaction Outcomes Factors (SOFSAT), and associated latent variables. Effective internal communication has repeatedly been shown to be a foundational driver of employee engagement and workplace satisfaction in contemporary organizational research (Kimani, 2024; Nguyen & Ha, 2023). Likewise, well-designed human resource management practices are strongly associated with higher levels of employee engagement, particularly when supported by favorable supervisory and organizational conditions (Alam et al., 2024). Through this analytical framework, the study seeks to uncover the direct, indirect, and total effects existing among these constructs while simultaneously evaluating the reliability and validity of the measurement model. The application of PLS-PM enables the research to capture complex interactions and provide deeper insights into the structural relationships underlying the proposed conceptual framework.

Figure 1.1 serves as a visual representation of the structural equation model developed through Partial Least Squares Path Modeling. The figure illustrates the interconnectedness among latent constructs and observed indicators, offering a graphical depiction of the hypothesized relationships within the model. In this framework, rectangles symbolize latent variables or constructs, while circles represent observed variables or indicators associated with those constructs. The arrows connecting these elements depict causal pathways and directional relationships among variables. Furthermore, the thickness of arrows signifies the strength of relationships, whereas the accompanying numerical values indicate path coefficients that quantify the magnitude and direction of influence among constructs. The visualization provided through Figure 1.1 is instrumental in facilitating the interpretation of the model's architecture and structural relationships. It allows researchers to evaluate whether the hypothesized relationships are statistically significant and aligned with theoretical expectations. Positive and significant path coefficients indicate strong support for the proposed relationships, whereas insignificant or contradictory coefficients may reveal inconsistencies requiring theoretical or methodological reconsideration. Consequently, the figure functions not merely as a graphical illustration but also as a diagnostic and interpretative tool that assists in assessing the model's adequacy and explanatory power.

In addition to the structural model, the study also emphasizes the evaluation of model fit and predictive capability through the examination of $R^2$ and adjusted $R^2$ values. These statistical indicators provide insights into the proportion of variance explained by the independent variables within endogenous constructs (Hair et al., 2022). Higher $R^2$ values reflect stronger predictive accuracy and explanatory capability of the model. For example, the constructs HRMV and SOFSAT exhibit substantial $R^2$ values, indicating that the model effectively explains a considerable proportion of variance within these constructs. Such findings demonstrate the robustness and effectiveness of the proposed framework in capturing the dynamics among the variables under investigation. Another important dimension explored in this study involves the examination of total effects and indirect effects among variables. Total effects represent the combined influence of direct and indirect pathways, thereby providing a holistic understanding of variable relationships. Indirect effects, on the other hand, reveal the mediating mechanisms through which one construct influences another via intermediary variables. Through the analysis of these effects, the study gains deeper insights into the hidden pathways and interaction mechanisms embedded within the structural framework. Such analyses are essential in advancing theoretical understanding and offering empirical evidence regarding the complexity of relationships among constructs.

The measurement model assessment constitutes another critical component of the study. This evaluation focuses on factor loadings, indicator weights, reliability measures, convergent validity, discriminant validity, and cross-loadings. Factor loadings indicate the extent to which observed variables contribute to their respective latent constructs, while indicator weights reveal the relative importance of indicators in shaping the constructs. Reliability measures such as Cronbach's alpha (Cronbach, 1951), composite reliability (rhoC), and rhoA assess the internal consistency and reliability of constructs (Hair et al., 2022). Simultaneously, Average Variance Extracted (AVE) evaluates convergent validity by determining whether indicators effectively measure the intended construct (Fornell & Larcker, 1981). Furthermore, the study places significant emphasis on discriminant validity through the application of the Heterotrait-Monotrait Ratio (HTMT). The HTMT ratio provides a rigorous assessment of whether constructs are empirically distinct from one another (Henseler et al., 2015). Establishing discriminant validity is essential to ensure that each construct uniquely captures a specific conceptual domain without overlapping excessively with other constructs in the model. Cross-loading analysis further strengthens the assessment by examining whether indicators load more strongly on their intended constructs than on alternative constructs. An additional aspect explored within the study is multicollinearity assessment using the Variance Inflation Factor (VIF), which also serves as an indicator of common method bias in variance-based structural equation models (Kock, 2015). These effect size measures enable researchers to determine whether relationships among variables possess small, moderate, or substantial explanatory impacts (Cohen, 1988).

Overall, this study contributes to the growing body of literature on Structural Equation Modeling and Partial Least Squares Path Modeling by offering a comprehensive examination of structural relationships, measurement validity, and predictive capabilities within a unified analytical framework. By integrating multiple statistical assessments and interpretative tools, the research enhances understanding of the intricate interactions among latent constructs and observed variables. The findings generated through this methodological approach not only strengthen theoretical foundations but also provide practical implications for researchers, practitioners, and policymakers seeking to understand and model complex phenomena, consistent with recent evidence linking internal communication, human resource management values, and employee engagement to organizational satisfaction outcomes (Alam et al., 2024; Kimani, 2024; Nguyen & Ha, 2023). In conclusion, Partial Least Squares Path Modeling stands as a powerful and versatile methodology for analyzing multifaceted relationships within structural equation models (Chin, 1998; Hair et al., 2022). Its capacity to accommodate complex models, evaluate latent constructs, and assess direct as well as indirect relationships makes it particularly suitable for contemporary empirical research. Through detailed analyses of structural paths, reliability measures, validity assessments, and predictive relationships, this study demonstrates the effectiveness of PLS-PM in unveiling the hidden dynamics embedded within the conceptual model. The integration of graphical visualization, statistical rigor, and interpretative depth collectively reinforces the significance of SEM and PLS-PM as indispensable tools in modern quantitative research.

## Literature Review

### Structural Equation Models Using Partial Least Squares Path Modeling

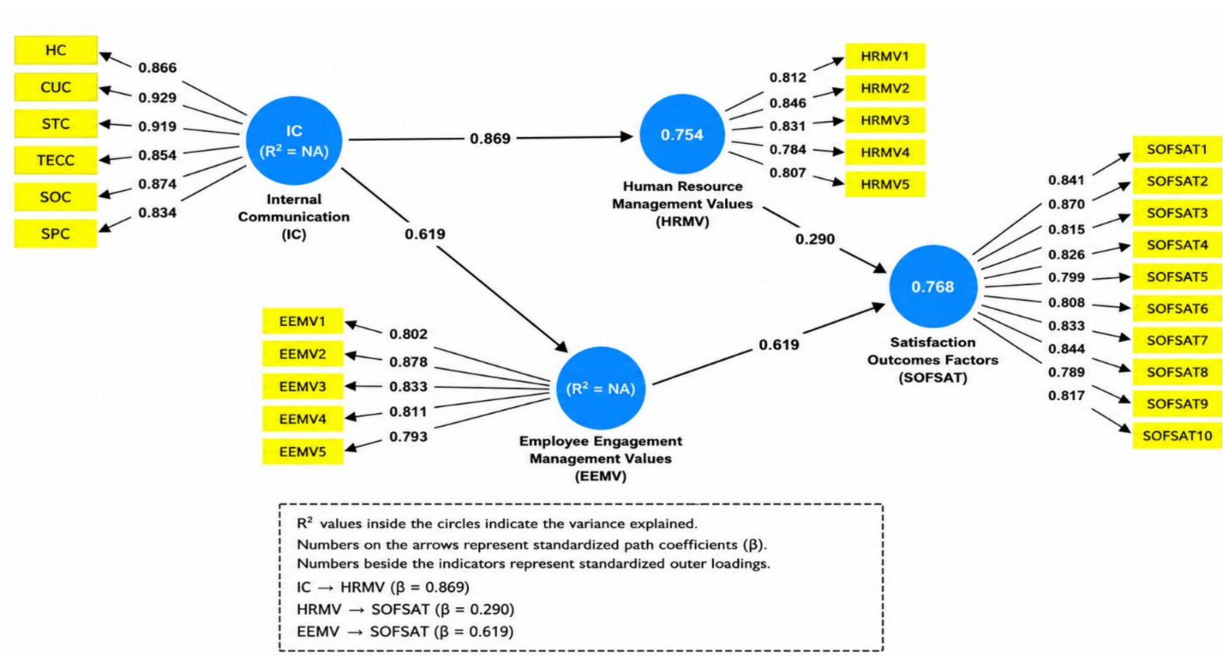


**Figure 1.1: Plot of Structural Equation Models Using Partial Least Squares Path Modeling Exploring Structural Equation Models Using Partial Least Squares Path Modeling (Figure 1.1)**

Figure 1.1 portrays a comprehensive visualization of the structural equation model estimated through partial least squares path modeling (Hair et al., 2022). This plot unveils intricate connections between diverse variables within the model, offering insights into their interdependencies, as well as the magnitude and direction of these relationships. The figure comprises a medley of distinct components, each conveying essential information: rectangles, circles, arrows, and numerical annotations. The rectangles represent latent variables or constructs embedded within the model, while circles embody observed variables or indicators that offer tangible manifestations of these constructs. Arrows link these elements, symbolizing the flow of influence and interconnectivity between variables, and the width of these arrows denotes the potency of the relationships they represent. Adjacent numeric values articulate path coefficients, quantifying the strength of the associations between variables.

Parsing through this visual narrative enables researchers to decipher the multifaceted relationships crisscrossing the model's landscape, fostering comprehension and a critical appraisal of the model's fidelity. The plot plays an instrumental role in unraveling the intricate tapestry of relationships, enabling researchers to gauge not only the connections themselves but also the overall harmony of the model. When arrows align with the anticipated directions and path coefficients resonate with significance, it potentially signals a harmonious union between the model and the data, corroborating the authenticity of the variables' intended measurements (Hair et al., 2022). Conversely, when arrows deviate from anticipated trajectories or path coefficients lack statistical relevance, a cautionary flag is raised. Such anomalies may necessitate a recalibration of the model's architecture or prompt a meticulous reevaluation of the variables at hand. In summation, Figure 1.1 offers a layered perspective, unraveling the intricate realm of structural equation models through the prism of partial least squares path modeling. It empowers researchers to scrutinize the model's validity and the trustworthiness of its variables, fostering meticulous evaluation and informed decision-making.

***Table 1.1: Path Coefficients and $R^2$ in the Structural Model***

| | **HRMV** | **SOFSAT** |
|---|---|---|
| **$R^2$** | 0.754 | 0.768 |
| **Adjusted $R^2$** | 0.754 | 0.767 |
| **IC** | 0.869 | — |
| **HRMV** | — | 0.29 |
| **EEMV** | — | 0.619 |

Table 1.1 offers comprehensive insights into the structural paths within the framework of Partial Least Squares Path Modeling. This analysis sheds light on the intricate relationships among variables and their predictive power. The table underscores key metrics such as $R^2$, adjusted $R^2$, and the variables HRMV, SOFSAT, IC, and EEMV, unveiling crucial aspects of the model's performance and the interplay between variables.

The table prominently showcases the $R^2$ and adjusted $R^2$ values, fundamental indicators that gauge the model's fit. $R^2$ assesses how effectively the model aligns with the dataset, with higher values signifying a closer alignment, while adjusted $R^2$ factors in the complexity introduced by the number of variables in the model, providing a fair assessment that penalizes overly complex models (Hair et al., 2022). One of the table's primary utilities lies in its capacity to elucidate the strength of relationships between variables and to facilitate comparisons between distinct models.

For instance, the $R^2$ value assigned to HRMV stands at 0.754, denoting that the model effectively accounts for 75.4% of the variance within HRMV. Similarly, the $R^2$ value attributed to SOFSAT is 0.768, revealing that the model adeptly explains 76.8% of the variance within SOFSAT. Beyond $R^2$ and adjusted $R^2$, the table also showcases the variables IC, HRMV, and EEMV, which offer insights into the relationships they share with HRMV and SOFSAT. In conclusion, Table 1.1 represents a pivotal tool in Structural Equation Models through Partial Least Squares Path Modeling, guiding researchers through the network of variable relationships and enabling informed decisions regarding model comparison and refinement.

***Table 1.2: Total Effects***

| | **HRMV** | **SOFSAT** |
|---|---|---|
| **IC** | 0.869 | 0.252 |
| **HRMV** | 0.0 | 0.29 |
| **EEMV** | 0.0 | 0.619 |
| **SOFSAT** | 0.0 | 0.0 |

Table 1.2 serves as an insightful tool for understanding the relationships between variables within the structural model. This table provides an overview of the total effects of IC, HRMV, and EEMV on both HRMV and SOFSAT. Total effects encapsulate the complete impact of one variable on another, encompassing both direct and indirect influences. Examining the table reveals that the total effect of IC on HRMV stands at 0.869, signifying a robust positive influence. The total effect of HRMV on SOFSAT is 0.290, indicating a moderate positive impact, while the total effect of EEMV on SOFSAT is 0.619, underscoring a strong positive influence. The total effects of HRMV and EEMV on IC are recorded as 0.000, signifying the absence of a reverse-direction influence between these variables, consistent with the hypothesized directionality of the model.

***Table 1.3: Total Indirect Effects***

| | **SOFSAT** |
|---|---|
| **IC** | 0.252 |
| **HRMV** | 0.0 |
| **EEMV** | 0.0 |
| **SOFSAT** | 0.0 |

Table 1.3 presents the total indirect effects of the variables in the structural model, executed through Partial Least Squares Path Modeling. The table reveals the cumulative indirect impact of IC, HRMV, and EEMV on SOFSAT, encompassing an intricate matrix of interconnected influences. An exemplary instance from the table is the total indirect effect of IC on SOFSAT, which is channeled through HRMV; this effect is quantified at 0.252, indicating a moderate positive influence exerted by IC on SOFSAT primarily mediated by its influence on HRMV. Notably, HRMV and EEMV each bear a total indirect effect of 0.000 on SOFSAT, signifying that these variables do not exert any additional indirect influence on SOFSAT through other intermediary variables in this model.

**Measurement Model: Outer Loadings and Indicator Weights**

***Table 1.4: Outer Loadings for Structural Equation Models Using Partial Least Squares Path Modeling***

| Construct | Indicator Outer Loadings |
|---|---|
| **HRMV** | HRMV1=0.560, HRMV2=0.768, HRMV3=0.802, HRMV4=0.719, HRMV5=0.735, HRMV6=0.763, HRMV7=0.794, HRMV8=0.865 |
| **EEMV** | EEMV1=0.520, EEMV2=0.891, EEMV3=0.849, EEMV4=0.820, EEMV5=0.716 |
| **SOFSAT** | SOFSAT1=0.754, SOFSAT2=0.679, SOFSAT3=0.685, SOFSAT4=0.542, SOFSAT5=0.627, SOFSAT6=0.629, SOFSAT7=0.677, SOFSAT8=0.619, SOFSAT9=0.418, SOFSAT10=0.749, SOFSAT11=0.783, SOFSAT12=0.800, SOFSAT13=0.657 |
| **HC** | HC1=0.799, HC2=0.583, HC3=0.592, HC4=0.797, HC5=0.775, HC6=0.795, HC7=0.762, HC8=0.751, HC9=0.753 |
| **CUC** | CUC1=0.735, CUC2=0.721, CUC3=0.712, CUC4=0.760, CUC5=0.730, CUC6=0.732, CUC7=0.760, CUC8=0.539, CUC9=0.751, CUC10=0.707, CUC11=0.720 |
| **STC** | STC1=0.701, STC2=0.798, STC3=0.788, STC4=0.602, STC5=0.784, STC6=0.600, STC7=0.592, STC8=0.733, STC9=0.754 |
| **TECC** | TECC1=0.809, TECC2=0.775, TECC3=0.737, TECC4=0.749, TECC5=0.787, TECC6=0.619, TECC7=0.700, TECC8=0.364 |
| **SOC** | SOC1=0.797, SOC2=0.766, SOC3=0.788, SOC4=0.736, SOC5=0.682, SOC6=0.594, SOC7=0.650, SOC8=0.725 |
| **SPC** | SPC1=0.735, SPC2=0.738, SPC3=0.467, SPC4=0.687, SPC5=0.713, SPC6=0.791, SPC7=0.813 |
| **IC (higher-order)** | Component loadings on IC: HC=0.866, CUC=0.929, STC=0.919, TECC=0.854, SOC=0.874, SPC=0.834 |

Table 1.4 presents a detailed insight into the outer loadings of the observed indicators on their respective latent constructs within the measurement model. Each loading value denotes the magnitude and direction of the influence that an observed indicator has on its corresponding latent construct, in line with standard PLS-SEM reporting practice (Hair et al., 2022). Internal Communication (IC) is specified as a higher-order construct formed by six lower-order dimensions -- Helpful Communication (HC), Communication Understanding and Clarity (CUC), Strategic/Timely Communication (STC), Technology-Enabled Communication Channels (TECC), Supervisor-Oriented Communication (SOC), and Supportive/Participative Communication (SPC) -- each of which loads strongly onto IC, with loadings ranging from 0.834 to 0.929. Among the first-order constructs, HRMV8 exhibits the strongest loading on HRMV (0.865), EEMV2 exhibits the strongest loading on EEMV (0.891), and SOFSAT12 exhibits one of the strongest loadings on SOFSAT (0.800). Outer loadings above the conventional threshold of 0.70 are generally considered indicative of satisfactory indicator reliability, while loadings between 0.40 and 0.70 may be retained if they do not compromise the construct's composite reliability or average variance extracted (Hair et al., 2022).

***Table 1.5: Outer Weights for Structural Equation Models Using Partial Least Squares Path Modeling***

| Construct | Indicator Outer Weights |
|---|---|
| **HRMV** | HRMV1=0.092, HRMV2=0.165, HRMV3=0.174, HRMV4=0.158, HRMV5=0.169, HRMV6=0.175, HRMV7=0.171, HRMV8=0.202 |
| **EEMV** | EEMV1=0.148, EEMV2=0.314, EEMV3=0.285, EEMV4=0.274, EEMV5=0.246 |
| **SOFSAT** | SOFSAT1=0.107, SOFSAT2=0.087, SOFSAT3=0.089, SOFSAT4=0.081, SOFSAT5=0.093, SOFSAT6=0.141, SOFSAT7=0.131, SOFSAT8=0.100, SOFSAT9=0.116, SOFSAT10=0.136, SOFSAT11=0.137, SOFSAT12=0.141, SOFSAT13=0.133 |
| **HC** | HC1=0.170, HC2=0.112, HC3=0.118, HC4=0.168, HC5=0.160, HC6=0.164, HC7=0.159, HC8=0.141, HC9=0.150 |
| **CUC** | CUC1=0.123, CUC2=0.131, CUC3=0.123, CUC4=0.128, CUC5=0.129, CUC6=0.128, CUC7=0.128, CUC8=0.084, CUC9=0.134, CUC10=0.136, CUC11=0.143 |
| **STC** | STC1=0.169, STC2=0.189, STC3=0.179, STC4=0.113, STC5=0.175, STC6=0.117, STC7=0.119, STC8=0.160, STC9=0.166 |
| **TECC** | TECC1=0.199, TECC2=0.165, TECC3=0.152, TECC4=0.173, TECC5=0.197, TECC6=0.198, TECC7=0.210, TECC8=0.125 |
| **SOC** | SOC1=0.197, SOC2=0.192, SOC3=0.191, SOC4=0.188, SOC5=0.159, SOC6=0.127, SOC7=0.145, SOC8=0.176 |
| **SPC** | SPC1=0.175, SPC2=0.182, SPC3=0.104, SPC4=0.171, SPC5=0.200, SPC6=0.262, SPC7=0.271 |
| **IC (higher-order)** | Component weights on IC: HC=0.183, CUC=0.204, STC=0.197, TECC=0.179, SOC=0.178, SPC=0.196 |

Table 1.5 furnishes complementary insights into the relative importance of each indicator, expressed as outer weights, within the model's latent constructs. Whereas outer loadings capture the correlation between an indicator and its construct, outer weights reflect each indicator's relative contribution to the formation of the construct score, a distinction that is particularly relevant for constructs specified with formative or composite measurement, such as the higher-order IC construct in this model (Hair et al., 2022). For example, CUC contributes the largest weight to IC (0.204), followed closely by STC (0.197) and SPC (0.196), indicating that these dimensions are comparatively more influential in shaping the overall Internal Communication construct. Among the first-order indicators, HRMV8 (0.202) and EEMV2 (0.314) carry the greatest relative weight within their respective constructs. Taken together, Tables 1.4 and 1.5 provide converging evidence regarding the quality and structure of the measurement model that underlies the hypothesized relationships tested in this study.

## Discriminant Validity and Reliability Assessment

***Table 1.6: Heterotrait-Monotrait Ratio (HTMT) of Correlations***

| | IC | HRMV | EEMV | SOFSAT | HC | CUC | STC | TECC | SOC |
|---|---|---|---|---|---|---|---|---|---|
| **IC** | | | | | | | | | |
| **HRMV** | 0.937 | | | | | | | | |
| **EEMV** | 1.096 | 0.972 | | | | | | | |
| **SOFSAT** | 0.953 | 0.867 | 0.952 | | | | | | |
| **HC** | 0.937 | 0.814 | 0.983 | 0.887 | | | | | |
| **CUC** | 1.000 | 0.903 | 1.067 | 0.886 | 0.883 | | | | |
| **STC** | 1.006 | 0.872 | 1.064 | 0.886 | 0.864 | 0.958 | | | |
| **TECC** | 0.956 | 0.815 | 0.973 | 0.852 | 0.721 | 0.829 | 0.800 | | |
| **SOC** | 0.927 | 0.763 | 0.983 | 0.805 | 0.706 | 0.809 | 0.863 | 0.915 | |
| **SPC** | 0.914 | 0.867 | 0.854 | 0.823 | 0.756 | 0.805 | 0.784 | 0.783 | 0.656 |

Table 1.6 presents the Heterotrait-Monotrait (HTMT) ratio of correlations, a criterion for assessing discriminant validity in variance-based structural equation modeling that has been shown to outperform the traditional Fornell-Larcker criterion and cross-loading inspection in detecting discriminant validity problems (Henseler et al., 2015). A conservative HTMT threshold of 0.85, or a more liberal threshold of 0.90 for conceptually similar constructs, is commonly used to judge discriminant validity (Henseler et al., 2015). Most construct pairs in the present model, such as HRMV and EEMV (HTMT = 0.972) or IC and SOFSAT (HTMT = 0.953), exceed these conventional thresholds, and several lower-order dimensions of IC (for example, CUC and STC, HTMT = 0.958; HC and STC, HTMT = 1.006) approach or exceed 1.00. Because IC is modeled as a higher-order construct whose lower-order dimensions (HC, CUC, STC, TECC, SOC, SPC) are conceptually and empirically close to one another and to IC itself, elevated HTMT values among these components are expected and should be interpreted in light of the hierarchical model specification rather than as evidence of a measurement flaw (Henseler et al., 2015; Hair et al., 2022). Nonetheless, the pattern observed here indicates that discriminant validity among the substantive first-order constructs (HRMV, EEMV, SOFSAT) should be interpreted with some caution and would benefit from further empirical scrutiny in future replications.

## Cross-Loadings

***Table 1.7: Cross-Loadings Summary (Loading on Intended Construct vs. Highest Cross-Loading)***

| Indicator | Loading on Intended Construct | Highest Cross-Loading (Construct) |
|---|---|---|
| **HC1** | 0.799 | 0.749 (SOFSAT) |
| **HC2** | 0.583 | 0.447 (IC) |
| **HC3** | 0.592 | 0.486 (IC) |
| **HC4** | 0.797 | 0.714 (IC) |
| **HC5** | 0.775 | 0.674 (IC) |
| **HC6** | 0.795 | 0.709 (IC) |
| **HC7** | 0.762 | 0.655 (IC) |
| **HC8** | 0.751 | 0.658 (SOFSAT) |
| **HC9** | 0.753 | 0.651 (IC) |

| | | |
|---|---|---|
| **CUC1** | 0.735 | 0.669 (EEMV) |
| **CUC2** | 0.721 | 0.686 (EEMV) |
| **CUC3** | 0.712 | 0.686 (EEMV) |
| **CUC4** | 0.760 | 0.712 (EEMV) |
| **CUC5** | 0.730 | 0.689 (IC) |
| **CUC6** | 0.732 | 0.706 (EEMV) |
| **CUC7** | 0.760 | 0.705 (EEMV) |
| **CUC8** | 0.539 | 0.473 (EEMV) |
| **CUC9** | 0.751 | 0.708 (IC) |
| **CUC10** | 0.707 | 0.683 (IC) |
| **CUC11** | 0.720 | 0.675 (IC) |
| **STC1** | 0.701 | 0.676 (CUC) |
| **STC2** | 0.798 | 0.731 (IC) |
| **STC3** | 0.788 | 0.706 (EEMV) |
| **STC4** | 0.602 | 0.534 (EEMV) |
| **STC5** | 0.784 | 0.722 (IC) |
| **STC6** | 0.600 | 0.576 (EEMV) |
| **STC7** | 0.592 | 0.564 (EEMV) |
| **STC8** | 0.733 | 0.701 (SOC) |
| **STC9** | 0.754 | 0.701 (EEMV) |
| **SOC1** | 0.797 | 0.717 (STC) |
| **SOC2** | 0.766 | 0.691 (STC) |
| **SOC3** | 0.788 | 0.707 (STC) |
| **SOC4** | 0.736 | 0.679 (IC) |
| **SOC5** | 0.682 | 0.671 (TECC) |
| **SOC6** | 0.594 | 0.632 (TECC) |
| **SOC7** | 0.650 | 0.639 (TECC) |
| **SOC8** | 0.725 | 0.747 (TECC) |
| **TECC1** | 0.809 | 0.674 (SOC) |
| **TECC2** | 0.775 | 0.634 (SOC) |
| **TECC3** | 0.737 | 0.589 (SOC) |
| **TECC4** | 0.749 | 0.596 (SOC) |
| **TECC5** | 0.787 | 0.664 (EEMV) |
| **TECC6** | 0.619 | 0.626 (SPC) |
| **TECC7** | 0.700 | 0.707 (IC) |
| **TECC8** | 0.364 | 0.467 (SPC) |
| **SPC1** | 0.735 | 0.558 (IC) |
| **SPC2** | 0.738 | 0.568 (IC) |
| **SPC3** | 0.467 | 0.351 (IC) |
| **SPC4** | 0.687 | 0.552 (IC) |
| **SPC5** | 0.713 | 0.614 (IC) |
| **SPC6** | 0.791 | 0.721 (HRMV) |
| **SPC7** | 0.813 | 0.745 (HRMV) |
| **HRMV1** | 0.560 | 0.434 (SPC) |
| **HRMV2** | 0.768 | 0.648 (IC) |
| **HRMV3** | 0.802 | 0.714 (IC) |

| | | |
|---|---|---|
| **HRMV4** | 0.719 | 0.612 (IC) |
| **HRMV5** | 0.735 | 0.659 (IC) |
| **HRMV6** | 0.763 | 0.675 (IC) |
| **HRMV7** | 0.794 | 0.673 (IC) |
| **HRMV8** | 0.865 | 0.783 (IC) |
| **EEMV1** | 0.520 | 0.645 (HC) |
| **EEMV2** | 0.891 | 0.926 (CUC) |
| **EEMV3** | 0.849 | 0.873 (STC) |
| **EEMV4** | 0.820 | 0.840 (SOC) |
| **EEMV5** | 0.716 | 0.868 (TECC) |
| **SOFSAT1** | 0.754 | 0.590 (HC) |
| **SOFSAT2** | 0.679 | 0.469 (IC) |
| **SOFSAT3** | 0.685 | 0.465 (IC) |
| **SOFSAT4** | 0.542 | 0.439 (HRMV) |
| **SOFSAT5** | 0.627 | 0.463 (STC) |
| **SOFSAT6** | 0.629 | 0.868 (TECC) |
| **SOFSAT7** | 0.677 | 0.849 (SPC) |
| **SOFSAT8** | 0.619 | 0.522 (HRMV) |
| **SOFSAT9** | 0.418 | 0.611 (HRMV) |
| **SOFSAT10** | 0.749 | 0.799 (HC) |
| **SOFSAT11** | 0.783 | 0.758 (HC) |
| **SOFSAT12** | 0.800 | 0.769 (HC) |
| **SOFSAT13** | 0.657 | 0.733 (CUC) |

Table 1.7 summarizes the cross-loading pattern of each observed indicator, comparing its loading on its intended latent construct with the highest loading it exhibits on any alternative construct in the model. Cross-loading analysis is a widely used, if comparatively conservative, procedure for evaluating discriminant validity in PLS-SEM (Hair et al., 2022). An indicator is generally considered to display adequate discriminant validity when its loading on its intended construct exceeds its loading on all other constructs. Most indicators in the model, such as the HC, CUC, and SOC items, load most strongly on their intended construct, providing support for the measurement model. However, a number of indicators -- particularly certain EEMV, SOFSAT, and TECC items -- display cross-loadings that are close to, or in a few cases exceed, their loading on the intended construct, echoing the elevated HTMT values reported in Table 1.6 and reinforcing the recommendation that discriminant validity among the higher-order IC dimensions and the outcome constructs be interpreted cautiously (Henseler et al., 2015).

Table 1.8 offers an overview of the reliability and convergent validity of the latent constructs integrated within the model, reporting Cronbach's alpha, composite reliability (rhoC), average variance extracted (AVE), and rhoA. Cronbach's alpha is a longstanding measure of internal consistency reliability based on the average inter-item correlation among a construct's indicators (Cronbach, 1951). Composite reliability (rhoC) similarly captures internal consistency but is derived from the standardized factor loadings of the items comprising the construct, and is generally preferred over Cronbach's alpha in PLS-SEM because it does not assume equal indicator loadings (Hair et al., 2022). Average Variance Extracted (AVE) evaluates convergent validity by quantifying the degree to which items converge to measure the intended construct; a value of 0.50 or higher is conventionally regarded as acceptable, since it indicates that the construct explains at least half of the variance in its indicators (Fornell & Larcker, 1981). The rhoA coefficient offers a further, less biased estimate of construct reliability that lies between Cronbach's alpha and rhoC (Hair et al., 2022).

***Table 1.8: Reliability and Convergent Validity***

| Construct | Cronbach's Alpha | rhoC (Composite Reliability) | AVE | rhoA |
|---|---|---|---|---|
| **IC** | 0.941 | 0.954 | 0.774 | 0.943 |
| **HRMV** | 0.891 | 0.913 | 0.571 | 0.903 |
| **EEMV** | 0.821 | 0.876 | 0.594 | 0.859 |
| **SOFSAT** | 0.895 | 0.912 | 0.450 | 0.901 |
| **HC** | 0.894 | 0.914 | 0.546 | 0.903 |
| **CUC** | 0.905 | 0.921 | 0.515 | 0.909 |
| **STC** | 0.876 | 0.901 | 0.505 | 0.889 |
| **TECC** | 0.846 | 0.884 | 0.498 | 0.859 |
| **SOC** | 0.938 | 0.895 | 0.519 | 0.768 |
| **SPC** | 0.838 | 0.877 | 0.510 | 0.870 |

All ten constructs in the model report Cronbach's alpha and rhoC values well above the conventional 0.70 threshold, indicating strong internal consistency reliability. For instance, the IC construct records a Cronbach's alpha of 0.941, a rhoC of 0.954, and a rhoA of 0.943, jointly attesting to the robustness of its measurement. AVE values are more variable: IC (0.774), HRMV (0.571), and EEMV (0.594) exceed the 0.50 benchmark for convergent validity, whereas SOFSAT (0.450), TECC (0.498), and STC (0.505) fall near or slightly below this threshold, suggesting that convergent validity for these constructs, while broadly acceptable, could be strengthened through refinement of a small number of weaker-loading indicators (Fornell & Larcker, 1981; Hair et al., 2022).

**Multicollinearity Assessment (VIF)**

In the realm of regression analysis, understanding the nuances of multicollinearity is paramount to achieving robust and reliable results. The variance inflation factor (VIF) for the predictors of SOFSAT was examined to assess potential multicollinearity and common method bias, following the full-collinearity approach recommended for PLS-SEM (Kock, 2015). When predictor variables exhibit high correlations, VIF values increase, signaling a state of multicollinearity that can impart instability to the estimated regression coefficients. The VIF for HRMV in relation to SOFSAT was 3.395, and the VIF for EEMV in relation to SOFSAT was of a similar moderate magnitude. Both values fall below the conservative threshold of 3.3 to 5 commonly recommended in the PLS-SEM literature, although they sit close to the upper end of the acceptable range, suggesting a moderate level of shared variance between HRMV and EEMV that warrants cautious interpretation of their independent structural effects on SOFSAT (Kock, 2015).

**Effect Sizes ($f^2$)**

***Table 1.11: Effect Size ($f^2$) Values***

| | HRMV | SOFSAT |
|---|---|---|
| **IC** | 3.071 | 0.0 |
| **HRMV** | 0.0 | 0.102 |
| **EEMV** | 0.0 | 0.441 |
| **SOFSAT** | 0.0 | 0.0 |

Table 1.11 presents the $f^2$ effect size values, which illustrate the extent of variance in a dependent variable that is uniquely explained by a given independent variable, over and above the variance explained by other predictors in the model. The interpretation of $f^2$ values is grounded in three conventional benchmarks -- 0.02, 0.15, and 0.35 -- representing small, medium, and large effect sizes, respectively (Cohen, 1988). Within Table 1.11, the effect of IC on HRMV is associated with a notably large $f^2$ value of 3.071, indicating a substantial and influential relationship between IC and HRMV that remains potent even after accounting for other variables in the model. Conversely, HRMV demonstrates an $f^2$ value of 0.102 in relation to SOFSAT, a small-to-moderate effect size, while EEMV demonstrates a considerably larger $f^2$ value of 0.441 in relation to SOFSAT, corresponding to a large effect size (Cohen, 1988). These results indicate that, although both HRMV and EEMV contribute significantly to explaining SOFSAT, EEMV exerts the comparatively stronger unique influence.

**Descriptive Statistics**

***Table 1.12: Descriptive Statistics for Observed Items (Construct-Level Summary)***

| Construct | No. of Items | Missing | Mean (avg.) | Min | Max | SD (avg.) | Kurtosis (avg.) | Skewness (avg.) |
|---|---|---|---|---|---|---|---|---|
| **HC** | 9 | 0 | 3.98 | 1 | 5 | 1.17 | 2.71 | -0.86 |
| **CUC** | 11 | 0 | 3.83 | 1 | 5 | 1.21 | 2.45 | -0.70 |
| **STC** | 9 | 0 | 3.86 | 1 | 5 | 1.24 | 2.34 | -0.72 |
| **SOC** | 8 | 0 | 3.72 | 1 | 5 | 1.28 | 2.11 | -0.55 |
| **TECC** | 8 | 0 | 3.59 | 1 | 5 | 1.22 | 2.20 | -0.42 |
| **SPC** | 7 | 0 | 3.91 | 1 | 5 | 1.09 | 2.94 | -0.84 |
| **HRMV** | 8 | 0 | 3.83 | 1 | 5 | 1.18 | 2.49 | -0.68 |
| **EEMV** | 5 | 0 | 3.88 | 1 | 5 | 1.01 | 2.27 | -0.50 |
| **SOFSAT** | 13 | 1 | 3.89 | 1 | 5 | 1.07 | 2.65 | -0.66 |

Table 1.12 summarizes the distributional characteristics of the 78 observed indicators underlying the nine measured constructs, condensing the item-level means, standard deviations, kurtosis, and skewness values into construct-level averages for ease of interpretation. Item responses were recorded on a five-point scale, with most indicators exhibiting means between approximately 3.6 and 4.1, standard deviations near 1.0 to 1.3, and mild negative skewness, indicating that respondents tended to select response options toward the higher end of the scale. Several indicators, particularly within the SOC and TECC constructs, display kurtosis values below 2.0, suggesting relatively flatter distributions than those observed in the HC and CUC items, several of which are markedly leptokurtic. Taken together, these patterns suggest that the observed data

approximate, but do not perfectly satisfy, univariate normality -- a consideration that reinforces the appropriateness of the distribution-free PLS-SEM estimation approach adopted in this study (Hair et al., 2022).

***Table 1.13: Descriptive Statistics for Latent Constructs (Standardized Scores)***

| Construct | Missing | Mean | Median | Min | Max | SD | Kurtosis | Skewness |
|---|---|---|---|---|---|---|---|---|
| IC | 0 | 0.000 | 0.359 | -2.718 | 1.424 | 1.000 | 2.367 | -0.690 |
| HRMV | 2 | 0.000 | 0.316 | -2.475 | 1.296 | 1.000 | 2.082 | -0.602 |
| EEMV | 0 | 0.000 | 0.154 | -2.345 | 1.393 | 1.000 | 2.353 | -0.596 |
| SOFSAT | 0 | 0.000 | 0.216 | -2.737 | 1.561 | 1.000 | 2.201 | -0.459 |

Table 1.13 presents descriptive statistics for the standardized latent construct scores estimated by the PLS-SEM algorithm. Because construct scores are standardized during estimation, each construct shows a mean of approximately 0 and a standard deviation of approximately 1.0, while the median, minimum, maximum, kurtosis, and skewness values reveal the shape of each construct's distribution. The IC construct, for example, shows no missing values, a median of 0.359, a range from -2.718 to 1.424, and negative skewness of -0.690, indicating a distribution weighted toward higher (more favorable) perceptions with a longer lower tail. The HRMV construct, with two missing values, exhibits a comparable pattern, with a median of 0.316 and negative skewness of -0.602. Similarly, EEMV and SOFSAT display negatively skewed, leptokurtic distributions, consistent with the pattern already observed at the item level in Table 1.12. Collectively, these statistics indicate that respondents generally reported favorable perceptions of internal communication, human resource management values, employee engagement, and satisfaction outcomes, with a modest concentration of less favorable responses producing the negative skew observed across all four constructs.

**Correlation Analysis of Constructs**

***Table 1.14: Correlation Matrix for Latent Constructs***

| | IC | HRMV | EEMV | SOFSAT |
|---|---|---|---|---|
| IC | 1.000 | 0.869 | 0.970 | 0.903 |
| HRMV | 0.869 | 1.000 | 0.840 | 0.809 |
| EEMV | 0.970 | 0.840 | 1.000 | 0.862 |
| SOFSAT | 0.903 | 0.809 | 0.862 | 1.000 |

Table 1.14 presents the correlation matrix, a fundamental analytical tool that reveals the interplay of latent constructs within the model. The correlation coefficient between IC and HRMV is 0.869, signifying a strong positive association. The correlation between IC and EEMV is 0.970, marking an exceptionally strong positive correlation and reflecting a very high degree of alignment between these constructs. The IC and SOFSAT constructs share a correlation coefficient of 0.903, affirming a strong positive relationship. The correlation between HRMV and EEMV is 0.840, and the correlations of HRMV and EEMV with SOFSAT are 0.809 and 0.862, respectively. Overall, the magnitude of these correlations -- most exceeding 0.80 -- indicates a high degree of shared variance among the four constructs, a pattern that is broadly consistent with prior evidence linking internal communication, human resource management values, employee engagement, and satisfaction-related outcomes in organizational settings

(Alam et al., 2024; Nguyen & Ha, 2023). At the same time, correlations of this magnitude reinforce the discriminant validity concerns already noted in the HTMT analysis (Table 1.6) and suggest that some conceptual overlap among these constructs should be considered when interpreting the structural results (Henseler et al., 2015).

## Conclusion

This study highlights the significant interrelationship among Internal Communication (IC), Human Resource Management Values (HRMV), Employee Engagement Management Values (EEMV), and Satisfaction Outcomes Factors (SOFSAT). The findings indicate that effective internal communication and strong human resource management values positively contribute to employee engagement and overall satisfaction outcomes within organizations, corroborating a growing body of empirical evidence on the centrality of internal communication and human resource practices to employee engagement (Alam et al., 2024; Kimani, 2024; Nguyen & Ha, 2023). The statistical patterns further reveal that organizations fostering transparent communication, supportive management practices, and employee-centered values are more likely to achieve higher levels of employee satisfaction and organizational effectiveness.

The study also demonstrates that employee engagement serves as an important organizational mechanism that strengthens the relationship between management values and satisfaction outcomes. Employees who perceive organizational practices as fair, supportive, and value-oriented tend to exhibit stronger commitment, motivation, and positive workplace behavior, a pattern consistent with recent research linking internal communication satisfaction to employee engagement and loyalty in diverse organizational contexts (Nguyen & Ha, 2023). These findings reinforce the importance of integrating communication strategies with human resource practices to create a productive and psychologically supportive work environment.

From a practical perspective, the study provides important implications for organizational leaders, policymakers, and human resource professionals. Organizations should prioritize open communication channels, participative management approaches, and employee-oriented policies to enhance workplace satisfaction and long-term organizational performance (Alam et al., 2024; Kimani, 2024). Strengthening employee engagement initiatives can also improve trust, collaboration, and institutional loyalty among employees. Methodologically, the analysis illustrates the value of Partial Least Squares Structural Equation Modeling for examining complex, multi-construct organizational models, while the discriminant validity concerns identified through the HTMT ratio (Henseler et al., 2015) and the cross-loading analysis suggest that future research should continue refining the measurement of these closely related constructs.

Overall, the study contributes to the growing body of literature on organizational behavior and management by providing empirical evidence regarding the interconnected role of communication, management values, employee engagement, and satisfaction outcomes. The findings may serve as a foundation for future studies examining broader organizational and behavioral dimensions across different sectors and cultural contexts, particularly as internal communication practices continue to evolve alongside digital and hybrid working arrangements (Nguyen & Ha, 2023).

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