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Navigating Airport Privatization: The Critical Role of Resources

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ABSTRACT

Airports are vital infrastructure assets, serving as key hubs for transportation and commerce while significantly contributing to economic and strategic development. Airport privatization, involving various models from full operational transfers to partial ownership restructuring, redistributes governmental rights and responsibilities to private entities, sparking considerable academic and professional interest. This study examines the critical role of resources—both tangible, such as infrastructure and financial investments, and intangible, including managerial expertise and stakeholder relationships—in shaping airport performance and resilience. By analyzing the interplay between these resources, the research highlights their profound impact on operational efficiency, adaptability, and strategic growth, particularly under privatized frameworks. The findings offer valuable insights for optimizing resource utilization to achieve sustainable development and competitiveness in the aviation sector.

Keywords: Airport privatization, Tangible and Intangible resources, Structure Equation Modelling

INTRODUCTION

In recent years, public-private partnerships (PPPs) have gained significant traction as a preferred model for the development and management of airports. As reported by the PPIAF database, a notable 141 airport PPP projects had been implemented worldwide by 2014, highlighting their global adoption and relevance (Farrell and Vanelslander, 2015). A defining characteristic of airport PPPs is their dual revenue structure, comprising income from aeronautical sources—such as landing fees and passenger charges—and non-aeronautical activities, including retail operations in duty-free shops, food and beverage services, hotel stays, parking facilities, and car rentals. Non-aeronautical revenue plays a pivotal role in the financial sustainability of airports, contributing around 40% to total global airport revenues (Calleja, 2017) and significantly driving profitability beyond its share of revenue generation (Graham, 2009).

Tangible and Intangible Resources

Physical, human, and organizational capital resources constitute the three categories of resources (Barney, 1991). The researcher discovered that resources may encompass assets, managerial practices, firm attributes, information, or knowledge under the firm's control, utilized for conceiving and executing their strategies (Mata et al., 1995). Physical and abstract resources and processes within an organization offer competitive advantages to firms (Ambastha et al., 2004).
The resources of the firm can be tangible and intangible like skilled employees, equipment's, efficient process etc. (Wernerfelt, 1984). Intangible resources include copyrights, patents, employees skills, culture and people dependent network (Richard, 1993) as shown in Figure 1.1.

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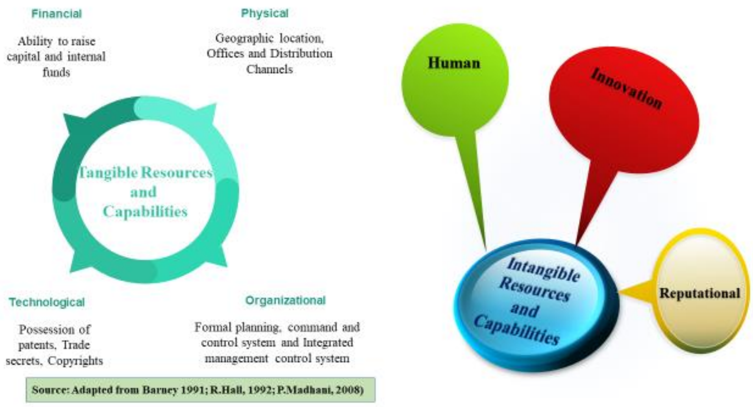

Figure 1.1: Tangible and Intangible Resources

Source: Barney, 1991.

Definition - Airport Resources

Resources and capabilities comprising of tangible and intangible assets like low-cost terminals can be developed by airports to attain a competitive edge and deliver value to customers (Njoya et al., 2011)**.** The researcher observed that obstacles related to human, monetary, and administrative resources impact the process of restructuring the source base (Chwiłkowska et al., 2020) depicted in Figure 1.2.

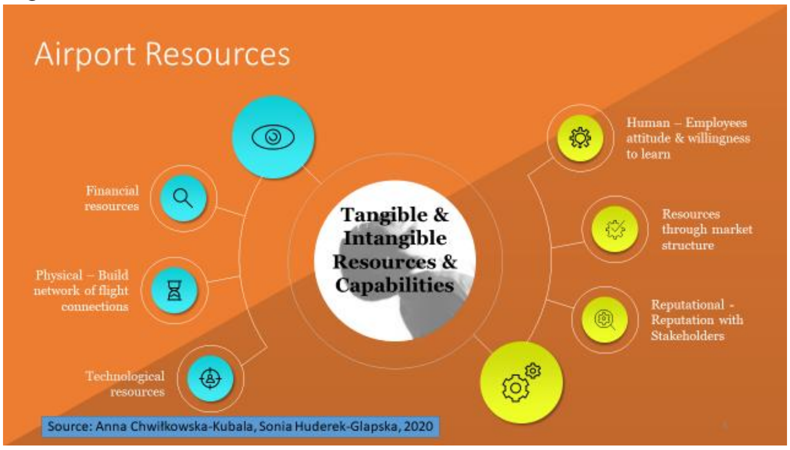

Figure 1.2: Airport Resources

Source: Chwilkowska et al., 2020.

LITERATURE REVIEW - RESOURCES

Financial Resources – the resources that cover operating expenses that include employee compensation, utilities, MRO facilities, infrastructure, and other services offered (Bazargan et al., 2003). Financial includes the sources and partnership element of the airport business model (Kalakou et al., 2013).

Aeronautical Revenue and Non-aeronautical Revenue

The aeronautical income includes revenue from the aircraft movements, total passenger handled and freight volume and ground support services like warehousing while non-aeronautical revenues includes income from duty-free and retail areas, rental space inside and outside terminal, car parking, ground handling services etc. (Liu, 2016)**.**
Enhancing airport economic development levels by focusing on designated airport economic demonstration zones in strategic locations (Wang et al., 2023). Policy implications derived from the study's findings can guide decision-makers in implementing targeted measures that promote resource optimization, output enhancement, and revenue diversification (Güner et al., 2022).

Managerial Resources - Managerial human capital encompasses the knowledge and experience acquired over time specific to the industry (Ripoll et al., 2021).

The study emphasizes the pivotal role of learning processes in the dynamic capabilities of large regional airports, noting that these processes are often intuitive rather than standardized, with employees' personal involvement being significant. Benchmarking activities are also highlighted as fundamental for learning within airport organizations (Chwiłkowska, 2021). The research offers a thorough literature review on human-digital collaboration in air freight logistics. However, the emergence of advanced digital systems fundamentally reshapes the role of human workers and collaborative processes. Key topics explored include security, human-technology interaction, and performance measurement in the digitalization era (Thums et al., 2023). The size of the airport directly influences digital transformation, while the effect of ownership is found to be insignificant. The findings highlight the significance of developing organizational readiness to accelerate the pace of innovation necessary for successful digital transformation (Halpern et al., 2021). The findings of this study emphasize the need for careful consideration of process characteristics, such as complexity, precision, and safety requirements, when selecting augmented or virtual reality devices. Additionally, device-specific factors, including ergonomics, display quality, interaction methods, and mobility are significant factors to determine technology (Eschen et al., T. 2018).

Technological Resources - Tangible technological resources include firms R&D, manufacturing, and products while Intangible resources include network relationship and reputation for technological excellence (Zahra, 2003). The article emphasizes the importance of collaboration and trust among managers and policymakers within the airport setting. Establishing a shared ethos and cultivating reciprocal confidence among stakeholders is essential for realizing the full potential of blockchain technology and addressing sustainability issues (Di et al., 2020). Resilient airports with sustainable strategies will be better positioned to offer air travelers a wider range of goods and services. Successful airports will also learn from the current crisis by diversifying their revenue streams and exploring non-passenger sources to compensate for the decline in air traffic (Serrano et al., 2020). The paper outlines the current trends in airport digitization and provides insights into the structural framework for implementing total airport management. The research highlights specific areas such as check-in, security screening, customs clearance, departure management, and passenger aid services necessitating technological enhancements (Zaharia et al., 2018).

Security Network – The Security network facilitates coordination and resources that include information sharing on business continuity during disruptions, system protection from cyber threats, consequence management, and securing critical infrastructure (Griffiths, 2008). Tech-based innovative solutions are predominantly in the pilot stage, aiming to enhance passenger comfort and airport security. However, adequate training and support are necessary to foster a positive outlook on digital transformation, particularly among senior airport staff and elderly passengers. Busy and profitable airports tend to show greater interest in adopting new technological innovations (Sreenath et al., 2021). The study emphasizes the importance of stakeholder collaboration particularly regarding operations, staffing, funding, and maintaining pressurizing flight schedules (Khan et al., 2021).

Airside Infrastructure – Airport airside infrastructure includes runway and hangar resources that play important role during disaster relief operations (Qin et al., 2021). Airside capacity is accessed by the number of slot allocation on an hourly basis (Knabe et al., 2016). The authors propose an airport taxiway planning approach, which incorporates a conflict resolution approach that prioritizes speed and follows a First Come-First Serve (FCFS) principle. This approach efficiently maximizes the taxiway route, improves resource utilization, and avoids taxiway conflicts. Moreover, the suggested strategy for airport taxiway planning effectively maps out taxiing routes, resolves conflicts, and improves the utilization of taxiway resources (Deng et al., 2022). The lack of proper decision support available to slot coordinators and the complexity of the problem contribute to inefficiencies during the initial allocation process. Consequently, these inefficiencies lead to significant slot misuse and underutilization of scarce airport resources (Zografos et al., 2012). The analysis reveals that long-term parking is the primary cause of parking congestion, primarily due to the unclear functional orientations of the parking lots. The congestion in parking lots not only hampers airport operations but also affects the efficiency of the ground access system (Xiao et al., 2015).

Terminal Facilities – The airport landside area comprises different resources whose operations influence airport stakeholders like airlines and employees and affect customer satisfaction. By integrating optimization techniques and simulation, this research offers a valuable framework for airport operators to make data-driven decisions regarding check-in and security control resource allocation. This study's findings offer robust implications for airport management and planning, supporting better resource utilization and service delivery at airports (Adacher et al., 2017). The findings reveal that several factors positively drive sustainability disclosure in European airports. Factors encompass passenger volume, cargo volume, terminal and gate density, and social media visibility. The main drivers include passenger volume, commercial revenue ratio, national income, domestic/leisure traveler share, and flight count. Business travelers negatively affect commercial revenues per passenger. Additionally, more retail space per passenger correlates with lower commercial revenues per square meter, indicating diminishing marginal revenue effects (Fuerst et al., 2011).

External Environmental – Externally imposed factors and restrictions beyond the control of airport management impact business model and operations (Kalakou et al., 2013). Elements like airport dimensions and the variety of natural surroundings contribute to the seasonal variations in domestic flights at the national level. The findings have implications for airport planning and management, as well as route optimization strategies. Understanding the drivers of flight seasonality can aid in the development of more efficient and effective transportation systems, considering regional variations and demand fluctuations (Wang et al., 2023).

Airports geared towards tourism, exhibiting superior efficiency, should be encouraged, and granted round-the-clock operations, especially during peak tourist seasons. Adjusting opening hours and utilizing specific terminals, gates, or runways based on seasonal variations could enhance operational efficiency. When conceptualizing aerodrome infrastructure policies, consideration should be given to tourist flows (Cifuentes et al., 2023). This study employs a spatial approach, utilizing a distance matrix and a shared destinations matrix tailored for various distances, to probe the impact of competition on efficiencies. It reveals that competition can exert both positive and negative effects on airport efficiency, contingent on the distance considered in the spatial model (Bergantino et al., 2020).

Institutional Resources – Institutional Resources like ownership form, regulations, management contracts and operational arrangements determine the building blocks for airport operations and functioning (Kalakou et al., 2013). The coefficient associated with the variable representing the effect of privatization indicates that, after accounting for various factors and heterogeneous trends, passenger traffic at the privatized airports saw an increase of about 30% compared to the anticipated levels under state control (Paratsiokas et al., 2022).

The study findings robustly demonstrate that group airports, managed collectively, outperform standalone airports in terms of efficiency. Moreover, the market shares of major airlines significantly contribute to enhancing airport efficiency. The findings highlight the potential benefits of airport consolidation and increased airport-airline cooperation for improving overall efficiency in the aviation industry (Park et al., 2021).

Structural Equation Modelling (SEM)

Structural Equation Modelling is a multivariate technique that incorporates measured and latent variables (Thakkar, 2013). SEM is an analytical tool to detect the interrelationship among variables similar to factor analysis (Weston et al., 2006).

Structural Equation Modeling (SEM) is a powerful Multi-Criteria Decision Making (MCDM) technique utilized to analyze and enhance logistics distribution performance. It is a sophisticated multivariate analysis method that examines structurally related relationships. SEM involves a multi-step procedure, including Factor analysis and various Regression tests, to estimate and demonstrate relationships between latent constructs and observed variables. This analysis technique is favored by researchers due to its ability to handle multiple interconnected dependencies in a single analysis.

Confirmatory Factor Analysis (CFA) plays a pivotal role in validating the measurement model used to assess the relationships between various constructs (Park et al., 2021). The study aims to investigate the impact of the external environment, institutional resources, tangible resources, and intangible resources on the performance of Public-Private Partnership (PPP) airports. The CFA process in this study involves evaluating the extent to which the observed variables or indicators representing these constructs accurately measure the underlying theoretical concepts. CFA helps determine whether the observed indicators, such as specific metrics or variables related to these constructs, indeed capture the essence of these theoretical concepts (Hoyle, 2000). Factor loadings indicate how strongly each indicator is associated with its respective construct (Brown et al., 2012). A substantial and consistent pattern of significant factor loadings would indicate that the indicators effectively measure the constructs they are intended to represent (Savalei et al., 2014). Furthermore, CFA assesses the reliability and validity of the measurement model (Sureshchandar, 2023). Construct reliability indicates whether the indicators consistently represent their corresponding constructs (Hancock et al., 2001). Convergent validity evaluates how well the indicators converge to measure the intended constructs (Carlson et al., 2012). Discriminant validity ensures that the constructs are distinct from one another and not measuring the same underlying concept (Farrell et al., 2009).

This analysis involves a first-order Confirmatory Factor Analysis (CFA) approach. In first-order CFA, each observed variable (indicator) is associated with a single latent construct (factor) (Byrne, 2005). This aligns with the way this study has described the relationships between external environment, institutional resources, tangible resources, intangible resources, and PPP airport performance. Each construct is measured by a set of observed variables, and the focus is on evaluating the measurement model and the relationships between the observed variables and their corresponding latent constructs.

To study the impact of External Environment and Institutional Resources on the PPP airport performance, following section presents the outcome of CFA analysis inclusive of Convergent validity- Outer loadings, Construct Reliability and Validity, AVE, Discriminant Validity and Path Diagram.

Table 1.1: Construct Reliability and Validity

CONSTRUCT RELIABILITY AND VALIDITY				
	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
External Environment Resources(EER)	0.879	0.886	0.917	0.734
Institutional Resources (IR)	0.804	0.857	0.860	0.606
Intangible Resources (ITR)	0.932	0.933	0.941	0.551
PPP Airport Performance (PAP)	0.888	0.890	0.918	0.691
Tangible Resources(TR)	0.967	0.968	0.970	0.584

- **External Environment Resources (EER):**
  The construct "External Environment Resources (EER)" demonstrates strong reliability and validity in this study. The Cronbach's alpha value of 0.879 indicates high internal consistency among the items related to external environment resources. This suggests that the items reliably measure the latent construct of external environment resources. The composite reliability values (rho_a and rho_c) of 0.886 and 0.917, respectively, reinforce the overall reliability of this construct (Hair et al., 2019). Additionally, the Average Variance Extracted (AVE) value of 0.734 indicates that a significant portion of variance is captured by the construct's indicators, supporting convergent validity.
- **Institutional Resources (IR):**
  The construct "Institutional Resources (IR)" also demonstrates strong psychometric properties. The Cronbach's alpha value of 0.804 indicates satisfactory internal consistency among the items representing institutional resources. The composite reliability values (rho_a and rho_c) of 0.857 and 0.860 further confirm the construct's reliability (Hair et al., 2019). The AVE value of 0.606 indicates that a substantial portion of variance is explained by the construct's indicators, suggesting convergent validity.
- **Intangible Resources (ITR):**
  The construct "Intangible Resources (ITR)" exhibits excellent reliability and validity. The very high Cronbach's alpha value of 0.932 reflects exceptional internal consistency among the items related to intangible resources. The composite reliability values (rho_a and rho_c) of 0.933 and 0.941 signify robust reliability, providing confidence in the construct's measurement (Hair et al., 2019). Despite the lower Average Variance Extracted (AVE) value of 0.551, the construct's strong Cronbach's alpha and composite reliability values indicate convergent validity.
- **PPP Airport Performance (PAP):**
  The construct "PPP Airport Performance (PAP)" demonstrates solid psychometric properties. The Cronbach's alpha value of 0.888 indicates good internal consistency among the items representing airport performance. The composite reliability values (rho_a and rho_c) of 0.890 and 0.918 suggest strong reliability of the construct's

measurement (Hair et al., 2019). The AVE value of 0.691 indicates reasonable convergent validity, with a substantial amount of variance explained by the construct's indicators.

- **Tangible Resources (TR):**

The construct "Tangible Resources (TR)" showcases exceptional reliability and validity. The very high Cronbach's alpha value of 0.967 highlights remarkable internal consistency among the items related to tangible resources. The composite reliability values (rho_a and rho_c) of 0.968 and 0.970 further underscore the construct's robust measurement (Hair et al., 2019). Despite the moderate Average Variance Extracted (AVE) value of 0.584, the high Cronbach's alpha and composite reliability values contribute to convergent validity.

In summary, the analysis of Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE) values reveals that the measurement model for all constructs in the study exhibits high internal consistency, reliability, and convergent validity. These psychometric properties enhance the credibility of the study's findings and provide a solid foundation for subsequent analyses and interpretations.

Discriminant Validity

Table 1.2: Heterotrait-Monotrait Ratio Matrix

Heterotrait-monotrait ratio (HTMT) - Matrix					
	External Environment Resources(EER)	Institutional Resources (IR)	Intangible Resources (ITR)	PPP Airport Performance (PAP)	Tangible Resources(TR)
External Environment Resources(EER)					
Institutional Resources (IR)	0.876				
Intangible Resources (ITR)	0.587	0.659			
PPP Airport Performance (PAP)	0.560	0.675	0.789		
Tangible Resources(TR)	0.624	0.764	0.862	0.775	

❖ **Heterotrait-Monotrait Ratio (HTMT) matrix**

The Heterotrait-Monotrait Ratio (HTMT) matrix Table 1.2 is a critical tool for evaluating the discriminant validity of constructs within a study (Henseler, 2017). It accomplishes this by comparing the correlations between constructs (Heterotrait correlations) to the correlations within a single construct (Monotrait correlations). This assessment is crucial in ensuring that the measured constructs are distinct and accurately capture different underlying concepts.

Analyzing the provided HTMT matrix:

- The HTMT value between "Institutional Resources (IR)" and "External Environment Resources (EER)" is 0.876, confirming a robust level of discriminant validity (Henseler et al., 2016).
- For "Intangible Resources (ITR)," the HTMT values are 0.587 with "External Environment Resources (EER)," 0.659 with "Institutional Resources (IR)," and 0.789 with "PPP Airport Performance (PAP)." These values are indicative of sound discriminant validity.
- Similarly, for "PPP Airport Performance (PAP)," the HTMT values are 0.560 with "External Environment Resources (EER)," 0.675 with "Institutional Resources (IR)," and 0.862 with "Intangible Resources (ITR)," reflecting sufficient discriminant validity.

- For "Tangible Resources (TR)," the HTMT values are 0.624 with "External Environment Resources (EER)," 0.764 with "Institutional Resources (IR)," 0.862 with "Intangible Resources (ITR)," and 0.775 with "PPP Airport Performance (PAP)," reinforcing the notion of adequate discriminant validity.

These HTMT values align well with the commonly used threshold of 0.85, recommended for assessing discriminant validity (Henseler et al., 2016). The results suggest that the constructs within this study exhibit satisfactory discriminant validity, underscoring their ability to accurately capture distinct underlying concepts.

Model Fit

Table 1.3: Fit Summary

FIT SUMMARY		
	Saturated model	**Estimated model**
SRMR	0.077	0.078
Chi-square	4348.365	4546.061
NFI	0.897	0.896

The fit summary Table 1.3 provides an assessment of the goodness-of-fit for both the saturated model (a model with perfect fit) and the estimated model (the actual model being evaluated) (Marsh & Balla, 1994).

Here's an interpretation of the provided fit summary:
SRMR (Standardized Root Mean Square Residual):
Saturated Model: SRMR = 0.077
Estimated Model: SRMR = 0.078

The SRMR measures the discrepancy between the observed correlations and the correlations predicted by the model. A lower SRMR indicates better fit. In this case, both the saturated and estimated models have similar SRMR values, suggesting that the estimated model's fit is relatively close to that of the saturated model (Taasoobshirazi & Wang, 2016).

Chi-square:
Saturated Model: Chi-square = 4348.365
Estimated Model: Chi-square = 4546.061

The chi-square test assesses the difference between the observed covariance matrix and the model-implied covariance matrix (Garson, 2013). A lower chi-square value indicates better fit (Moshagen, 2012). In this case, the estimated model has a slightly higher chi-square value compared to the saturated model, indicating that the estimated model's fit is not as good as the perfect fit of the saturated model.

NFI (Normed Fit Index):
Saturated Model: NFI = 0.897
Estimated Model: NFI = 0.896

The NFI measures the proportion of the improvement in fit achieved by the estimated model compared to a null model (Moss, 2009). A higher NFI indicates better fit. In this case, both the saturated and estimated models have similar NFI values, suggesting that the estimated model's fit is comparable to that of the saturated model (Singh, 2009).

Total Direct and Indirect effect of constructs:

Table 1.4: Total indirect effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	P values
External Environment Resources(EER) -> PPP Airport Performance (PAP)	-0.124	-0.128	0.055	0.024
Institutional Resources (IR) -> PPP Airport Performance (PAP)	0.228	0.232	0.057	0.000

Table 1.4 provides information about the total indirect effects, including the mean, standard deviation, T statistics, and p-values. Following is the interpretation of the values in this table:
External Environment Resources (EER) -> PPP Airport Performance (PAP):

Interpretation: The total indirect effect from External Environment Resources (EER) to PPP Airport Performance (PAP) is -0.124. The calculated T statistic (2.263) indicates that this effect is statistically significant (p-value = 0.024), suggesting that other constructs mediate a significant indirect relationship between EER and PAP.

Institutional Resources (IR) -> PPP Airport Performance (PAP):

Interpretation: The total indirect effect from Institutional Resources (IR) to PPP Airport Performance (PAP) is 0.228. The calculated T statistic (3.975) indicates that this effect is highly statistically significant (p-value = 0.000), suggesting a significant indirect relationship between IR and PAP mediated by other constructs.

Hence, the total indirect effects represent the combined influence of multiple paths between constructs. The T statistics and p-values help determine the statistical significance of these indirect effects.

Table 1.5: Specific indirect effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	P values
Institutional Resources (IR) -> Intangible Resources (ITR) -> PPP Airport Performance (PAP)	0.228	0.232	0.057	0.000
External Environment Resources(EER) -> Tangible Resources(TR) -> PPP Airport Performance (PAP)	-0.124	-0.128	0.055	0.024

Table 1.5 presents specific indirect effects along with their mean, standard deviation, T statistics, and p-values. Following is the interpretation of the provided information:

Institutional Resources (IR) -> Intangible Resources (ITR) -> PPP Airport Performance (PAP):

Interpretation: The mean specific indirect effect from Institutional Resources (IR) to Intangible Resources (ITR) and then to PPP Airport Performance (PAP) is 0.228. The calculated T statistic (3.975) indicates that this effect is highly statistically significant (p-value = 0.000), suggesting a significant indirect relationship between IR, ITR, and PAP.

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External Environment Resources (EER) -> Tangible Resources (TR) -> PPP Airport Performance (PAP):

Interpretation: The mean specific indirect effect from External Environment Resources (EER) to Tangible Resources (TR) and then to PPP Airport Performance (PAP) is -0.124. The calculated T statistic (2.263) suggests that this effect is statistically significant (p-value = 0.024), indicating a significant indirect relationship between EER, TR, and PAP.

These specific indirect effects help to understand the combined influence of two consecutive paths on a target variable. The T statistics and p-values provide insights into the statistical significance of these specific indirect effects, indicating whether the observed relationships are likely to be meaningful or due to chance.

Total effects

H1: External Environment will have a positive effect on the PPP airport performance.
H2: Institutional Resources will have a positive effect on the PPP airport performance.
H1a: External Environment will have a positive effect on the Tangible Resources
H1b: Tangible Resources will have a positive effect on the PPP airport performance.
H2a: Institutional Resources will have a positive effect on Intangible Resources
H2b: Intangible Resources will have a positive effect on the PPP airport performance.

Table 1.6: Total Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	P values
External Environment Resources(EER) -> PPP Airport Performance (PAP)	0.037	0.030	0.115	0.744
External Environment Resources(EER) -> Tangible Resources(TR)	-0.581	-0.584	0.042	0.000
Institutional Resources (IR) -> Intangible Resources (ITR)	0.625	0.629	0.037	0.000
Institutional Resources (IR) -> PPP Airport Performance (PAP)	0.653	0.648	0.111	0.000
Intangible Resources (ITR) -> PPP Airport Performance (PAP)	0.364	0.367	0.080	0.000
Tangible Resources(TR) -> PPP Airport Performance (PAP)	0.213	0.218	0.089	0.017

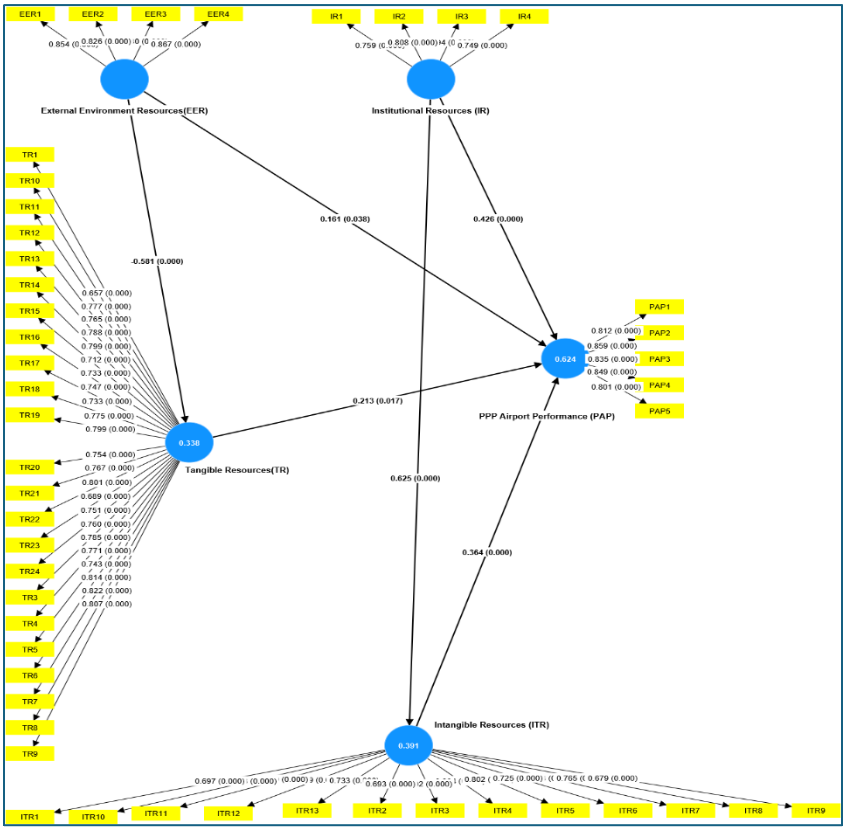

Figure 1.3: SEM Model
Source: Author

Table 1.6 provides information about total effects, including their mean, standard deviation, T statistics, and p-values. Following is the interpretation of the provided data:

Mediation Analysis

Mediation is a statistical concept and analytical technique used to understand the underlying mechanisms through which an independent variable influences a dependent variable. In other words, introducing a third variable called the mediator helps explain why or how a particular relationship between two variables occurs.

The basic idea behind mediation is that the relationship between the IV and DV is not direct, but rather it is mediated through the mediator variable. In other words, the IV affects the mediator, and in turn, the mediator affects the DV. This can be understood in terms of a causal chain or pathway:

IV (EER, IR, ITR, TR) -> MV (Mediator) -> DV (PAP)

Mediation analysis is crucial for understanding the underlying processes that drive relationships between variables. It helps researchers identify mechanisms, understand why certain relationships exist, and provides a more nuanced understanding of the relationships between variables. Here Mediation analysis is conducted using structural equation modeling (SEM). Researchers typically assess the significance of the indirect effect to determine if mediation is present and the extent to which the mediator explains the relationship between the IV and DV. In this context, mediation analysis aims to answer whether the effects of EER, IR, ITR, and TR on PAP are mediated by other factors. This involves assessing whether the introduction of mediators changes the strength and significance of relationships.

The relationship between Institutional Resources (IV) and PPP Airport Performance (DV) is being studied, with Intangible Resources (MV) as the mediator. The values provided for mediation effects could be:

1. **Institutional Resources (IV) -> Intangible Resources (MV) Mediation:**
   - The path coefficient of 0.625 signifies the effect of Institutional Resources (IV) on Intangible Resources (MV).

- The T statistic of 16.799 and a p-value of 0.000 indicate that this effect is statistically significant, implying that higher levels of Institutional Resources are associated with increased Intangible Resources.

2. **Intangible Resources (MV) -> PPP Airport Performance (DV) Mediation:**
   - The path coefficient of 0.364 represents the impact of Intangible Resources (MV) on PPP Airport Performance (DV).
   - The T statistic of 4.535 and a p-value of 0.000 suggest that this effect is also statistically significant. This implies that higher levels of Intangible Resources are associated with improved PPP Airport Performance.

Considering both mediation paths together, it can be inferred that the relationship between Institutional Resources and PPP Airport Performance is partially mediated by Intangible Resources. This suggests that the influence of Institutional Resources on PPP Airport Performance is, at least in part, explained by the presence of Intangible Resources.

Hence, mediation analysis enriches the interpretation of the study's results by revealing the intricate interplay between variables and shedding light on the underlying processes through which they influence each other. It offers valuable insights into potential mechanisms, helping researchers and decision-makers make more informed and targeted interventions to enhance PPP Airport Performance.

H1: External Environment Resources (EER) -> PPP Airport Performance (PAP)

Interpretation: The mean total effect from External Environment Resources (EER) to PPP Airport Performance (PAP) is 0.037. The calculated T statistic (0.326) indicates that this effect is not statistically significant (p-value = 0.744), suggesting that the observed relationship between EER and PAP might be due to chance.

H1a: External Environment Resources (EER) -> Tangible Resources (TR)

Interpretation: The mean total effect from External Environment Resources (EER) to Tangible Resources (TR) is -0.581. The calculated T statistic (13.819) indicates that this effect is highly statistically significant (p-value = 0.000), suggesting a significant direct relationship between EER and TR.

H2a: Institutional Resources (IR) -> Intangible Resources (ITR)

Interpretation: The mean total effect from Institutional Resources (IR) to Intangible Resources (ITR) is 0.625. The calculated T statistic (16.799) indicates that this effect is highly statistically significant (p-value = 0.000), indicating a significant direct relationship between IR and ITR.

H2: Institutional Resources (IR) -> PPP Airport Performance (PAP):

Interpretation: The mean total effect from Institutional Resources (IR) to PPP Airport Performance (PAP) is 0.653. The calculated T statistic (5.880) indicates that this effect is highly statistically significant (p-value = 0.000), suggesting a significant direct relationship between IR and PAP.

H2b: Intangible Resources (ITR) -> PPP Airport Performance (PAP):

Interpretation: The mean total effect from Intangible Resources (ITR) to PPP Airport Performance (PAP) is 0.364. The calculated T statistic (4.535) indicates that this effect is highly statistically significant (p-value = 0.000), suggesting a significant direct relationship between ITR and PAP.

H1b: Tangible Resources (TR) -> PPP Airport Performance (PAP):

Interpretation: The mean total effect from Tangible Resources (TR) to PPP Airport Performance (PAP) is 0.213. The calculated T statistic (2.384) indicates that this effect is statistically significant (p-value = 0.017), suggesting a significant direct relationship between TR and PAP.

These total effects provide insights into the direct relationships between predictor variables and the outcome variable (PPP Airport Performance in this case). The T statistics and p-values help determine the statistical significance of these direct effects, indicating whether they are likely to be meaningful or due to chance.

SUMMARY

The Structural Equation Modeling (SEM) analysis conducted in this study explored the intricate relationships and dynamics among key variables within the context of a complex research framework. The analysis encompassed multiple stages, each revealing insights into various aspects of the research hypotheses. Here is an overarching summary of the SEM analysis:

1. **Measurement Model and Reliability Analysis:** The initial stage involved assessing the measurement model's validity and reliability. Constructs like "External Environment Resources (EER)," "Institutional Resources (IR),"

"Intangible Resources (ITR)," "PPP Airport Performance (PAP)," and "Tangible Resources (TR)" were evaluated based on their reflective and formative nature. Reliability metrics such as Cronbach's alpha, composite reliability (rho_a), and average variance extracted (AVE) were used to determine the internal consistency and convergent validity of the constructs. The obtained values, ranging from 0.800 to 0.932, indicated high reliability and validity, thus affirming the suitability of the measurement model.

2. **Discriminant Validity:** The examination of discriminant validity ensured that the constructs were distinct and not merely measuring the same underlying concept. The square root of AVE and the correlation matrix were compared, revealing that the constructs' AVE values were greater than their correlations with other constructs. This supported the discriminant validity, reinforcing the robustness of the measurement model.
3. **Outer Loadings and Benchmark Values:** The outer loadings depicted the relationships between latent constructs and their respective indicators. These values indicated the strength of each indicator's contribution to its assigned construct. The outer loadings were compared against benchmark values, demonstrating that the indicators adequately reflected the latent constructs they were meant to represent.
4. **Path Coefficients and Mediation Analysis:** The analysis of path coefficients elucidated the direct and indirect effects between variables in the research framework. Significant relationships were identified through T statistics and p-values. Mediation analyses unveiled how certain variables, such as "IR" mediating the relationship between "EER" and "ITR," influenced each other. Total and specific indirect effects were assessed, providing insights into the pathways through which variables influenced each other.
5. **Fit Summary and Model Evaluation:** The fit summary provided essential information about the adequacy of the model. Fit indices such as the SRMR, NFI, and Chi-square compared the estimated model against a saturated model. The close fit between the estimated model's fit indices and those of the saturated model indicated a good model fit.

In conclusion, the SEM analysis shed light on the complex web of relationships among constructs like "EER," "IR," "ITR," "PAP," and "TR." The reliability of measurements, the discriminant validity, and the significant path coefficients collectively validated the theoretical framework. The mediation analyses illuminated the mediating roles of certain variables in influencing others. Overall, this comprehensive SEM analysis provided a thorough understanding of the underlying dynamics and implications of the research variables, contributing to a deeper comprehension of the research phenomenon.

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