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IDENTIFYING FACTORS THAT INFLUENCE PEOPLE'S ATTITUDE TOWARD PUBLIC PRIVATE PARTNERSHIP (PPP) PROJECTS

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Abstract: Over the last twenty-five years many infrastructure projects have been successfully pursued through the Public-Private Partnership (PPP) approach across the United States (US). While the PPP project delivery model remains same in principle, the PPP acceptance rate across the different States in the US has been significantly different. Literature review shows that researchers have identified factors that influence PPP projects at program and project level but the factors associated with end users' influence on PPPs are not yet identified. The knowledge gap leaves Federal Agencies with minimal information to adequately plan for PPP success. The main objective of this research is to identify factors that influence people's acceptance. Through logical reasoning we selected several demographic and road use factors that could influence end users' PPP acceptance. The data for all such factors was obtained from several government sources for California, Florida and Texas. Using SPSS, we conducted Principal Component Analysis (PCA) to identify the most influential factors. Results show that Regional Development, Congestion, and Vehicle Miles Travelled were the most influential factors affecting PPP acceptance.

1 INTRODUCTION

The United States (US), that had an unchallengeable supremacy as the global infrastructure leader, now stands 16th on the list (Deye, 2015). Some of this decline can be attributed to limited funding availability. In today's market, relying on government funds for meeting infrastructure needs could further impact negatively on the rank. Public-Private Partnership (PPP) model has been adopted by many nations to support infrastructure demands and has been embraced by several states in the US. A PPP project allows private sector to take risks (and thus the rewards) in non-traditional ways. This could include risks of designing, constructing, financing, operating and maintaining infrastructure. The private sector is allowed to recover the investments either through tolls or from public agencies. While many countries around the world have used PPPs as a long term solution to several infrastructure problems, barriers still exist for ascertaining success of PPPs in the US.

PPPs enable government agencies to transfer risks (responsibilities) to private sector. As the number of transferred risk increases, the PPP becomes more complex. For example, when the risks associated with designing, building and financing are transferred, the PPP will be known as Design-Build- Finance (DBF). Similarly, when additional risks of operating and maintaining are also transferred, the resulting PPP will be known as Design-Build- Finance-Operate-Maintain (DBFOM). Many other similar PPPs with varying levels of risk transfers have been used around the world. While PPPs have been used on many infrastructure projects around the world, not all projects can be pursued as PPPs.

An ideally designed PPP requires optimal risk sharing between public and private sector (FHWA, 2012). The risks must be transferred (or retained) to the party that is most capable of dealing with those risks. One of such risks is end-user's low acceptance which eventually affects the project's future revenue streams. PPPs wherein the private sector agrees to get reimbursed through toll collection are the ones where the private sector is taking the risk of lower revenues due to lower user acceptance. If a PPP is well accepted by local users, the tolls could ensure a profitable financial outcome. Conversely, if the end-users do not accept the PPP, then it is destined for a major financial crisis. Nevertheless, end-users form a major group of stakeholders and have a significant influence on the overall success of a PPP. Limited efforts have been observed that have focused on studying the reasons influencing end-users' PPP acceptance (Ng et al., 2012).

The authors of this research work believe that demographic factors of a region could have influence on a PPP's acceptance or rejection. As a first step to validate this hypothesis, the authors have attempted to identify the demographic and road use factors from California, Texas and Florida. These states are considered to be experienced in PPP projects (Papajohn et al., 2011; Cui & Lindly, 2010). Several PPP have been pursued in these states and, leaving a few instances, people have accepted the PPP project delivery model in essence. This enabled the three states to pursue PPP projects repeatedly and gain enough expertise. This was possible because the people in these states embraced PPP projects. This acceptance is thus considered as the desired state for PPPs in rest of the US. In this research several demographic and road use variables were identified that could influence PPP acceptance. The data was collected for 23 metropolitan cities across the three states and was subject to Principal Component Analysis (PCA) to identify the principal factors affecting PPP acceptance.

2 RESEARCH MOTIVATION

US had the world's most modern roadways, but slowly and gradually they have aged and have deteriorated. As per American Society of Civil Engineers (ASCE) the current assessment of US infrastructure resulted in a D+ grade and the roads and highways got a further lower grade of D. The report card also indicates that the highway systems have been underfunded for years and has resulted in $836 billion backlog of funding (ASCE, 2017). In addition the gas tax of 18.4 cents per gallon has not been increased since 1997 (FHWA, 2015) which has seriously constrained the Highway Trust Fund's capability to support highway projects. The ever increasing infrastructure demand mismatched with the gradually decreasing funds could further deteriorate the highway networks in the US. Involving private sector to pool their resources through PPPs will enable the US agencies to lessen the funding gap. Hence government agencies and the end users in the US will have to embrace the PPP model as one of the main stream project delivery options. The long term benefits that come with PPPs combined with the short term US financial needs implies that PPPs will be required in the US for at least a few decades to come. The vital support that PPP project delivery offers to the US mandates that these projects are planned meticulously to ensure success.

Currently, 33 US states have PPP enabling legislation (Pula, 2016). While PPPs have been used successfully around the world in several countries (Papajohn et al., 2011), the US PPP experience is relatively new. As a result decision makers could find themselves in an ambiguity about the success of a PPP project. Several critical success factors and risks have been documented in the literature that could affect the outcome of a PPP project. As more states are in the process of getting the PPP legislations it is necessary that the agencies take diligent steps to ensure PPP success in the new states. Other PPP research is focussed towards issues such as investment environment, procurement, economics viability, financial viability, risk management, governance issue, and integration research, (Ke et al., 2009). One such factor that has received relatively low attention from researchers is about end-user acceptance of PPPs (Ng et al., 2012).

End-users represent a major stakeholder group in PPPs. Their acceptance or rejection of a PPP has a significant impact on the outcome of PPPs. However, very limited attention has been paid towards understanding the end-user groups. Through this research, an attempt has been made to identify the demographic and road use factors that could have an influence on the outcome of a PPP project. To the authors' knowledge this kind of research has not be conducted before and so this research work will draw the agencies' and researchers' attention towards a possible area of research and exploration.

3 LITERTURE REVIEW

PPPs have been in existence since a very long time but they have regained their importance during the past few decades due to the governments' funding shortages (Levinson et al., 2006). In the US the PPPs are relatively new when compare to the PPP programs in countries like Australia, UK and Canada. Over the past 25 years, 33 US states have passed PPP enabling legislation and few more are planning for it or are already in the process (Papajohn et al., 2011; Cui & Lindly, 2010). While majority of the PPPs were successful, a few PPPs that could not meet the intended objectives tainted the overall US PPP programs. To some extent, this led to loss of end-users' trust in public sectors' decision making capability (Ortiz and Buxbaum, 2009) and the Government Accountability Office also stressed that public agencies should conduct rigorous analysis to protect end users' interests (GAO, 2008). This led to extra scrutiny and concerns about PPPs. Even though end-users have a significant impact on the PPP outcomes, almost no research has been focused on identifying the factors that could influence end-users' behavior.

PPP research has been focused on several research areas. This is evident from the recent study by Neto et al. (2016). The researchers reviewed 660 technical papers published between 1990 and 2014. These include research work in the area of contract performance which has highest number of papers to contract termination which has the lowest number of papers. Out of the 660 papers only 22 were focused on urban studies and 19 on social sciences. In percentage this is approximately 6%. Similar findings were also reported by Tang et al. (2010), who reviewed PPP papers published in six leading journals from 1998 to 2007. Ng et al. (2012) pointed out that the end users' perspectives were not considered during project development process and they proposed a framework for including end users through a model named as Public Private People Partnerships (P4). All these findings clearly imply that negligible attention has been paid towards the concerns about end-users. In reality, the end-users collectively form a major group of stakeholders having a direct influence on PPP success but very less attention has been paid to understand their concerns. The government agencies do have programs meant to understand and address public concerns. They conduct public meetings and have outreach programs wherein the end users' concerns are documented and addressed (NCHRP, 2010). But barriers still exist between people's expectations and agencies' execution plans. The barriers can be broken when the factors affecting people's decisions are recognized and addressed. While some research work were focused on identifying success factors (Aziz, 2007; Kwak et al., 2009; Doloi, 2012; Zhang, 2005), the demographic factors affecting PPP success have not been identified or studied. Public agencies continue pursuing PPPs while taking a risk of lower than desired PPP acceptance rate by end users.

4 RESEARCH METHODOLOGY

Factors Analysis (FA) is a variety of statistical techniques with an objective of representing a given set of variables into a small number of hypothetical variables (Kim & Mueller, 1978). It is a method for exploring a direct relation between variables and unobserved factors that are normally small in number (Tryfos, 1997). FA can be divided as Exploratory Factor Analysis (EFA) and Principal Component Analysis (PCA). Since this research is focused on identifying the main factors that could influence PPP acceptance, we have used PCA in this research.

4.1 A Brief Introduction to PCA

Principal Component Analysis (PCA) is a data analysis technique widely accepted and used by almost all scientific disciplines. It is often used to reduce a complex data set into lower dimension to explore the hidden factors (Shlens, 2014). According to Abdi and Williams (2010), PCA extracts maximum information from a dataset, reduces and describes the data, and analyzes the structure of the observation and variables. For example, Wuensch (2012) used PCA to identify principal factors that influence consumers' decision before buying beer. Wuensch considered Cost, Size, Alcohol Content, Brand Reputation, Color, Aroma and Taste as the variables that could matter to a beer buying consumer. Through PCA, Wuensch identified that Aesthetic Quality of beer, a combination of Taste, Aroma, and Color, was one of the major factors affecting consumer decision. The second principal factor was a combination of Size, Alcohol Content, and Cost. These components were collectively named Cheap Drink by Wuensch. On similar lines through this research we have attempted to identifying factors that can collectively indicate end-users' acceptance of PPPs.

In PCA, a set of observed variables correlated to each other converts into set of values of linearly uncorrelated variables known as principal components while the possible factors are always less than the original variables. In PCA, a set of y components are extracted from x variables. Those y components are having maximum variance in the x variables. *"PCA determines the most accurate lower dimensional representation of the data in terms of capturing the data directions that have the most variance"* (Chiang et al., 2000). Mathematically this can be expressed as (James et al., 2014):

For n observations (sample size) having p features denoted as X_1, X_2, X_3,… X_p the first principal component can be represented as a linear combination

$$Z_1 = \phi_{11}X_1 + \phi_{21}X_2 + \phi_{31}X_3,\ldots,+\phi_{p1}X_p \tag{1}$$

Where,

$$\sum_{j=1}^{p}\phi_{j1}^2 = 1 \tag{2}$$

$\phi_{11},\ldots,\phi_{p1}$ are the factor loadings of the first principal component that make a principal component loading vector $\phi_1 = (\phi_{11} \quad \phi_{21} \quad \phi_{31} \quad \phi_{41}\ldots \quad \phi_{p1})^T$.

Given a $n \times p$ data set **X**, and assuming that each of the variables in **X** has been centered to have a mean of zero, the linear combination in equation (3) has the largest sample variance.

$$z_{i1} = \phi_{11}x_{i1} + \phi_{21}x_{i2} + \phi_{31}x_{i3},\ldots,+\phi_{p1}x_{ip} \tag{3}$$

Using the above equations, the first principal component loading vector requires solving the optimization problem:

$$\max_{\phi_{11},\ldots,\phi_{p1}} \left\{ \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{p}\phi_{j1}x_{ij}\right)^2 \right\} \text{ subject to } \sum_{j=1}^{p}\phi_{j1}^2 = 1 \tag{4}$$

It turns out that the above optimization problem (4) is maximizing the sample variance of n values of z_{i1} and the terms z_{i1}, $z_{i1}\ldots z_{n1}$ will be the scores of the first principal component. The optimization problem in equation (4) has to be solved via Eigen decomposition which is beyond the scope of this paper. However, the process is briefly described here. Principal components are generated using Eigenvalues and Eigenvectors. Each principal component is orthogonal to the other component that helps in enclosing maximum area on a co-ordinate plane. Usually, the eigenvector with the highest eigenvalue forms the first principal component. The second principal component, perpendicularly bisecting the first component best fits with the error produce by the first component. If present, the third component eradicates the error from the first and second principal components and the chain continues further. Interested readers can refer to Shlens J. (2014) or any similar resource. Besides this the authors believe that it is necessary to include a few terminologies in this paper for a better understanding of the content.

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy: Abbreviated as KMO, indicates the proportion of variance which could be caused by the underlying factors. Getting a high value (close to 1) indicates that analysis will be useful, but a value less than 0.5 indicates that the PCA results are not good (Chan, 2012; Parinet et al. 2004).

Bartlett's Test of Spericity: This test indicates whether the correlation matrix between the variables is an identity matrix. If the correlation matrix is an identity matrix it would indicate that variables are unrelated. A low p-value (less than 0.05) indicates that there is significant relationship among the variables and the PCA analysis is acceptable (Parinet et al. 2004).

Extracting Principal Components: The process includes extraction of principal components from the variables used. The amount of variance is represented by the Eigenvalues taken by each component. Each component is a linear combination of the p variables. According to Knafl, the minimum cumulative percentage of the extracted components with Eigenvalues more than 1 should be equal to greater than 80% (Knafl, (n.d.)).

Communalities: Communality is the sum of the square loadings for each variable across the obtained components/factors. As per Hatcher, it is the variance in observed variables accounted for by a common factor (Hatcher, 1994).

Rotated Component Matrix: Rotated component matrix contains the factor loading values of the variables. Each value represents orthogonal measurement across the components. Factor loading values helps in describing the underlying nature of a particular factor. Mostly, a factor loading value higher than 0.60 or more is consider reliable (Yong & Pearce, 2013).

With the easy availability and widespread use of software the process of conducting PCA has become very fast and convenient. Analysis for this research was conducted using SPSS software. Readers interested to know the SPSS steps are requested to refer Wuensch (2012).

5 THE DEMOGRAPHIC FACTORS

In this research, 8 demographic and road use variables were considered that could affect PPP acceptance rate. These variables were selected based on logical reasoning. These factors are congestion cost, vehicles miles travelled, per capita income, population density, average education, traffic count, travel time to work and cost of living. Data was taken from government websites and transportation agencies. Each demographic factor is standardized and normalized to enable PCA analysis. All the variables were considered during the study.

5.1 List of Demographic Factors

Congestion Cost: In the larger urban areas significant delays are observed due to congestion. This negatively impacts commute and commerce. Congestion affect commuters dually through loss of time and waste of monies. A survey indicates that in California alone road users are burden with $44 billion each year due to insufficient transportation framework (TRIP, 2014).

Vehicles Miles Travelled: Vehicle Miles Traveled (VMT) is defined as the miles traveled by vehicles within a specified time period and region. FHWA provides state wise monthly and yearly VMT statistics and these have been used in this research.

Per Capita Income: The United States Census Bureau defines per capita income as a mean income calculated for every individual. It is the ratio of aggregate income of a particular group to the overall population in that group (U. S. Census Bureau).

Population Density: Population density is defined as a ratio of average population per square mile in a specific region/corridor and the data available from U. S. Census Bureau was used for this research.

Average Education: For this research, variable Education has been defined as the weighted average of number of years of education held by people of the region. The data was calculated from Census.org by converting degree into equivalent years of education and were multiplied by the number of people having those degrees.

Traffic Count: FHWA considers Traffic Count as the number of vehicles travelling on a freeway per day. The values are based on recorded trends of hourly traffic count.

Travel Time to Work: Travel Time to Work is the time taken by a commuter to drive to work place. In this research, the Travel time to Work of the selected 23 cities is either equal to or greater than the national average of 25.4 minutes (U.S. Census Bureau).

Cost of Living: Cost of Living is defined as the cost to have a specific standard of living. While the average annual cost of living in US is $28,458 the Cost of Living in all 23 cities selected for analysis is higher than the national average.

6 ANALYSIS

In this research, we considered only the top three most populated US states having PPP enabling legislation. These states are California, Texas and Florida. The primary focus was to assess the demographic factor responsible for PPP success and the acceptance in these states. Currently only 33 states have PPP enabling legislation. Within these 33 states the PPP acceptance rate is not guaranteed and it could happen that within these states one PPP project is successful but the other could be a failure. The 8 variables used in this research are coded as "*Cost"* for Daily Cost of Congestion; *"VMT"* for Daily Vehicle Miles Travelled for each individual; "*Income*" for Per Capita Income Per Day; "*Density"* for Population Density; *"Education"* for Average education for people of 25 years or higher age; "*Traffic Count"* for Daily Traffic Count; "*Travel Time"* for Average Travel Time to Work; and *"Cost of Living"* for Cost of Living Per Day. The analysis was conducted using SPSS and following results were obtained.

7 RESULTS AND CONCLUSION

PCA results require checking several parameters for assessing the validity of the tests and then interpreting the results.

7.1 Validity of PCA

Kaiser's Measure of Sampling Adequacy: As per research KMO values range from 0 to 1 and for the values to be acceptable the KMO value must be greater than 0.5. In the test, the KMO value was 0.604 which is acceptable (Chan, 2012 & Parinet et al. 2004).

Bartlett's Test of Spericity: This test confirms that there is some correlation between variables. The Chi-Square value was 122.577 and the significance value was 0.00 which indicates that the correlation matrix is not an identity matrix. This was also confirmed by visually observing the correlation matrix.

Communalities: The analysis results indicate that all the communalities are higher than 0.70 and their average is 0.819. The results are provided in Table 1.

Table 1: Communalities

Variables	Initial	Extraction
Cost of Delay (daily)	1.000	.908
Vehicle Miles Travelled (daily)	1.000	.969
Per Capita Income (per day)	1.000	.820
Average Travel Time (daily)	1.000	.720
Cost of Living (daily)	1.000	.778
Average Education	1.000	.714
Traffic Count Daily	1.000	.884
Population Density	1.000	.852

It must be noted here that PCA is a large sample test. It is desirable to get large samples to conduct PCA but researchers have demonstrated that if the communalities are higher than 0.6 (MacCallum et al., 1999; Henson & Roberts, 2006) and if the average of communalities is greater than 0.7 (Field, 2009; Yong & Pearce, 2013), PCA conducted using relatively small sample size are acceptable; the results obtained from such analysis will be stable.

Rotated Component Matrix: Rotated component matrix contains the factor loading values of the variables. Each value represents orthogonal measurement across the components. Table 2 consists of factor matrix displaying the loading values for all the components for each factor. Factor loading values helps in describing the underlying nature of a particular factor. Mostly, a factor loading value higher than 0.60 or more is consider reliable but in this analysis loading values more than 0.70 are taken into consideration (Yong & Pearce, 2013).

Table 2: Rotated Component Matrix

Variables	1	2	3
Population Density	**0.905**		
Cost of Living (daily)	**0.823**	0.307	
Average Education	**0.770**	0.332	
Per Capita Income (per day)	**0.751**	0.499	
Traffic Count Daily		**0.901**	
Cost of Delay (daily)	0.384	**0.837**	
Average Travel Time (daily)		**0.794**	
Vehicle Miles Travelled (daily)			**0.984**

Scree Plot: Scree plot indicates three components that have Eigen values greater than 1.00. The components having Eigen value more than one are retained and are considered to be strong. Figure 1 shows the scree plot obtained during the analysis. Clearly three components are strong as their eigenvalues are greater than 1.

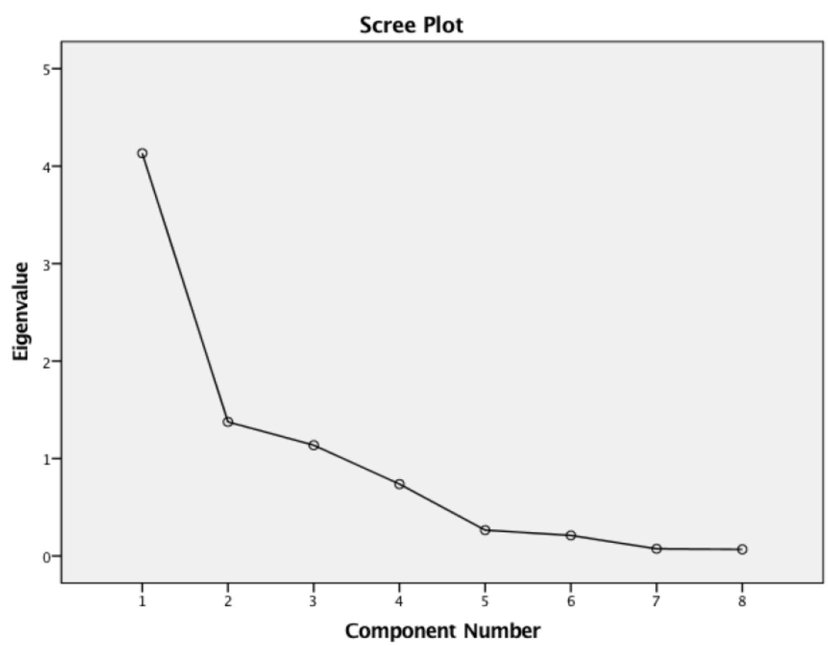

Figure 1 Scree Plot Indicating Three Principal Components

Naming Components: Result in Table 2 and Figure 1 indicate that the first principal component has heavy factor loading values for per capita income (0.751), cost of living (0.823), average education (0.77), and population density (0.905). This component can be recognized as Regional Development. Component 2 has higher factor loading value for cost of delay (0.837), average travel time (0.794) and traffic count daily (0.901). The component can be recognized as Congestion in the region. The third principal component has only one higher factor loading value for vehicle miles travelled daily and so the variable itself describes the component as Daily Vehicle Miles Travelled.

8 DISCUSSION

The analysis provided us three principal factors that will influence PPP acceptance in the three states. These three factors are:

a. Regional Development of a region,

b. Congestion in the region, and

c. Vehicle Miles Travelled.

The results indicate that a well-developed region will be good for PPP acceptance. Development of a region in this research has been defined as a region that can provide a comparatively high per capita income, where cost of living is high, provides good education to the residents, and has high population density. Regions (cities or counties) in the US where such demographic conditions exist will be good locations to have a PPP project.

Congestion which can occur due to higher traffic count in the region combined with geographical situations requiring people to travel longer commutes was found to be a factor affecting PPP acceptance. Congestion could force people to waste monies due to traffic delay from congestion. Hence, regions having such geographical and demographic resemblance will very likely to welcome PPP projects.

Lastly, regions wherein people are required to travel more are the ones where PPPs projects will be welcomed. This could be because when people are required to travel longer distances, they will prefer having better highways through PPPs to reduce the issues associated with higher vehicle miles travelled on daily basis.

8.1 Implication for Government Agencies, Limitations and Further Research

Using this research approach agencies can conduct similar research with more data and more number of variables. In this research macro level data was used, but agencies could conduct micro level surveys (by conducting questionnaire survey to end users in the region) to understand the end users' preferences. While the results of this research are acceptable, conducting micro level questionnaire surveys could help identify other important factors.

A similar research can be conducted in states that do not have PPP legislation and do not plan to accept PPPs. In such states, the variables can be selected that would influence people's PPP rejection. The results from all such research can help the agencies to develop outreach programs to help people make correct decisions. Alternatively, the results can also be used to design PPP models that would suite the local demographic demands.

9 CONCLUSION

This research lays the initial groundwork by identifying demographic variables that influence PPP acceptance. The results for the states of California, Texas and Florida indicate that within these three states corridors having higher development and congestion, and requiring riders to travel more miles will be good areas for PPP acceptance. Other regions with similar demographic and geographical conditions will also support PPPs. PCA can conveniently enable agencies to conduct similar demographic research. The results from such demographic studies can be used to develop outreach program or design PPPs to meet the public demands.

REFERENCES

Aziz, A. M. A. (2007). Successful Delivery of Public-Private Partnerships For Infrastructure Development. Journal of Construction Engineering and Management, American Society of Civil Engineers (ASCE), 133(12), 918-931

Abdi H., and Williams L.J. (2010). Principal component analysis. John Wiley & Sons. Vol. 2 Pp. 433-459.

ASCE (2017) “Infrastructure Report Card - Roads”, American Society for Civil Engineers.

Chan C. T. W (2012) The Principal Factors Affecting Construction Project Overhead Expenses: An Exploratory Factor Analysis Approach. Construction Management and Economics. Vol. 30, Pp. 903–914

Chiang, L. H., Russell, E. L., & Braatz R. D. (2000). Fault diagnosis in chemical processes using Fisher discriminant analysis, discriminant partial least squares, and principal component analysis. Chemometrics and Intelligent Laboratory Systems, Vol. 50, Pp. 243-252

Cui, Q. and Lindly, J.K. (2010). Evaluation of Public Private Partnership Proposals. University Transportation Center for Alabama report # 730-941, Tuscaloosa, AL.

Deye, A. (2015). US infrastructure public-private partnerships: Ready for takeoff? Harvard Kennedy School Review. Retrieved from http://harvardkennedyschoolreview.com/us-infrastructure-public-private-partnerships-ready-for-takeoff/

Doloi, H. (2012). Understanding Impacts of Time and Cost Related Construction Risks on Operational Performance of PPP Projects. International Journal of Strategic Property Management, Vol. 16(3) pp. 316-337.

FHWA (2012). “Risk Assessment for Public-Private Partnerships: A Premier” available at https://www.fhwa.dot.gov/ipd/pdfs/p3/p3_risk_assessment_primer_122612.pdf

FHWA (2015). “Highway History – Ask the Rambler”. Federal Highway Administration. Retrieved from https://www.fhwa.dot.gov/infrastructure/gastax.cfm on 4/19/2017.

Field, A. (2009). Discovering Statistics Using SPSS: Introducing Statistical Method (3rd ed.). Thousand Oaks, CA: Sage Publications.

GAO (2008). “Highway Public-Private Partnerships: Securing Potential Benefits and Protecting the Public Interest Could Result from More Rigorous Up-Front Analysis”.GAO-08-1052T, US Government Accountability Office.

Hatcher, L. (1994). A step-by-step approach to using the SAS system for factor analysis and structural equation modeling. Cary, North Carolina: SAS Institute Inc.

Henson R. K. and Roberts J. K (2006). Use of Exploratory Factor Analysis in Published Research Common Errors and Some Comment on Improved Practice. Educational and Psychological Measurement. Vol. 66(3), Pp. 393-416

James G., Witten D., Hastie T., and Tibshirani R. (2014). An Introduction to Statistical Learning with Applications in R. Springer, ISBN 978-1-4614-7137-0

Ke, Y., Wang, S. Q., Chan, A., and Cheung, E. (2009). Research Trend of Public-Private Partnership In Construction Journals. Journal of Construction Engineering and Management, 135(10).

Kim, J. & Mueller, C. W. (1978). Introduction to factor analysis. Sage Publications.

Knafl, G. J. (n.d.) Factor analysis. Oregon Health and Science University. Retrieved from http://www.unc.edu/~gknafl/research/FA/factor.analysis.presentation.pdf

Kwak, Y. H., Chih, Y. & Ibbs, C. W. (2009). Towards a comprehensive understanding of public private partnerships for infrastructure development. California Management Review, 51(2)

Levinson, D.; Garcia, R. C.; Carlson, K. (2006). A framework for Assessing Public-Private Partnerships. Institutions and Regulatory Reform in Transportation. Edward Elgar Publishers, 2006.

MacCallum R. C., Widaman K. F., Zhang S., and Hong S. (1999). Sample Size in Factor Analysis. Psychological Methods. Vol 4 (1), Pp. 84-99.

NCHRP (2010) “Effective Public Involvement Using Limited Resources”. Synthesis 407, Report published by Transportation Research Board of the National Academies, Washington DC

Neto D. C. S., Cruz C. O., Rodrigues F., and Silva P. (2016). Bibliometric Analysis of PPP and PFI Literature: Overview of 25 Years of Research. Journal of Construction Engineering and Management, Vol. 142(10).

Ng, S. T., Wong, J. M. W., and Wong K. K.W (2012). A public private people partnerships (P4) process framework for infrastructure development in Hong Kong. Cities, Vol. 31, p. 370-381

Ortiz, I. N., & Buxbaum, J. N. (2009). Public sector decision making for public-private partnerships: A synthesis of highway practice. Washington, D.C.: National Cooperative Highway Research Program.

Papajohn, D., Cui Q., and Bayraktar M. E. (2011). Public-Private Partnerships in U.S. Transportation: Research Overview and a Path Forward. Journal of Management in Engineering, Vol. 27(3), pp. 126-135

Parinet B., Lhote A., Legube B., (2004). Principal component analysis: an appropriate tool for water quality evaluation and management—application to a tropical lake system. Ecological Modelling Vol. 178, Pp. 295–311

Pula K. (2016) Public-Private Partnerships for Transportation Categorization and Analysis of State Statutes. National Conference of State Legislatures, Washington DC.

Shlens J. (2014) A Tutorial on Principal Component Analysis. Google Research, California.

Tang L., Shen Q., Cheng E. W. L (2010). A Review of Studies on Public–Private Partnership Projects in the Construction Industry. International Journal of Project Management. Vol. 28, Pp 683–694.

TRIP (2014). California transportation by the numbers: Meeting the state's need for safe and efficient mobility. Retrieved from http://www.tripnet.org/docs/CA_Transportation_by_the_Numbers_TRIP_Report_Sep_2014.pdf

Tryfos, P. (1997). Methods for business analysis and forecasting: Text & Cases. Wiley. Retrieved from http://www.yorku.ca/ptryfos/f1400.pdf

Wuensch, K. L. (2012). Principal components analysis: SPSS. Retrieved from http://faculty.ksu.edu.sa/ABID/609QUA/PCA-SPSS.pdf

Yong A. G., and Pearce S. (2013). A Begineer's Guide to Factor Analysis: Focusing on Exploratory Factor Analysis. Tutorials in Quantitative Methods for Psychology. Vol. 9(2), p. 79-94

Zhang, X. (2005). Critical Success Factors for Public–Private Partnerships in Infrastructure Development. Journal of Construction Engineering and Management. Vol. 131 (1), Pp. 3-14.