

# A Multidimensional factor structure modelling approach to decode parental decision towards play school selection in India

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## ARTICLE DETAILS

### Article History

Published Online: 11 May 2018

### Keywords

Confirmatory Factor Analysis,  
Exploratory Factor Analysis, Parental  
decision, Play School

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## ABSTRACT

Parents have a tremendous responsibility in the formative years of children to cater them with the best learning opportunities. Selection of play schools is thus a crucial issue in this regard. The present study aims at exploring factors that influence parental decision in play school selection based on principal-components-based exploratory factor analysis. Extension to EFA output was made and the factor structure model was confirmed using uni-dimensionality, reliability and validity tests. The study confirms a 5 factor structure model with primal, comfort, divergent being the most important constructs affecting parental decision in play school selection.

## 1. Introduction

Indian parents, particularly in urban areas are greatly concerned with the level of education for their children, even at a very tender age when the child is just ready to enter a play school. A play school is considered to be the stepping stone in making the child ready to face the fierce competition in getting admitted to a reputed/ renowned school in next two/three years time. It is imperative therefore to identify the factors which parents deem important while choosing a play school for their children. There has been very little empirical study made in India in this context, though a complex decision making process that incorporates economic, social and psychological parameters is involved here. It has to be considered that studies made in first world countries do not have much relevance due to the basic differences in state's involvement in education, socio-economic structures, freedom of choice, level of parental involvement and perception of quality education by parents. This study, thus being quite unique in nature, focuses on exploring the factors which parents rate to be most important while choosing a particular play school. A confirmatory factor analysis helps to identify the most important and relevant factors while a Structural Equation Modelling approach helps predict the future decision.

## 2. Review of Past Studies

While reviewing past studies on understanding and build a theoretical base on what can be important for parents to consider while making an informed choice, it is also crucial understanding how important parental involvement is in the overall imparting of education for a child. (Marcon, 1991) assesses the involvement of parents in child's early development and academics. The different relationship between parent involvement and outcomes of preschool between boys and girls is identified in this research. (Słowiacek, 1994) shows that the parental involvement is uni-dimensional and the child is a self constructor of his/ her schooling experience. To make decisions regarding their children's education, parents will rely

on their personal values and perception of value of education, which is purely subjective, as well as information collected from others within their social and professional networks. (Smrekar & Goldring, 1999). Mehrotra and. Panchamukhi (2007) validates parental perceptions of quality as a factor in ascertaining school choice. The study provides an interesting assessment of the indicators that Indian parents deem important when choosing a school. (Turk, 2015) identifies practicality, affordability, location and previous experience, knowledge as relevant factors in play school selection. He also states that the environment for learning is of importance for the parents as it makes their kids ready for next stage of formal learning. (Goldfield, 2012) highlights the importance of physical activities in preschool. Factors which affect physical activities of children in play School were studied by (Brown & Pfeiffer, 2009). According to them the activities of preschool are sedentary in nature. (Roskos, 1988) studied the reading and writing pattern of the children. The results showed their sustaining power and also how much they learn through play. (Cress, 2016) tried to differentiate between children on the basis of their behavioral and emotional aspects using normative assessment. This investigation helped in finding out how many students need extra educational help out of the total strength. Learning styles of students were analyzed (Hassan, 2012) using the non-parametric test, Kruskal Wallis test. Student on the basis of their behavior and streams were compared. (Blake, 2003) highlights use of multidimensional scaling for perceptual studies using similarity data. In a study by Ashraf (2012), parents enunciated the presence of well-qualified, knowledgeable, ethical and experienced teachers with effective ways of teaching as a factor of great concern. They seem to be also concerned with the academic credibility of the school. This credibility includes aspects such as high standards of education, schools' academic results, modern updated curriculum, English as a medium of instruction, teaching of important subjects including reading and writing, and co-curricular activities. The location of school, physical facilities, availability of transport facility, affordable fees, distance between home and school, cleanliness are other important

indicators of quality as reported by parents. In their research on parental choice, *Hughes et al. (1994)* found locality to be mentioned as a reason for the choice of school. *Morgan et al. (1993)* found the quality of the education and the vicinity of the school to the residence to be important reasons for the selection of a particular school. *Hammond and Dennison (1995)* found teacher quality, examination results, and discipline and school reputation to be the most important factors.

Though different authors have researched on the decision process of parents or in exploring the likely factors influencing parental decision, very little or scarce work has been done on the modelling aspect of the decision process and confirming a hypothesized model structure especially in Indian context. We felt necessary to address this unexplored area and hence considered it as our research gap in this study.

**3. Objectives**

We have framed two basic research objectives with the former aiming at finding factors that influence parental motivation and decision in play school selection. The second objectives use the output of the first study to hypothesize a model which is then aimed to confirm factors that influence parental decision in play school selection.

**4. Research Framework**

**a) Research Design**

Cross-sectional design with descriptive research forms the basis of our study since it facilitates finding different consumer characteristics as detailed in research objectives.

**b) Data Collection**

Primary Data forms the basis of the present descriptive study with questionnaire, an instrument for data capturing, forming an integral part of data collection. The instrument is a mix of both open and close ended questions. The sample size required was estimated using the following formula:  $N = [ \{ t^2 \times p ( 1 - p ) \} / m^2 ]$  where N: Required Sample Size, t: confidence level at 95% (standard value of 1.96), m: margin of error at 5% (standard value of 0.05) and p: estimated prevalence of consumer knowledge about play schools (85%). N was calculated to be 196. A final sample of 550 respondents were considered and the sample was split in the ratio of 40:60 with 40% i.e. 220 samples being used for EFA and the balance 60% i.e. 330 samples used to confirm the factor structure model.

**c) Sampling Technique / Procedure**

In accordance to our research objectives, judgmental or purposive sampling, a non-probabilistic sampling method is chosen to arrive at optimal results. This method uses knowledge and professional judgment of the researchers.

**d) Methodology**

In order to develop a parsimonious representation for the various constructs in the survey, some of which are new constructs, we conducted an initial principal-components-based exploratory factor analysis (EFA). The application of EFA is based on the concept of the Factor Models, the Orthogonal Factor Model to be precise. The present study uses varimax rotation in order to get results those are interpretable and

checks the adequacy of factor analysis. All three criteria of conducting EFA were tested:

1. **Criteria of sample size adequacy**
2. **Kaiser-Meyer-Olkin’s sampling adequacy criteria (KMO) with MSA (individual measures of sampling adequacy for each item)**
3. **Bartlett’s sphericity test**

The number of factors to be extracted is based on certain criteria (mentioned below) but no 100% full proof statistical tests exist. However, the following important ones were considered.

- i. **Eigen value Criteria** – The criteria says eigen values to be > 1.
- ii. **Scree Plot** - The adequate number of factors is before the sudden downward inflexion of the plot.

The factors thus obtained from EFA forms the latent variables in Factor Structure Model or Structural Equation Modelling (SEM) or Confirmatory Factor Analysis (CFA) studies. Structural Equation Modelling may be regarded as a confirmatory method that provides an exhaustive method to validate the measurement model of latent constructs. The validating procedure is called Confirmatory Factor Analysis (CFA). The CFA method assesses Unidimensionality, Validity and Reliability of a latent construct and same is carried for each of the latent constructs. The assessment for each element is performed as follows:

1. **Unidimensionality** - It is ensured if factor loading for every item > 0.5.
2. **Reliability** -
  - a. Internal Reliability – The same is achieved when Cronbach’s Alpha > 0.7.
  - b. Composite Reliability – It is achieved if its value > 0.6. CR is calculated as

$$CR = \frac{(\sum_{k=1}^{K_j} \lambda_{jk})^2}{(\sum_{k=1}^{K_j} \lambda_{jk})^2 + \theta_{jk}} \text{ where } \theta_{jk} = \sum_{k=1}^{K_j} (1 - \lambda_{jk}^2)$$

- c. Average Variance Extracted –An AVE > 0.5 is required for every construct and considered as a good measure. The AVE for construct  $\xi_j$  is defined as follows:

$$AVE(\xi_j) = \frac{\sum_{k=1}^{K_j} \lambda_{jk}^2}{\sum_{k=1}^{K_j} \lambda_{jk}^2 + \theta_{jk}}$$

where  $\lambda_{jk}$  is the indicator loading and  $\theta_{jk}$  the error variance of the kth indicator (k = 1,...,Kj) of construct  $\xi_j$  and is calculated as  $\theta_{jk} = \sum_{k=1}^{K_j} (1 - \lambda_{jk}^2)$  and Kj is the number of indicators of the construct  $\xi_j$ .

3. **Validity** - Validity of an instrument is its ability to measure what it is supposed to measure and usually assessed from content validity, criterion validity and construct validity. Modern validity theory suggests construct validity as the most important validity measurement (Messick, 1995). Campbell and Fiske (1959) proposed two aspects to assess the Construct Validity of a test, namely Convergent validity and Discriminant validity.

- a. **Convergent Validity** - It is achieved if AVE > 0.5 and CR > 0.7 (Fornell-Larker, 1981; Chin, 1998).
- b. **Discriminant Validity**- It is one of the key building blocks of model evaluation (e.g.,Bagozzi and Phillips 1982; Hair et al. 2010). A very important requirement for discriminant validity is that the correlation between exogenous constructs should not exceed 0.85. Also, Each construct's average variance extracted (AVE) needs to be < its squared correlations with other constructs in the model (Fornell-Larker, 1981) i.e  $AVE(\xi_j) > \max r_{ij}^2 \forall i \neq j$  where  $r_{ij}$  is the correlation coefficient between the construct scores of constructs  $\xi_i$  and  $\xi_j$ .
- c. **Construct Validity**- It is achieved when certain fitness indices achieve the adequate level. These indices are indicative of how fit the variables are in measuring the latent variables or constructs. The different model fit categories include Absolute Fit, Incremental Fit and Parsimonious Fit.

- ✓ **Absolute fit indices** (McDonald and Ho, 2002; Joreskog and Sorbom, 1993) include **Chi-Square test, RMSEA, GFI and AGFI**.
- ✓ **Incremental fit indices** are also referred to as comparative (Miles and Shevlin, 2007) or relative fit indices (McDonald and Ho, 2002). **AGFI (Adjusted Goodness of Fit Index), NFI (Normed Fit Index) CFI (Comparative Fit Index)**, introduced by Bentler (1990), **TLI (Trucker-Lewis Index, 1973)**, also known as NNFI (non-normed fit index) is included in this category
- ✓ **Parsimony fit indices** (Mulaik et al, 1989) include **PGFI** (based on the GFI), **PNFI** (based on the NFI), **PCFI** (based on the CFI). Information Criteria forms yet another measures of parsimony fit index of which **Akaike Information Criteria (AIC)** or Consistent version of AIC i.e. CAIC (Akaike, 1974) is probably the best of the known such indices. They are used for model comparison and smaller values of it indicate a better model fit.

Literature suggests huge choice of fit indices but which one to include in the report is very critical since there is no absolute model fit assessment rule or norm. Furthermore, selection of those indices suggesting best fit only may suppress the most important information related to the model. Thus, reporting of a variety of fit indices is important (Crowley and Fan, 1997) as they indicate different aspects of the model fit. Hair et al. (1995,

2010) and Holmes-Smith (2006) have recommended the use of at least one fitness index from each category of model fit.

**e) Computing Language & Software Used**

The researchers in their ensuing work have used R 3.4.1 version for conducting PCA and EFA and AMOS (Ver. 20) for SEM and CFA studies.

**5. Findings**

**Findings of Objective 1.**

The dataset was first examined and tested if it is fit to be put to PCA & EFA. Corplot (correlation plot) was first extracted to explore the type of relationship that exists amongst the attributes. Corplot of attributes is shown in Fig. 1. Also test of multi collinearity; a situation in which two or more explanatory variables is highly related linearly, was tested. However VIF (variance inflation factor), a measure of existence of multicollinearity, were found to be < 10 thereby indicating absence of multicollinearity in the data set (Fig. 2). Thus, no attributes were dropped.

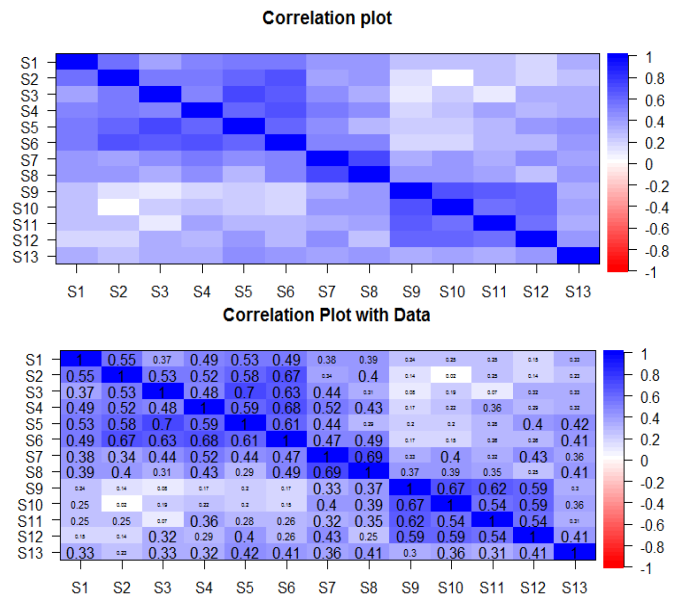


Fig – 1; Corplot, Source: R Output of primary data

vif(data)	
S1	1.873960
S2	2.547841
S3	2.720734
S4	2.416228
S5	3.008316
S6	3.081055
S7	2.643782
S8	2.656833
S9	2.551646
S10	2.554253
S11	2.191951
S12	2.476898
S13	1.563548

cronbach(PCA_EFadata)	
sample.size	220
no.of.items	13
alpha	0.8865193

Fig – 2; Cronbach's Alpha & VIF; Source: R Output of PCA & EFA primary data

PCA was done to find out the relative importance of the attributes or components (Fig. 3). Those having standard deviation values > 1 were considered important but how many components to be retained for conducting EFA was checked from Scree Plot (Fig. 4). Scree Plot is a graphical representation

of the Eigen values against the number of factors. It was found that 10 components had standard deviation > 1 but Scree plot suggested sharp decline in variances after component 2. Again one can observe a decline in variance in the Scree plot after

component 5 after which the curve tapers gradually. Thus EFA was done with 5 components initially and checked for components 4, 3 and 2 to ascertain the best result.

PCA Summary - Importance of Components

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13
Standard deviation	4.853	3.082	2.014	1.958	1.745	1.598	1.456	1.272	1.154	1.063	0.971	0.905	0.832
Proportion of Var.	0.427	0.172	0.073	0.069	0.055	0.046	0.038	0.029	0.024	0.020	0.017	0.015	0.013
Cumulative Prop.	0.427	0.599	0.672	0.742	0.797	0.843	0.882	0.911	0.935	0.956	0.973	0.987	1.000

Fig – 3; Principle Component Analysis; Source: R Output of primary data

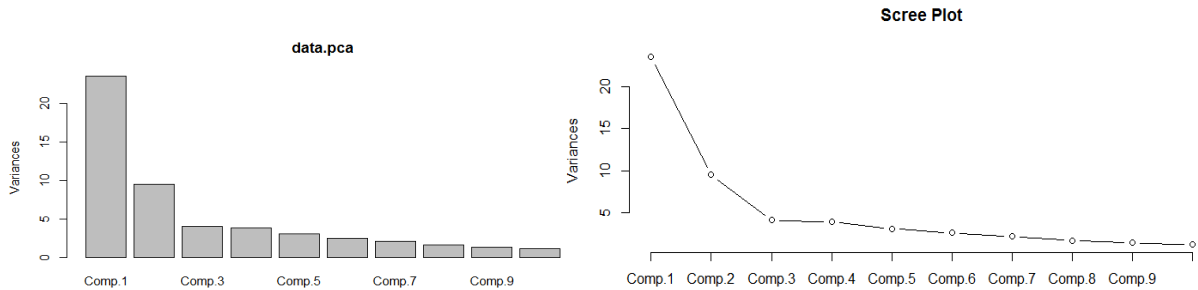


Fig – 4; Scree Plot; Source: R Output of primary data

Before EFA was done, KMO test was done to check if there are a significant number of factors in the dataset, R-Output of

KMO yields overall MSA (measure of sampling adequacy) = 0.83. MSA for each item found out is:

S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
0.86	0.83	0.80	0.88	0.85	0.87	0.82	0.77	0.81	0.80	0.83	0.81	0.88

Overall MSA value of 0.83 in the present study suggests it is meritorious. Also, MSA value for each item > 0.5 i.e. they are in the acceptable range. Adequacy of Factor Analysis was further confirmed by conducting Bartlett's Test of Sphericity. The chi sq value was found to be 698.86 with p. value of 1.66874e-100, thus indicating H0 to be rejected and H1 accepted i.e. variables are

correlated in the population. Also, Criteria of sample size adequacy with a sample size of 200 was met (200 is fair, Comfrey and Lee, 1992, p.217). EFA with 5 factors and varimax rotation were conducted and the results obtained are shown in Fig. 5.

EFA Results

Uniquenesses:

S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
0.594	0.147	0.202	0.005	0.308	0.313	0.383	0.005	0.278	0.335	0.370	0.351	0.679

Loadings:

	Factor1	Factor2	Factor3	Factor4	Factor5
S1	0.173	0.499	0.216	0.193	0.207
S2		0.868	0.255	0.152	0.103
S3		0.323	0.807	0.165	0.114
S4	0.145	0.374	0.278	0.225	0.840
S5	0.198	0.445	0.623		0.250
S6		0.552	0.435	0.285	0.325
S7	0.299	0.150	0.325	0.584	0.242
S8	0.239	0.269		0.924	
S9	0.824	0.121		0.161	
S10	0.760		0.151	0.234	
S11	0.714	0.256		0.106	0.190
S12	0.722		0.344		
S13	0.340	0.131	0.313	0.286	
Avg.	0.441	0.362	0.374	0.301	0.283

	Factor1	Factor2	Factor3	Factor4	Factor5
SS loadings	2.650	1.949	1.773	1.596	1.062
Proportion Var	0.204	0.150	0.136	0.123	0.082
Cumulative Var	0.204	0.354	0.490	0.613	0.695

Fig – 5; Exploratory Factor Analysis Output; Source: R Output of primary data

Test of the hypothesis that 5 factors are sufficient was done and the chi square statistic found is 31.92 with the p-value being 0.102, thereby suggesting that we accept H0 i.e. 5 factors are sufficient. Test of the hypothesis that 2, 3 and 4 factors are sufficient were also tested. In all the cases, the p-value < 0.05

and hence H0 was rejected and H1 accepted i.e. the factors (2 to 4) are not sufficient. Selection of the attributes within a factor is based on the criteria that attribute loadings must be greater than or equal to the average loadings of that factor. Attributes meeting this criterion have only been retained within that factor.

However, if an attribute meets this criterion for more than one factor, then the attribute is loaded on to that factor in which it has a higher loading. The 5 factors and the attributes included in each factor are indicated with a different colour (red) and names given to each of the factors.

- ✓ **Factor 1: S9, S10, S11, S12:** Pick and drop, Known school, Co-education, Personal care n attention.
- ✓ **Factor 2: S1, S2, S6:** Fee structure, Safety & Security, Infrastructure
- ✓ **Factor 3: S3, S5:** Brand, Extracurricular activities.
- ✓ **Factor 4: S7, S8:** Nearby, School where child's friends go
- ✓ **Factor 5: S4:** Type of training

The 5 factors have been named as Primal (Factor 1); Comfort (Factor 2); Divergent (Factor 3); Convenience (Factor 4); Type of Training (Factor 5). The total variance explained is 70% out of which the first two Factors contribute 35% which is 50% of the total variance is explained by all the factors.

**Findings of Objective 2.**

While most variables used in SEM are latent variables, it is also acceptable to use observed variables (Kline, 2005,p. 12). An observed variable captures the construct when it is sufficiently narrow or unambiguous to the respondents (Sackett and Lawson, 1990; Wanous et al., 1997). Rossiter (2002) argues that a single-item measure is sufficient if the construct is singular and concrete in the minds of the raters, and Drolet and Morrison (2001) recommend the use of single-item measures that meet Rossiter's criteria. Bergkvist and Rossiter (2007) demonstrate how some single-item concrete measures can be superior to multi-item measures. We contend that our measure of Type of Training (variable S4) is unambiguous, singular, and concrete in the minds of our responders.

CFA was conducted with a separate lot of 330 respondents using similar questionnaire as that of EFA study. The AMOS output of the default (proposed) model shows 45 degrees of freedom with distinct sample moments being 78 as obtained from the formula:  $n(n+1)/2$  and number of distinct parameters to be estimated being 32. Thus, with 46 degrees of freedom the proposed model is over identified. Also, Chi-square value of 127.96 with Probability level = .000 indicates Chi-square/ Degrees of Freedom being 2.844. The proposed model and the measurement model output, derived from AMOS output is shown in Fig. 6.

**The Proposed Model**

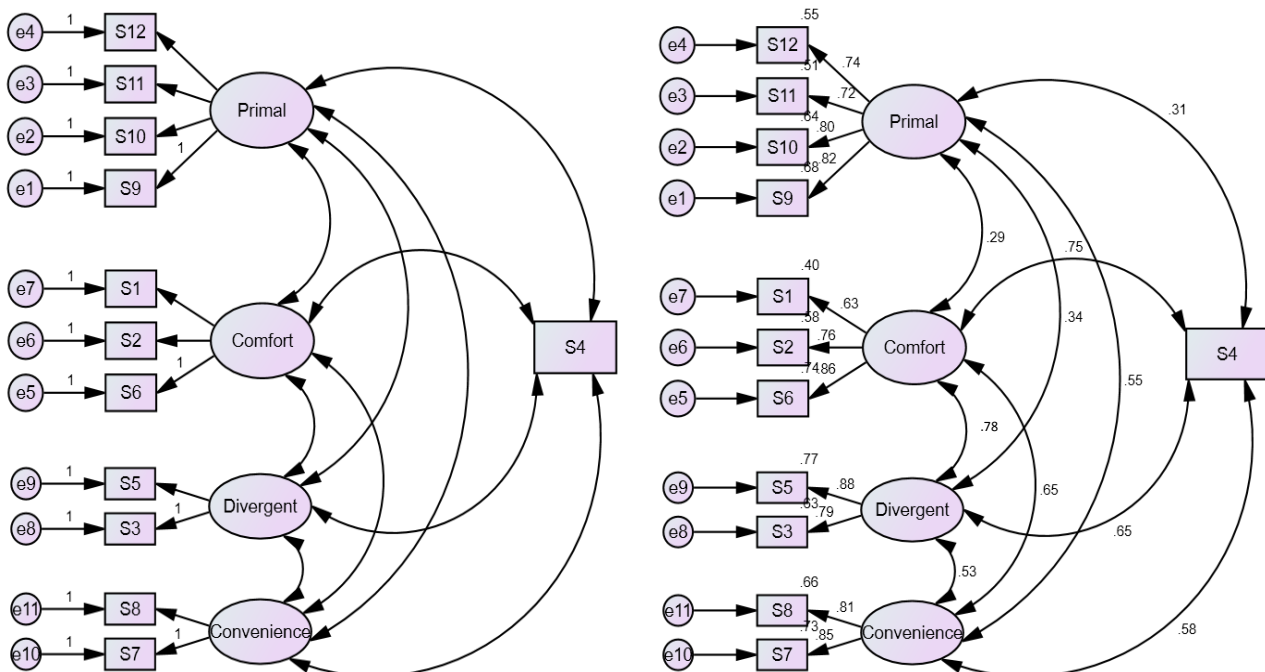


Fig – 6; Proposed Model Output; Source: AMOS Output of primary data

Next, the measurement model was analyzed and for each and every construct, the SE: Std. Est.(Loading), SSE: Squared Std. Est., MEV: Measurement Error Variance was taken from AMOS output and CR: Composite Reliability, AVE: Average Variance Extracted, Cr.α: Cronbach's Alpha calculated. For all the constructs (Primal, Comfort, Divergent and Convenience), it is seen that, AVE > 0.5 thereby establishing convergent validity.

Correlations between constructs have been found to < 0.85 which establishes discriminant validity. Furthermore, the square root of AVE is indicated on the diagonal of Fig. 11 and is found to be greater than the construct correlations which further establish discriminant validity. Also, Cronbach's Alpha > 0.8 for all the constructs suggests high internal consistency. Construct wise outputs are shown in Fig. 7 to 10.

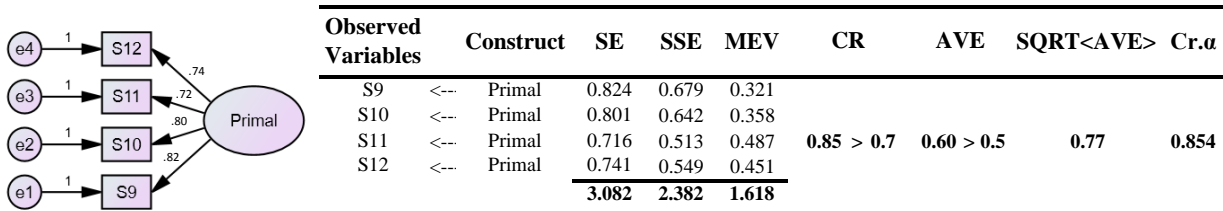


Fig – 7; Validity measurement of Primal Construct; *Source: Author's calculation*

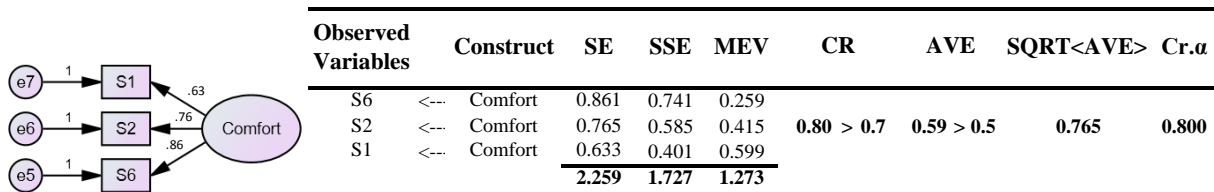


Fig – 8; Validity measurement of Comfort Construct; *Source: Author's calculation*

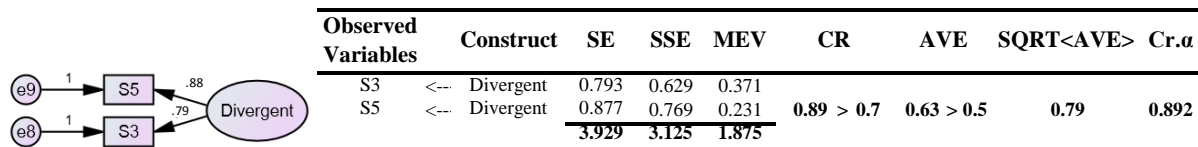


Fig – 9; Validity measurement of Divergent Construct; *Source: Author's calculation*

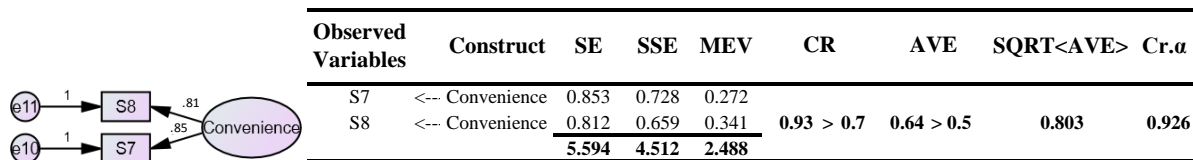


Fig – 10; Validity measurement of Convenience Construct; *Source: Author's calculation*

NB: SE: Std. Est.(Loading), SSE: Squared Std. Est., MEV: Measurement Error Variance, CR: Composite Reliability, AVE: Average Variance Extracted, Cr.α: Cronbach's Alpha

	No. of Measures	Primal	Comfort	Divergent	Convenience	S4	Cr.α	CR	AVE
<b>Primal</b>	4	<b>0.772</b>					<b>0.85</b>	0.854	0.772
<b>Comfort</b>	3	0.293	<b>0.765</b>				<b>0.79</b>	0.000	0.765
<b>Divergent</b>	2	0.336	0.789	<b>0.791</b>			<b>0.82</b>	0.892	0.791
<b>Convenience</b>	2	0.552	0.645	0.533	<b>0.803</b>		<b>0.82</b>	0.926	0.803
<b>S4 (Type of Training)</b>	1	0.311	0.753	0.654	0.581	N/A	N/A	N/A	N/A

Fig – 11; Correlation Matrix between Constructs; *Source: Author's calculation*

We checked the construct validity from absolute fit, incremental fit and parsimony fit point of view. The summary of the different fit indices is presented in Fig. 12. From the AMOS output the authors have considered the stricter cut off levels and it is observed that the results fall within the accepted level; however in few of the cases it is found to be marginal in nature

as shown below. Usually, construct validity is achieved if at least one index of each of the three fit measures (absolute, incremental and parsimony) falls within the acceptable range. The present study shows healthy outcome for construct validity establishment.

Fit Indices Values and their Acceptance Level			
Name of Fit	Index Values	Level of Acceptance	Remarks
<b>Absolute Fit</b>			
Chi-Square (ChiSq)	$p = 0.08$	$> 0.05$	Accepted cut off achieved
RMSEA	0.057	$< 0.08$	Accepted cut off achieved
GFI	0.907	$> 0.9$	Accepted cut off achieved
<b>Incremental Fit</b>			
AGFI	0.911	$> 0.9$	Accepted cut off achieved
CFI	0.947	$\geq 0.95$	Accepted cut off achieved marginally
TLI	0.903	$> 0.9$	Accepted cut off achieved marginally
NFI	0.948	$\geq 0.95$	Accepted cut off achieved marginally
<b>Parsimonious Fit</b>			
ChiSq/df	2.844	$2 < \text{ChiSq}/df < 5$	Accepted cut off achieved
PGFI	0.497	$< 0.5$	Accepted cut off achieved marginally
PNFI	0.489	$< 0.5$	Accepted cut off achieved marginally

Fig – 12; Fit Indices and their acceptance levels; *Source: AMOS Output*

## 6. Conclusion

The constructs explored from the initial study have been confirmed to a satisfactory level and it allows us to conclude that five factors or constructs influence parental decision in play school selection. Primal is the most important factor followed by comfort and divergent in order of decreasing importance. The present research attempt is expected to aid play schools to fine tune their offerings and also enrich academic research in the chosen area.

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