Chapter 5

Data Analysis & Typology of Disposers

This chapter presents the statistical analyses carried out on the main study dataset along with the findings in a series of reports, tables and figures. The chapter starts with the pretest reporting, pilot study findings and a descriptive statistics of the respondents that made up the sample, followed by a detailed description of the steps taken to conduct exploratory and confirmatory data analyses. Next, the result of the descriptive statistics of the measurement scales for the 10 constructs: Value Seeking Tendency, Innovation Seeking Tendency, Tendency to De-clutter, Lifestyle Factors, Storage Factors, Product Working Condition, Disposition Channel, Disposition Tendency, Disposition Behavior and Impulse Disposition Behavior are reported. The results of Partial Least Square (PLS) based Structural Equation Modeling (SEM) approach for the assessment of the measurement and structural model are presented. Next, tests of internal reliability consistency, convergent validity, discriminant validity, and predictive validity are examined on the basis of PLS outputs to evaluate and adjust the measurement model. Further, the assessment of the structural model was carried out. The R^2 values of the endogenous constructs helped predict the explanatory power of the model. Also, path coefficient (β) and t-values are calculated to determine the direction and significance of the hypothesized relationship. The explanatory power of the model and Goodness- of-fit (GOF) are also discussed in this chapter. In the second part, a discussion of the five demographic variables i.e. age, income, gender, family type, job transferability and work status is presented as the moderator elements in the disposition tendency model. The procedure has been presented as per a multi group discussion.

5.1 Pre-testing Procedures

Semi-structured interview method in the exploratory phase helped identify the ten constructs of the disposition tendency model. This qualitative research phase which generated an initial pool of 55 items was purified with the help of expert opinion (Churchill, 1979). The screening process took place in two stages which helped develop a preliminary questionnaire for the pretest with 48 items that had the consensus of all the three experts.

Pretest: The first pretest survey questionnaire was conducted among 35 Ph.D. students from the School of Management, Pondicherry University. The intent of this test was to verify the outline, phrasing and if it was essential to bring clarity to any measurement item. The pretest helped find and discard or refine some ambiguous statements in the questionnaire which were either extracted from

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literature or developed following the field study. The final version of the questionnaire was developed for the pilot study with all the changes incorporated.

5.2 Pilot Study Findings

A pilot study was done to mainly to assess the validity and reliability of the instrument. Further, the study intended to assess and purify the instrument so as to minimize the number of unforeseen problems in the main study (Lewis et al., 2005; Cooper, Schindler, & Sun, 2006).

The sample size ranging from 15-30 respondents are considered acceptable for pilot studies (Malhotra, 2008). However, the objective of the study was to have sound overall predictability, and therefore, 180 respondents were surveyed for the pilot study and 168 useable responses that emerged were used for measuring internal consistency for each of the measures. Since this study consists of reflective measures for all dimensions, internal consistency was ascertained using reliability coefficients (Petter, Straub, & Rai, 2007). Reliability helps establish that all the respective items are consistent and measuring the same phenomenon (Jarvis, MacKenzie, & Podsakoff, 2003). The Cronbach's alpha reliability coefficients were calculated were well above the 0.7 cut off for all measures which confirmed the internal consistencies (Table 5.2). Hence, the survey instrument was confirmed fit for use in the main study.

Another key objective was to examine the construct dimensionality to avoid possibilities of eventual misspecification of measurement model (MacKenzie et al., 2005). The key purpose of the pilot test was to check for preliminary dimensionality of individual constructs. This was done by carrying out exploratory factor analysis (Gerbing and Anderson, 1988). A principal components factor analysis with Promax rotation was performed individually to assess each construct. Both KMO (> 0.5) and Barlett's test ($p < 0.05$) of individual constructs showed satisfactory results (Hair et al., 2006). The pilot survey follows the procedures of the real data collection phase. Table 5.1 provides demographic information of the participants. To summarize, after the pretest and pilot test, a total of 43 out of the 48 initial items were retained for the final questionnaire. The final questionnaire showed good content validity. The scale of individual constructs showed satisfactory scale reliability as a result of the pretest and pilot test.

Table 5.1 Demographic Information of the Respondents N=168

Demographics	Frequency (%)
Age 25-29	52 (31.0)
30-49	89 (53.0)
50 and above	27 (16.1)
Income Less than 5 Lakhs	72 (42.9)
5 Lakhs and above	96 (57.1)
Gender Male	114 (67.9)
Female	54 (32.1)
Family type Nuclear Family	114 (67.9)
Joint Family	54 (32.1)
Job transferability Transferable	61 (36.3)
Non transferable	107 (63.7)
Work Status Unemployed	49 (29.2)
Employed	119 (70.8)

Table 5.2 Reliability Analysis of Pilot Study

Construct	No. of original items	Cronbach's Alpha
Tendency to De-clutter	6	0.901
Value Seeking Tendency	5	0.870
Innovation Seeking Tendency	4	0.869
Lifestyle Factor	4	0.934
Storage	2	0.917
Disposition Channel	5	0.912
Product Working Condition	5	0.947
Disposition Tendency	6	0.970
Disposition Behavior	6	0.954
Impulse Disposing Behavior	5	0.869

Table 5.3 shows the EFA results with details of items deleted.

Table 5.3 Factor Analysis and Reliability of the Final Instrument (Pilot Study)

Construct	No. of Items	Factor loading	KMO	Eigen-value	% of Variance	Cronbach's α	Items Deleted
Tendency to De-clutter	5	DC4-0.880 DC6-0.820 DC3-0.810 DC1-0.793 DC2-0.717	0.831	3.391	67.830	0.901	DC5
Disposition Behavior	5	DisB4-0.942 DisB1-0.942 DisB6-0.93 DisB3-0.908 DisB5-0.874	0.916	4.236	84.729	0.954	DisB2
Disposition Tendency	6	DisT1-0.926 DisT2-0.923 DisT6-0.904 DisT5-0.898 DisT3-0.896 DisT4-0.895	0.931	5.232	87.195	0.970	Nil
Disposition Channel	5	DispCh4-0.949	0.866	3.759	75.186	0.912	Nil

Construct	No. of Items	Factor loading	KMO	Eigen-value	% of Variance	Cronbach's α	Items Deleted
		DispCh2-0.887 DispCh5-0.875 DispCh1-0.840 DispCh3-0.776					
Innovation Seeking Tendency	4	IS3-0.907 IS4-0.891 IS1-0.743 IS2-0.718	0.729	2.893	72.335	0.869	Nil
Impulse Disposing Behavior	4	Impdisp5-0.961 Impdisp1-0.932 Impdisp2-0.809 Impdisp4-0.692	0.651	2.915	72.885	0.869	Impdisp 3
Lifestyle Factor	3	LS1-0.944 LS3-0.934 LS4-0.932	0.770	2.699	89.966	0.934	LS2

Storage	2	Storage1-0.945 Storage2-0.945	0.55	1.713	85.658	0.917	Nil
Value Seeking Tendency	5	VS1-0.918 VS4-0.833 VS3-0.753 VS5-0.698 VS2-0.68	0.855	3.31	66.192	0.870	Nil
Product Working Condition	4	WC2-0.934 WC4-0.925 WC3-0.916 WC5-0.914	0.789	3.517	87.92	0.947	WC1

5.3 Final survey

The survey data was collected over a time span of 9 months starting from July 1, 2013 to March 31, 2014. Link to the web survey was sent in batches adding up to a total of 2000 respondents who were invited via Facebook, LinkedIn and Google+ accounts and also via second hand product disposition online Facebook forums (Second to None and Thrift Bazaar). Respondents were sent an inbox message which informed about the purpose of the study and gave a link to the Web survey. After 15 days of sending the invite in order to improve the response rate, a gentle reminder message was sent to the intended respondents who did not take up the survey. A second reminder thread was again sent or phone calls made (if numbers were available) after another 15 days requesting those who did not take up the survey to participate. Final notification was sent to respondents to intimate them about the survey deadline of March 31 2014.

5.3.1 Data Preparation

Data preparation is a critical process that involves cleaning raw data and refining it for data analysis and visualizations. Since the web survey was created using Google form, the data is entered automatically into a database. The survey link was sent to 2000 individuals. A total of 720 participants responded to the invitation and accepted to take up the survey. The completed surveys were downloaded and 72 responses were found to be unusable. In order to ensure respondents do not skip key questions, all questions were made compulsory. This helped in getting 648 complete and useable responses which were loaded into SPSS version 20 software for generating descriptive statistical reports and for generating analysis to check for normality and multicollinearity. For performing PLS-SEM analysis, Smart PLS 2.0 M3 was used to evaluate the measurement and structural models. The online survey data was downloaded as an Excel.CSV file before importing it to Smart PLS for further data analysis.

5.3.2 Normality Test

The assumption of normality of the data set was examined by means of two statistical analyses: 1) Shapiro-Wilk test and 2) skewness and kurtosis (Table 5.4). The results from the Shapiro-Wilk test exhibit that all variables have significant values of 0.00. This indicates that the data are not normal (non-normal). Further, skewness and kurtosis statistics confirm that the data distribution is non-normal, and the data had skewness and kurtosis above the recommended threshold, -3 to +3. The box plot, Q-Q plot and the histogram provided evidence for significant deviation from normality. Therefore, it shows that the data normality distribution assumption was violated, thus, further supporting the use of PLS-SEM.

Table 5.4 Tests of Normality

Component	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic		Sig.
VS Total	.172	648	.000	.899		.000
DCTotal	.107	648	.000	.955		.000
ISTotal	.143	648	.000	.906		.000
DisTTotal	.305	648	.000	.777		.000
DisBTotal	.281	648	.000	.772		.000
LSTotal	.166	648	.000	.891		.000
StorTotal	.302	648	.000	.757	648	.000
WCtotal	.311	648	.000	.813	648	.000
DispChnnlTotal	.346	648	.000	.628	648	.000
ImpDisTotal	.231	648	.000	.827		.000

a. Lilliefors Significance Correction.

5.3.3 Multicollinearity

Tests to assess if the data met the assumption of collinearity indicated no multicollinearity issues. This study used the variance inflation factor (VIF) statistic to determine if the constructs were too highly correlated. A traditional rule of thumb posits that the tolerance of less than 0.20 or 0.10 and/or VIF of 5 or 10 and above indicates a multicollinearity problem. The maximum VIF value for all the ten constructs of this study came to 2.27, which is well below the threshold of 5 (Table 5.5). A condition index greater than 30 suggests a serious problem with collinearity. The condition indices values were found to be less than 30 (Table 5.6). Thus, Multicollinearity did not pose a threat to the validity of the measures at the indicator level of this study.

Table 5.5 Multicollinearity

COEFFICIENTS		
	Collinearity statistics	
Dimension	Tolerance	VIF
VS	.577	1.734
DC	.783	1.277
IS	.742	1.347
DIST	.440	2.271
DISB	.846	1.182
LS	.870	1.150
STOR	.801	1.249
WC	.689	1.450
DISPCHNNL	.983	1.017
IMPDISP	.884	1.131

Table 5.6 Collinearity Diagnostics

Model	Eigen value	Condition Index	(Constant)	VS Total	DC Total	IS Total	DisT Total	DisB Total	LS Total	Stor Total	WC Total	DispChnl Total	ImpDisp Total
1	9.759	1	0	0	0	0	0	0	0	0	0	0	0
2	0.373	5.117	0.01	0	0.01	0	0	0.02	0.21	0.01	0.05	0	0
3	0.21	6.811	0	0.02	0	0.02	0	0.59	0.06	0.04	0.01	0.01	0.02
4	0.148	8.113	0	0	0	0	0.17	0.01	0.01	0.15	0.02	0.01	0
5	0.14	8.355	0	0	0	0	0.62	0.02	0.01	0.02	0.02	0	0.16
6	0.106	9.601	0	0	0	0	0.03	0.01	0.01	0.14	0.31	0.46	0.01
7	0.092	10.313	0	0	0	0	0.03	0.14	0.31	0.01	0	0	0.56
8	0.076	11.322	0	0.01	0.23	0.01	0	0.01	0.01	0	0.01	0.59	0.01
9	0.055	13.283	0	0	0	0	0	0	0	0.02	0	0	0
10	0.059	13.372	0	0.61	0.57	0.03	0.37	0	0.02	0.18	0.05	0.01	0.01

5.3.4 Profile of Respondents

The respondents profile provides insight into the demographic characteristics of respondents which is reported in Table 5.7. The respondents were comprised of male (66.7%) and female (33.3%). About 44.4% of the respondents' had annual income below Rs.5 Lakhs and the remaining 55.6% of the respondents had income above. Among the total respondents 31.5% were young followed by 51.8% middle aged, and the rest 16.7 were old. 68.5% of the respondents were in a nuclear family and the remaining 31.5 % were in a joint family. The analysis also shows that 70.3% of the respondents were employed. The majority of the respondents (64.8%) were in non-transferable jobs and hence did not face much need to re-locate for work.

Table 5.7 Profile of Respondents

Demography	Indicators	Frequency (n=648)	Percentage
	25-39	204	31.5
Age	40-49	336	51.8
Demography	**Indicators**	**Frequency (n=648)**	**Percentage**
	50 & Above	108	16.7
House hold Income	Less than 5 Lakhs	288	44.4
	Above 5 Lakhs	360	55.6
Family Type	Nuclear Family	444	68.5
	Joint Family	204	31.5
Gender	Male	432	66.7
	Female	216	33.3
Work Status	Working	456	70.3
	Not working	192	29.7
Job Transferability	Transferable	228	35.2
	Non transferable	420	64.8

5.3.5 Descriptive Statistics

The mean, standard deviation, variance, minimum value and maximum value for all the 10 constructs - de-clutter tendency, value seeking tendency, innovation seeking tendency, storage, lifestyle, product working condition, disposition channel, disposition tendency, disposition behavior and impulse disposing behavior - were examined using the statistical software SPSS version 20.0. Table 5.8 outlines the descriptive statistics for all the constructs.

Table 5.8 Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Value Seeking Tendency	648	1	7	4.874	1.333
Innovation Seeking Tendency	648	1	7	3.232	1.371
Tendency to De-clutter	648	1	7	5.028	1.287
Life style	648	1	7	3.488	2.163
Storage	648	1	7	4.278	1.744
Product Working Condition	648	1	7	3.385	1.449
Disposition Channel	648	1	7	5.195	1.227
Impulse Disposition	648	1	7	3.932	1.589
Disposition Tendency	648	1	7	3.220	1.715
Disposition Behavior	648	1	7	4.152	1.781

5.3.6 Missing Data

In this study, a missing value analysis was not required as the Web survey was designed by making all questions compulsory and skip logic was not required. The system automatically checked for incomplete responses and did not allow submission of such surveys. Hence, all the downloaded responses were complete and did not require statistical analysis of missing data.

5.4 Disposer Categories

Disposers were classified based on their scores related to de-clutter (DC) tendency, innovation (IS) seeking tendency and value seeking (VS) tendency (Tables 5.9, 5.10 and 5.11).

5.4.1 Disposer categories based on their de-clutter tendency

The majority of disposers (55.1 %) were found to have high de-clutter tendency scores indicating they were neat and organized spring cleaners. Around 37.8% of the disposers were average spring cleaners while only 7.1 % of them were found to be poor spring cleaners.

Table 5.9 Disposer Categories Based on their De-Clutter Tendency

Category	Frequency	Percent
Poor spring cleaners	46	7.1
Average spring cleaners	245	37.8
Neat and organised spring cleaners	357	55.1
Total	648	100.0

5.4.2 Disposer categories based on their value seeking tendency

The majority of the respondents (59.3%) had high value seeking tendency scores indicating that they deeply focused on product value maximization. While 26.4% of them had moderate value seeking tendency, 14.4 % were spend thrifts and had low value seeking tendency scores.

Table 5.10 Disposer Categories based on their Value Seeking Tendency

Category	Frequency	Percent
Spendthrifts	93	14.4
Moderately frugal	171	26.4
Deeply focused on product value maximization	384	59.3
Total	648	100.0

5.4.3 Disposer categories based on their innovation seeking tendency

About 51.4% of disposers had low innovation seeking tendency scores, 33.6% of them had moderate and 15% had high innovation seeking tendency scores. So, most of the disposers were found to be low innovators.

Table 5.11 Disposer Categories Based on their Innovation Seeking Tendency

Category		Frequency	Percent
	Low innovation seeking tendency	333	51.4
	Moderate innovation seeking tendency	218	33.6
	High innovation seeking tendency	97	15.0
	Total	648	100.0

5.5 Disposer Typology

The understanding of product disposition can be enhanced by developing a comprehensive disposer typology to conceptualize, classify and measure disposition tendency of individuals. Hence, an attempt has been made to develop disposer typology based on scores of value seeking tendency (VS), de-clutter tendency (DC) and innovation seeking tendency (IS) was derived. Depending on whether a disposer scored high, medium or low on each of the three constructs, namely, value seeking tendency, de-clutter tendency and innovation seeking tendency.

Analysis of the Disposer Typology

Innovation seeking tendency was measured using Roehrich Scale for consumer innovativeness (1995) and value seeking tendency was measured using Lastovicka's frugality scale with slight modifications. Items were generated on the basis of the feedback from qualitative field study of the disposers for measuring de-clutter tendency.

Eighteen disposer types are identified by dividing the scores on Value Seeking (VS), De-Cluttering (DC) and Innovation Seeking (IS) into thirds. The majority of the respondents (18.4%) were found to be sustainable disposers (High VS- Low IS- High DC) while 11.3 % of the respondents were highly frugal moderate spring cleaners (Hi VS- Moderate DC- Low IS). Around 11 % of the respondents were moderate accumulator-spring cleaners (High VS- Moderate IS -Moderate DC). Interestingly, around 7.6 % of the respondents were moderates (Moderate VS- Moderate IS- Moderate DC). At the same time, 7.4 % were moderate spring cleaner-accumulators (Low IS- Moderate VS-Moderate DC). Interestingly 5.6 % of respondents were found in each of the three categories, namely, fine accumulators (High VS- High IS- HighDC), intelligently innovative- active spring cleaners (High IS- Moderate VS- High DC) and moderate value seeking active spring cleaners (Moderate VC- Moderate IS- High DC). The percentage of respondents in the remaining categories (namely compulsive cleaners, purgers, hoarders, cluttered value seekers, moderately tidy value seekers cleaners, innovative disposers, moderate retainers and moderately frugal and tidy innovators) were less than 5%. Table 5.12 presents the Disposer Typologies identified from the study. The results are exploratory and can form the basis for further research.

Table 5.12 Disposer Typology

Typology	Score Profile	Frequency	Percent
Compulsive cleaner	Low VS- Low IS- High DC	23	3.5
Purger	Low VS- High IS- High DC	12	1.9
Sustainable disposer	**High VS- Low IS- High DC**	**119**	**18.4**
Fine accumulator	High VS- High IS- High DC	36	5.6
Hoarders/cluttered retainer	Low DC- Low IS- High VS	12	1.9
Cluttered value seeker	Low DC- High VS- High IS	1	.2
Highly frugal moderate spring cleaner	**High VS- Moderate DC- Low IS**	**73**	**11.3**
Moderately tidy value seeker	High VS- High IS- Moderate DC	24	3.7
Moderate purger	High DC- Low VS- Moderate IS	36	5.6
Spring cleaner accumulator	Low IS- Moderate VS-Moderate DC	48	7.4
Intelligently innovative active spring cleaner	High IS- Moderate VS- High DC	36	5.6
Innovator disposer	High DC- High IS- Moderate VS	11	1.7
Moderate retainer	Low DC- Low IS- Moderate VS	12	1.9
Moderate accumulators and moderate spring cleaner	**High VS- Moderate IS -Moderate DC**	**71**	**11.0**
Moderate keeper and moderate cleaner	Low IS- Moderate DC- Moderate VS	36	5.6
Moderately frugal and tidy innovator	High IS- Moderate DC- Moderate VS	13	2.0
Moderately value seeking active spring cleaner	Moderate VC- Moderate IS- High DC	36	5.6
Moderates	Moderate VS- Moderate IS- Moderate DC	49	7.6
Total		648	100.0

5.6 Disposition Behavior across Disposition Tendency Categories

In order to understand the impact of disposition tendency on actual disposition behavior, a cross- tabulation table was created (Table 5.13). While respondents with very low disposition tendency scores were seen to retain more than dispose, respondents with high disposition tendency were seen to actively dispose more than retain (Fig 5.1). This confirms that disposition tendency influences actual disposition behavior.

Table 5.13 Disposition Behavior across DisT Categories

DisT Category	DisB Category			Total
	Retain	Moderately dispose	Actively dispose	
Retainer	248	9	199	456
Disposer	32	2	158	192
Total	280	11	357	648

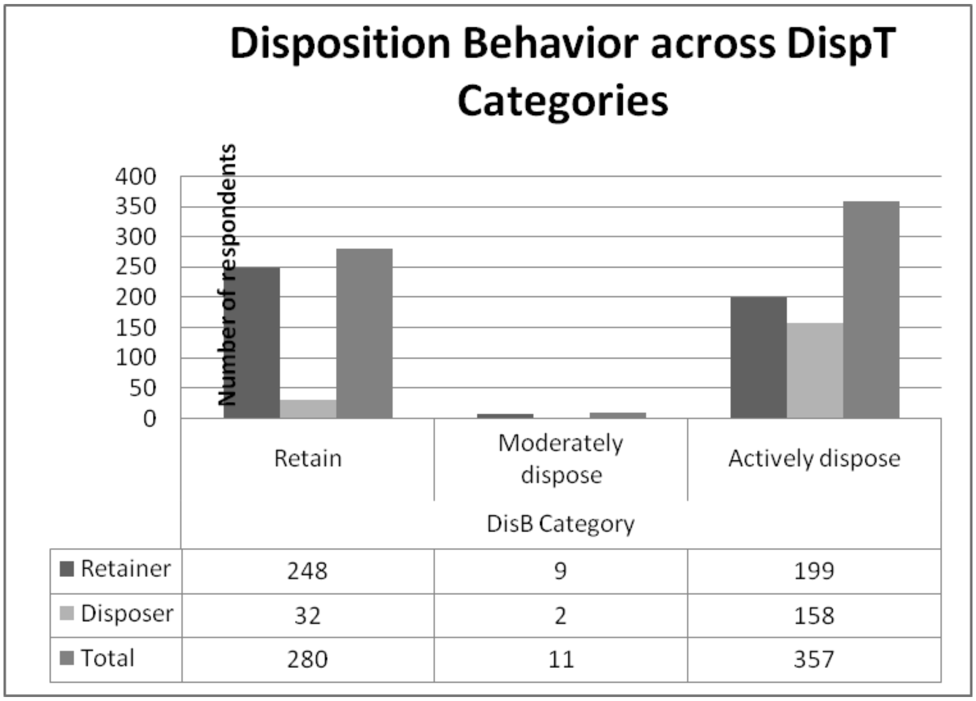

Fig 5.1 Disposition behavior across DisT categories

5.7 Impulse Disposing Behavior across Disposition Tendency Categories

Table 5.14 shows the influence of disposition tendency on impulse disposing behavior. The impact of disposition tendency on actual disposition behavior was analyzed by cross-tabulation (Table 5.14). A large percentage of both retainers and disposers showed high impulse disposing tendency. While, the respondents with low disposition tendency scores were seen to be involved in planned disposing (34.2%), moderate impulse disposing (23.7%) and high impulse disposing behavior (42%), respondents with high disposition tendency were seen to actively dispose more (62.5%) than resort to moderate impulse disposing behavior (31.3%). A very negligible percentage of these respondents (6.2%) with high disposition tendency showed planned disposing behavior (Fig 5.2). This confirms that disposition tendency influences impulse disposing behavior

Table 5.14 Impulse Disposing Behavior across DisT Categories

DisT Category	ImpDisB category		
	Low ImpDisB	Moderate ImpDisB	High ImpDisB
Retainer	156	108	
Disposer	60	12	120

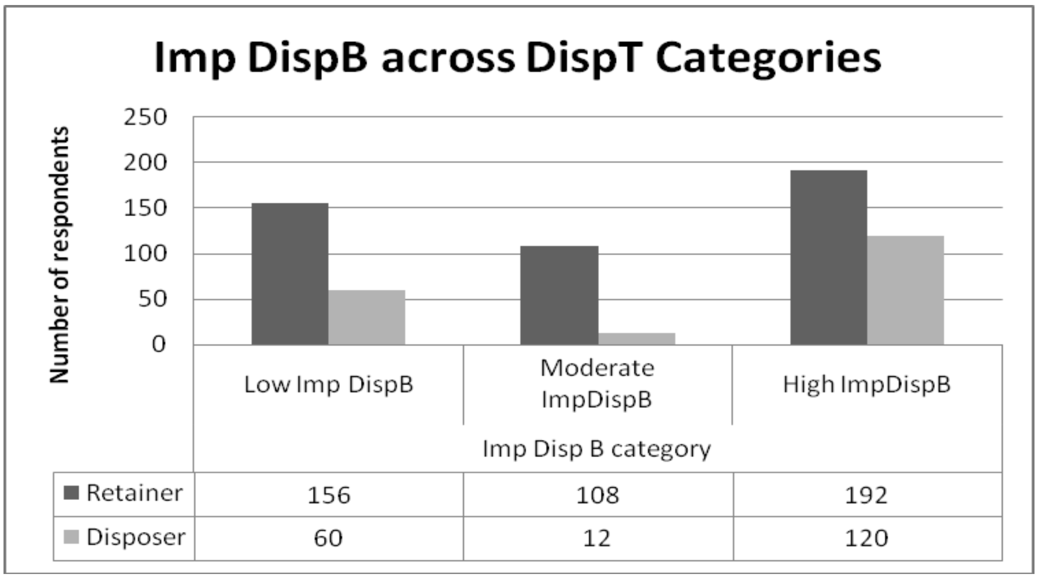

Fig 5.2 Impulse Disposition Behavior across DisT categories

5.8 Measurement Model Assessment

The measurement model, also referred to as the outer model specifies the relationship between indicators and latent variables. This study tested the research model using Smart PLS 2.0 M3 (Ringle et al., 2004). The Partial Least Square (PLS) integrates factor analysis and linear regressions. Hence, it is appropriate to use for confirmatory factor analysis and concurrent testing of multiple hypotheses. It is especially suited to exploratory studies as it makes minimal distribution assumptions and works even when the sample size is small.

This statistical software program is used to evaluate internal consistency reliability, indicator reliability, convergent validity and discriminant validity. The following subsections present the findings for each of the analysis used to evaluate the validity of the measurement model for this study.

5.8.1 Factor Analysis and Reliability

Factor analysis was conducted to identify the underlying structure of the measurement items and to validate the constructs used in the study. The results of the factor analysis, including factor loadings and variance explained, are detailed below to provide transparency regarding the dimensionality of the constructs and to demonstrate the robustness of the measurement model.

Table 5.14 Factor Analysis and Reliability

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.819
Approx. Chi-Square	28404.589
Bartlett's Test of Sphericity df	903
Sig.	.000

Pattern Matrix

To provide a clear understanding of how the measurement items loaded onto the identified factors, the pattern matrix resulting from the exploratory factor analysis is presented below. This table displays the factor loadings for each item, indicating their association with the extracted components.

Table 5.15 Pattern Matrix

Pattern Matrix[a]										
	Component									
	1	2	3	4	5	6	7	8	9	10
DisT1	0.926									
DisT2	0.923									
DisT6	0.904									
DisT5	0.898									
DisT3	0.896									
DisT4	0.895									
DisB4		0.942								
DisB1		0.942								
DisB6		0.93								
DisB3		0.908								
DisB5		0.874								
DispCh4			0.949							
DispCh2			0.887							
DispCh5			0.875							
DispCh1			0.84							
DispCh3			0.776							
DC4				0.88						
DC6				0.82						
DC3				0.81						
DC1				0.793						
DC2				0.717						
WC2					0.934					
WC4					0.925					

Pattern Matrix[a]										
	Component									
	1	2	3	4	5	6	7	8	9	10
WC3					0.916					
WC5					0.914					
VS1						0.918				
VS4						0.833				
VS3						0.753				
VS5						0.698				
VS2						0.68				
Impdisp5							0.961			
Impdisp1							0.932			

Impdisp2							0.809			
Impdisp4							0.692			
IS3								0.907		
IS4								0.891		
IS1								0.743		
IS2								0.718		
LS1									0.944	
LS3									0.934	
LS4									0.932	
Storage1										0.945
Storage2										0.945

Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 7 iteration

Communalities of Measurement Items

To further illustrate the contribution of each measurement item to the extracted factors, the communalities for all items are presented below. These values indicate the proportion of each item's variance that is explained by the retained factors, supporting the adequacy of the factor solution.

Table 5.16 Communalities of Measurement Items

	Initial	Extraction
VS1	1	0.792
VS2	1	0.737
VS3	1	0.734
VS4	1	0.763
VS5	1	0.611
DeClutter3	1	0.732
DeClutter2	1	0.735
DeClutter1	1	0.789
DeClutter4	1	0.752
DeClutter6	1	0.721
IS2	1	0.676
IS1	1	0.76
IS3	1	0.871
IS4	1	0.762
DisTQ1	1	0.884
DisTQ2	1	0.853

DisTQ3	1	0.857
DisTQ4	1	0.921
DisTQ5	1	0.849
DisTQ6	1	0.873
DisBQ1	1	0.848
DisBQ3	1	0.82
DisBQ4	1	0.879
DisBQ5	1	0.835
DisBQ6	1	0.878

Communalities (Continued)

	Initial	Extraction
LS1	1	0.902
LS3	1	0.882
LS4	1	0.87
Storage2	1	0.918
WC2	1	0.905
WC3	1	0.856
WC4	1	0.962
WC5	1	0.863
DispCh1	1	0.734
DispCh2	1	0.784
DispCh3	1	0.663
DispCh4	1	0.893
DispCh5	1	0.788
Impdisp 1	1	0.905
Impdisp 2	1	0.713
Impdisp 3	1	0.625
Impdisp 4	1	0.857

Component Correlation Matrix

To further evaluate the relationships among the extracted components, the component correlation matrix is presented below. This matrix displays the intercorrelations between the retained factors, providing additional evidence regarding the distinctiveness and appropriateness of the factor solution.

Table 5.17 Component Correlation Matrix

Component	1	2	3	4	5	6	7	8	9	10
1	1.000	.361	.012	.320	-.204	-.452	.165	.350	-.012	.367
2	.361	1.000	.043	.134	-.017	-.189	.073	.199	.032	.043
3	.012	.043	1.000	-.024	-.041	-.001	-.115	-.023	-.066	.002
4	.320	.134	-.024	1.000	-.115	.053	.018	.095	-.058	.067
5	-.204	-.017	-.041	-.115	1.000	.379	.137	.066	.184	-.137
6	-.452	-.189	-.001	.053	.379	1.000	-.128	-.047	.050	-.246
7	.165	.073	-.115	.018	.137	-.128	1.000	.233	-.038	.102
8	.350	.199	-.023	.095	.066	-.047	.233	1.000	.006	.076
9	-.012	.032	-.066	-.058	.184	.050	-.038	.006	1.000	.022
10	.367	.043	.002	.067	-.137	-.246	.102	.076	.022	1.000

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

5.8.2 Indicator Reliability

Indicator reliability checks how well the indicators are related to their respective constructs. Smart PLS 2.0 software was used to assess individual item reliability of the measurement model by examining the loadings of the items for reflective constructs. Chin (1998a) suggested 0.60 thresholds for factor loadings while Fornell and Larcker (1981) suggested that factor loadings above 0.70 and Average Value Extracted (AVE) values above 0.50 indicate satisfactory convergent validity.

A measurement model is said to have satisfactory indicator reliability if each item's loading is at least 0.7 and is considered significant at the level of 0.05. Hulland (1999) suggested 0.50 cut off for factor loadings. Literature shows authors recommending a minimum loading of 0.40 as acceptable (Hair et al., 1998; Henseler et al., 2009). Sufficient care was taken while eliminating indicators. Indicators with low reliability were discarded only if they substantially increased composite reliability scores (Henseler et al., 2009).

All items in the measurement model exhibited loadings ranging from a lower bound of 0.709 to an upper bound of 0. 973. All items exceeded 0.7 cut off and were significant at the level of 0.001. Table 5.15 shows the item wise loadings and T-statistic values on their respective constructs. Based on the results, all items used for this study have demonstrated satisfactory indicator reliability.

Table 5.15 Significance of the Factor Loadings

Variables	Indicators	Original Sample (O)	Standard Error (STERR)	T -value	P-value
Tendency to De-clutter	DC1	0.908	0.010	88.543	0.000
	DC2	0.862	0.016	54.492	0.000
	DC4	0.821	0.023	35.512	0.000
	DC6	0.814	0.019	44.102	0.000
Disposition Behavior	DisB1	0.909	0.007	128.383	0.000
	DisB3	0.900	0.008	112.134	0.000
	DisB4	0.936	0.006	159.363	0.000
	DisB5	0.918	0.006	148.568	0.000
	DisB6	0.938	0.006	167.509	0.000
Disposition Tendency	DisT1	0.941	0.004	234.713	0.000
	DisT2	0.917	0.005	182.778	0.000
	DisT3	0.927	0.005	183.634	0.000
	DisT4	0.962	0.003	372.637	0.000
	DisT5	0.922	0.005	185.851	0.000
	DisT6	0.934	0.004	226.448	0.000
Disposition Channel	DispChnnl1	0.934	0.229	4.084	0.000
	DispChnnl2	0.719	0.232	3.094	0.000
	DispChnnl4	0.862	0.200	4.307	0.000
	DispChnnl5	0.926	0.207	4.474	0.000
Innovation Seeking Tendency	IS1	0.838	0.020	42.777	0.000
	IS2	0.835	0.015	54.016	0.000
	IS3	0.924	0.008	114.701	0.000
	IS4	0.798	0.019	41.090	0.000
Impulse Disposition	ImpDisp1	0.964	0.008	115.185	0.000
	ImpDisp4	0.929	0.015	62.208	0.000
	ImpDisp5	0.790	0.032	24.513	0.000
Lifestyle	LifeStyle1	0.937	0.153	6.108	0.000

Variables	Indicators	Original Sample (O)	Standard Error (STERR)	T -value	P-value
Factor	Lifestyle3	0.941	0.155	6.062	0.000
	Lifestyle4	0.943	0.162	5.819	0.000
Storage	Storage1	0.962	0.004	231.286	0.000
	Storage2	0.965	0.004	257.210	0.000
Value Seeking Tendency	VC1	0.827	0.017	48.826	0.000
	VC2	0.821	0.019	43.740	0.000
	VC3	0.867	0.012	73.926	0.000
	VC4	0.832	0.014	59.790	0.000
	VC5	0.709	0.025	28.986	0.000
Product Working Condition	WC2	0.955	0.003	316.139	0.000
	WC3	0.900	0.010	88.740	0.000
	WC4	0.973	0.003	317.292	0.000
	WC5	0.918	0.007	142.169	0.000

5.8.3 Composite Reliability

Another measure of reliability in PLS analysis is convergent validity which was proposed by Fornell and Larcker (1981). Convergent validity suggests that a set of indicators are correlated demonstrating that they represent the same underlying construct. Thus, convergent validity indicates adequate internal consistency reliability of the underlying structural model. This can be evaluated by:

Composite Reliability: This measure is considered to be better than Cronbach's alpha because it is not influenced by the number of indicators. Composite reliability of 0.70 or greater is considered adequate to establish a convergent validity of the measurement model. Table 5.16 shows that the CR of each construct for this study ranges from 0.910 to 0.980 and this is above the recommended threshold value of 0.7. Thus, the results indicate that the items used to represent the constructs have satisfactory internal consistency reliability.

Average Variance Extracted/Convergent Validity: Another method to confirm the convergent validity of the measurement model is by evaluating the average variance extracted (AVE). AVE estimate represents the average variance extracted of a construct by its corresponding items. Fornell and Larcker (1981) suggest that an AVE value of at least 0.5 indicates sufficient convergent validity. This signifies that a latent variable is able to account for more than half of the variance of its indicators on average (Henseler et al., 2009). The AVE values of this study ranged between 0.660 and 0.930 which were well above the prescribed 0.5 threshold (Table 5.16)

Table 5.16 Convergent Validity

Variables	Indicators	Loadings	Cronbach's Alpha	Composite Reliability	AVE
Tendency to de-clutter	DC1	0.932	0.880	0.910	0.730
	DC2	0.880			
	DC3	0.872			
	DC4	0.797			
	DC6	0.734			
Value seeking tendency	VC1	0.827	0.870	0.910	0.660
	VC2	0.821			
	VC3	0.867			
	VC4	0.832			

	VC5	**0.709**			
Innovation seeking tendency	**IS1**	**0.818**	**0.870**	**0.910**	**0.720**
	IS2	**0.860**			
	IS3	**0.880**			
	IS4	**0.777**			
Storage	**Storage1**	**0.954**	**0.920**	**0.960**	**0.930**
Variables	**Indicators**	**Loadings**	**Cronbach's Alpha**	**Composite Reliability**	**AVE**
	Storage2	0.917			
Lifestyle	LifeStyle1	0.961	0.940	0.960	0.880
	Lifestyle3	0.908			
	Lifestyle4	0.879			
Product working condition	WC2	0.920	0.950	0.970	0.880
	WC3	0.885			
	WC4	0.984			
	WC5	0.892			
Disposition Channels	DispChnnl1	0.921	0.920	0.920	0.750
	DispChnnl2	0.735			
	DispChnnl3	0.944			
	DispChnnl4	0.887			
	DispChnnl5	0.797			
	DisT1	0.941			
	DisT2	0.917			
	DisT3	0.927			

Disposition tendency	DisT4	0.962	0.970	0.980	0.870
	DisT5	0.922			
	DisT6	0.933			
Disposition behavior	DisB1	0.886	0.950	0.970	0.850
	DisB2	0.198			
	DisB3	0.907			
	DisB4	0.814			
	DisB5	0.783			
Impulse disposing behavior	ImpDisp1	0.884	0.890	0.930	0.810
	ImpDisp2	0.752			
	ImpDisp4	0.885			
	ImpDisp5	0.865			

Figure 5.3 below shows initial structural model before the items were deleted. There were 43 items that emerged from EFA.

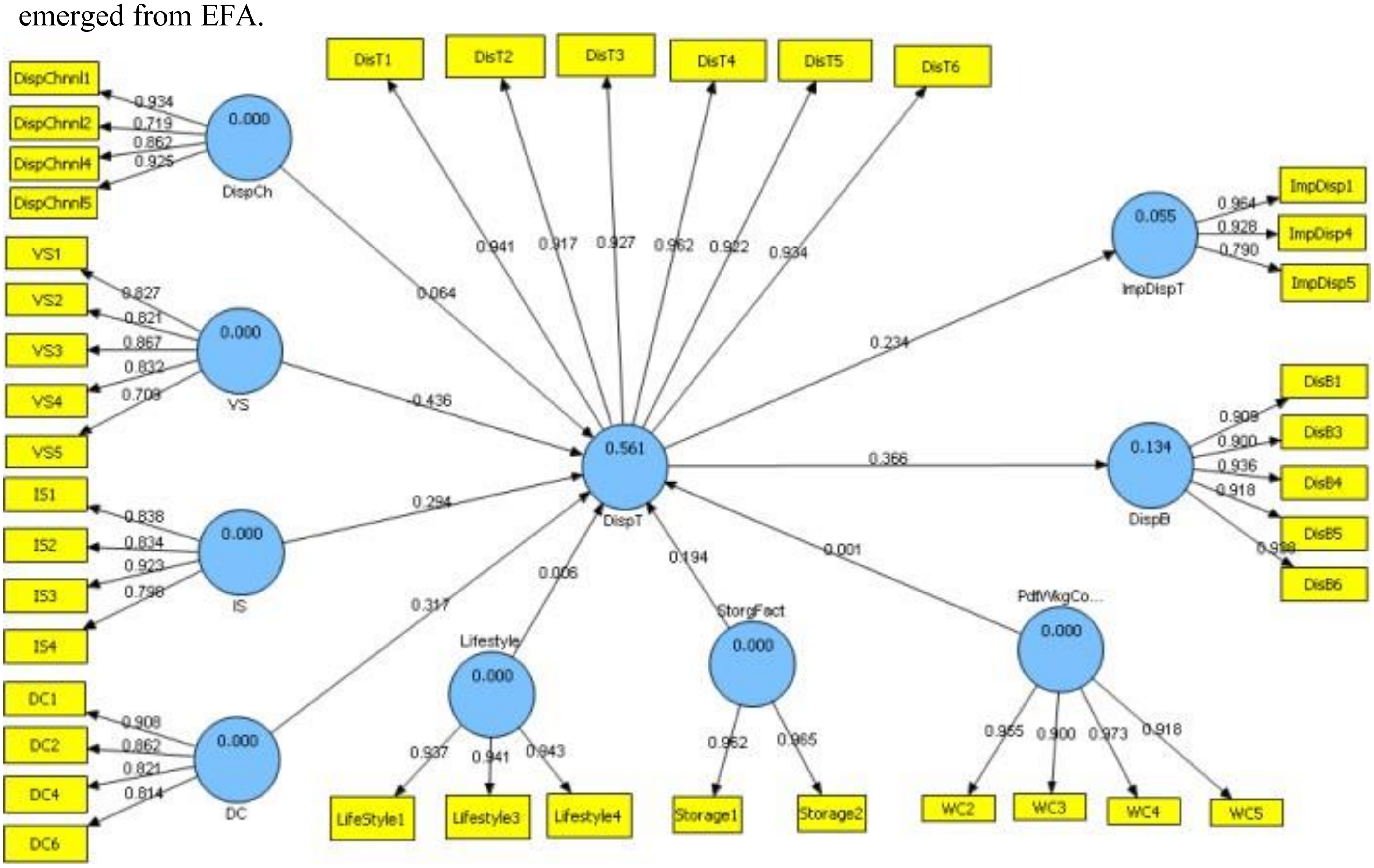

Fig 5.3 Structural Model (Initial Model before item deletion)

Figure 5.4 below shows the final structural model that evolved after item deletion. Three items got deleted. There were 40 items after item deletion

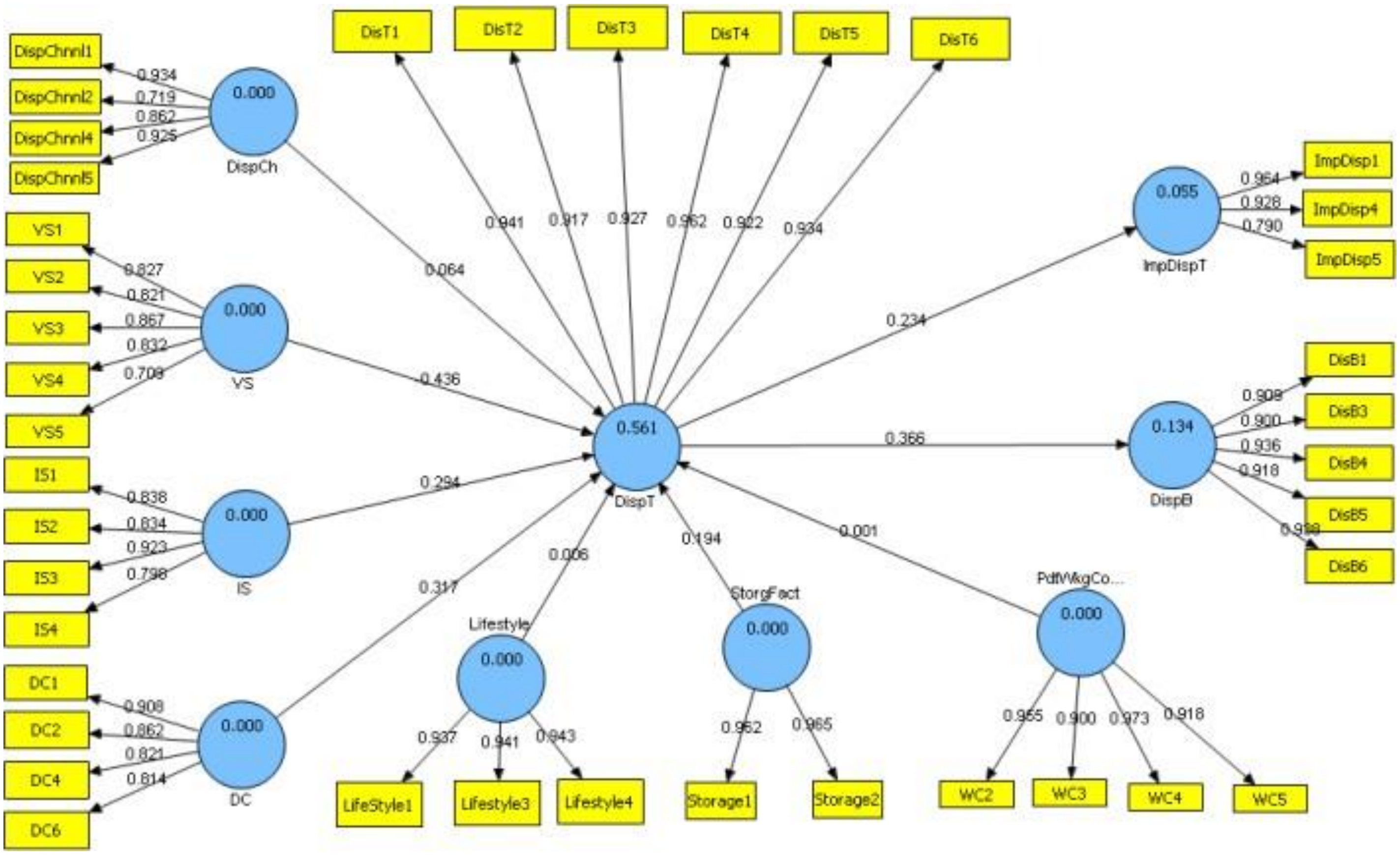

Fig 5.4 Final Structural Model (after item deletion)

Figure 5.5 below shows the final model that emerged after bootstrapping. All the 40 items were retained as they were found to be significant

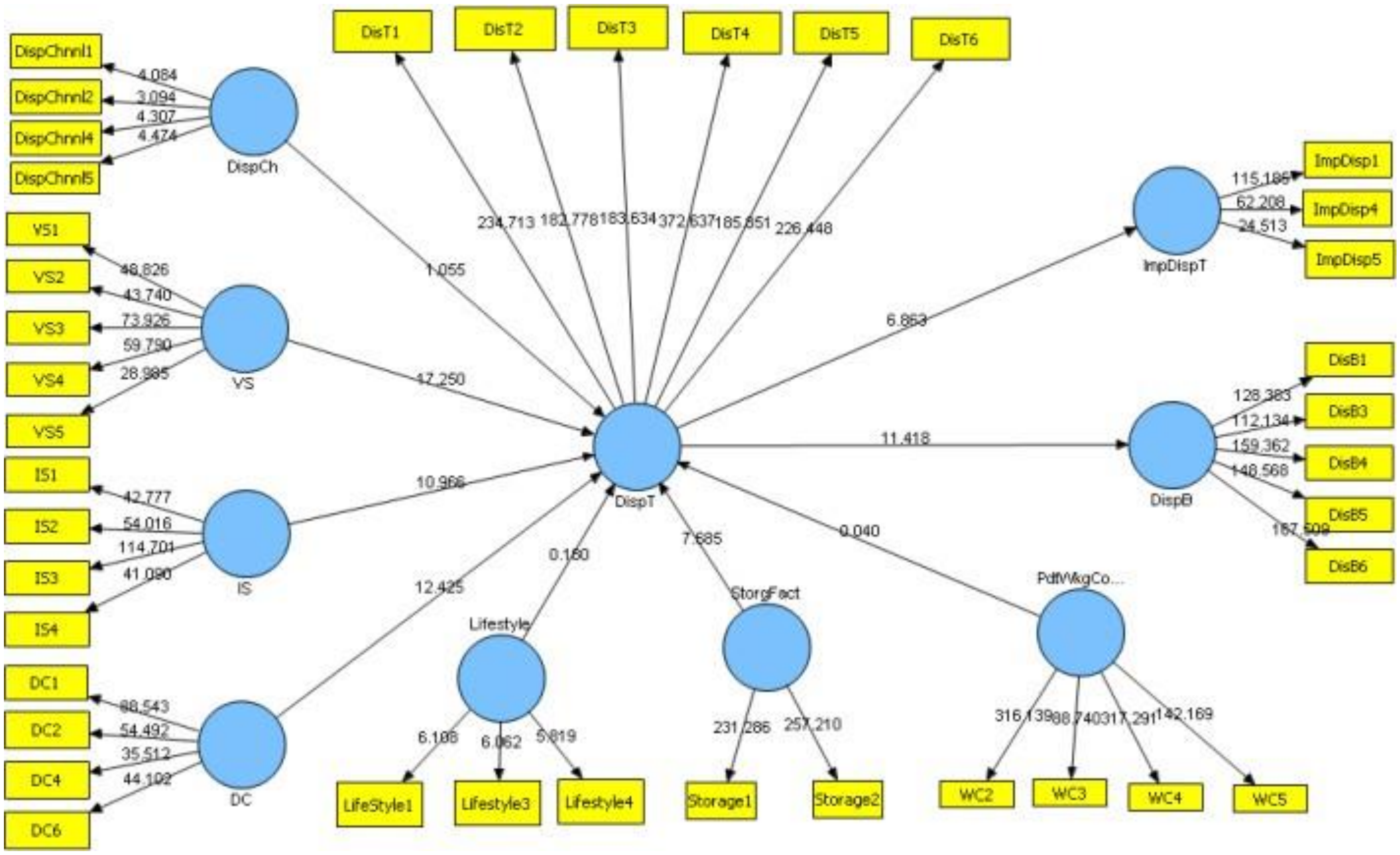

Fig 5.5 Final Model (Items after bootstrapping)

5.8.4 Discriminant Validity (Cross Loadings)

Discriminant validity is used to make a distinction between measures of constructs and to ensure items measure what they intend to measure (Urbach & Ahlemann, 2010). In PLS, two measures of discriminant validity are commonly used—cross loading (Chin, 1998b) and Fornell-Larcker's criterion (Fornell & Larcker, 1981).

Examination of the indicators' loadings with respect to all construct correlations help assess discriminant validity. Table 5.17 displays the output of cross loadings produced by SmartPLS 2.0 algorithm function. It is clear from the table that all measurement items load higher against their respective intended latent variable compared to other variables. The table also demonstrated that the loading of each indicator was greater than all of its cross-loadings. The results confirm that all the reflective constructs in the measurement model are distinctly different from each other.

Table 5.17 Cross Loadings of the Indicators

Variables	Indicators	DC	DisB	DispCh	DisT	IS	Imp DisT	Life style	WC	STOR	VS
Tendency to De-clutter	DC1	**0.908**	0.181	-0.015	0.414	0.157	0.173	-0.047	-0.215	0.128	-0.048
	DC2	**0.862**	0.144	0.027	0.382	0.100	0.041	0.003	-0.111	0.136	0.036
	DC4	**0.821**	0.132	-0.046	0.260	0.187	0.248	-0.062	-0.151	0.056	-0.020
	DC6	**0.814**	0.160	-0.051	0.333	0.235	0.267	-0.099	-0.158	0.113	-0.124
Disposition Behavior	DisB1	0.148	**0.909**	0.132	0.275	0.168	0.048	0.034	-0.038	0.047	-0.166
	DisB3	0.142	**0.900**	0.049	0.317	0.199	0.108	-0.014	0.034	0.067	-0.161
	DisB4	0.149	**0.936**	0.089	0.329	0.207	0.102	0.015	-0.026	0.053	-0.195
	DisB5	0.203	**0.918**	0.109	0.389	0.226	0.106	0.046	-0.021	0.048	-0.211
	DisB6	0.188	**0.938**	0.123	0.353	0.212	0.099	0.016	-0.051	0.077	-0.200
	Lifestyle4	-0.062	0.015	-0.074	-0.028	0.011	0.046	**0.943**	0.191	0.035	0.036
Storage Factors	Storage1	0.143	0.029	0.003	0.370	0.130	0.052	0.038	-0.209	**0.962**	-0.269
	Storage2	0.112	0.092	-0.025	0.388	0.136	0.069	0.076	-0.144	**0.965**	-0.250
Value Seeking Tendency	VS1	-0.100	-0.133	0.007	-0.360	0.095	-0.029	0.033	0.332	-0.251	**0.827**
	VS2	0.112	-0.166	-0.025	-0.423	-0.134	-0.129	0.026	0.338	-0.220	**0.821**
	VS3	0.005	-0.217	-0.001	-0.477	-0.099	-0.136	0.030	0.380	-0.228	**0.867**
	VS4	0.033	-0.150	-0.112	-0.414	-0.165	0.033	0.018	0.348	-0.164	**0.832**
	VS5	-0.237	-0.154	0.008	-0.437	0.042	-0.066	0.079	0.207	-0.228	**0.709**
Working Condition	WC2	-0.188	-0.013	-0.055	-0.221	0.135	0.118	0.198	**0.955**	-0.172	0.357
	WC3	-0.218	0.016	-0.045	-0.176	0.058	0.177	0.166	**0.900**	-0.083	0.311
	WC4	-0.243	-0.036	-0.048	-0.231	0.092	0.167	0.244	**0.973**	-0.138	0.400
	WC5	-0.077	-0.040	-0.008	-0.255	0.076	0.072	0.150	**0.918**	-0.260	0.400

5.8.5 Discriminant Validity Fornell and Larcker Criterion

To assess whether the measurement model meets the Fornell-Larcker's criterion, AVE value of each construct was generated using the SmartPLS algorithm function. Then the square roots of AVE were calculated manually. The results showed all square roots of AVE to be greater than the constructs' correlations with other factors. The bolded elements in Table 5.18 represent the square roots of the AVE while non-bolded values represent the inter-correlation value between constructs. Based on table 5.18, all off-diagonal elements are lower than square roots of AVE (bolded on the diagonal). Hence, the result confirms discriminant validity based Fornell and Larker's criterion.

Table 5.18 Inter Correlation Matrix

Variable	DC	DisB	DispCh	DisT	IS	ImpDisT	Lifestyle	PdtWkg Condtn	Storage	VC
Tendency to Declutter	**0.852**									
Disposition Behavior	0.1827	**0.920**								
Disposition Channel	-0.021	0.1091	**0.865**							
Disposition Tendency	0.4165	0.3657	0.0591	**0.934**						
Innovation Seeking Tendency	0.1933	0.222	-0.0295	0.4105	**0.850**					
Impulse Disposition	0.2023	0.1026	-0.1159	0.2338	0.2902	**0.897**				
Life Style	-0.057	0.0218	-0.07	-0.026	-0.006	0.0139	**0.940**			
Product Working Condition	-0.188	-0.023	-0.0402	-0.239	0.0972	0.138	0.2023	**0.937**		
Storage	0.1317	0.0634	-0.0118	0.3931	0.1378	0.0629	0.0596	-0.1822	**0.964**	
Value Seeking Tendency	-0.044	-0.205	-0.03	-0.524	-0.07	-0.0847	0.0464	0.3959	-0.269	**0.813**

*** Square root of the AVE on the diagonal**

5.9 Structural Model

The following sub segments examine the tests conducted to assess the validity of the structural model for this study. The validity of the structural model is measured using the coefficient of determination (R2) and path coefficients.

5.9.1 Coefficient of Determination (R2)

Coefficient of determination is a measure used in model analysis to assess the ability of the model to explain and predict future outcomes. The R2 value indicates the level of explained variability in the model. Thus, a larger R2 value increases the predictive ability of the structural model. This study used SmartPLS algorithm function to obtain the R2 values. Then, bootstrapping function helped generate the t-statistics values. For this study, the bootstrapping generated 2000 samples from 648 cases. The result of the structural model is presented in Figure 5.7.

Based on Figure 5.7, innovation seeking tendency, de-clutter tendency, value seeking tendency, storage factors, lifestyle factors, product working condition and disposition channels are able to explain 56.1%

of the variance in disposition tendency (DisT). Meanwhile, disposition tendency explains 13.4 % of the variance in disposition behavior and 5.5% of variance in impulse disposing behavior. Given the fact that it is an exploratory study, the results seem to be quite satisfactory.

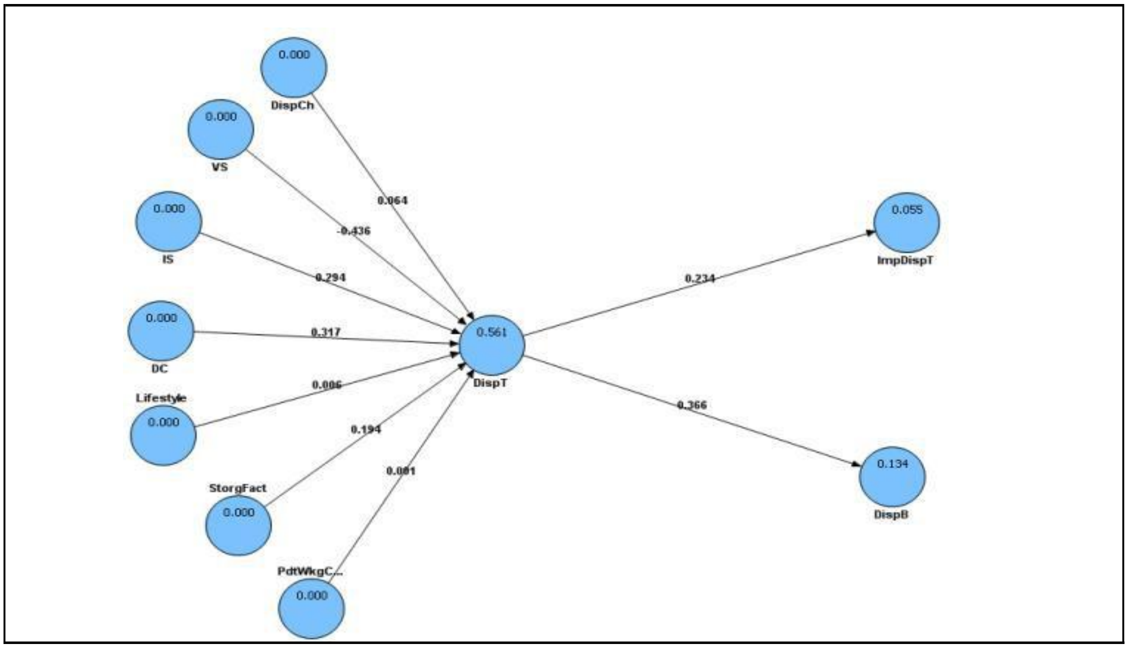

Figure 5.6 Results of Structural Model

Final Model (Boot Strapping)

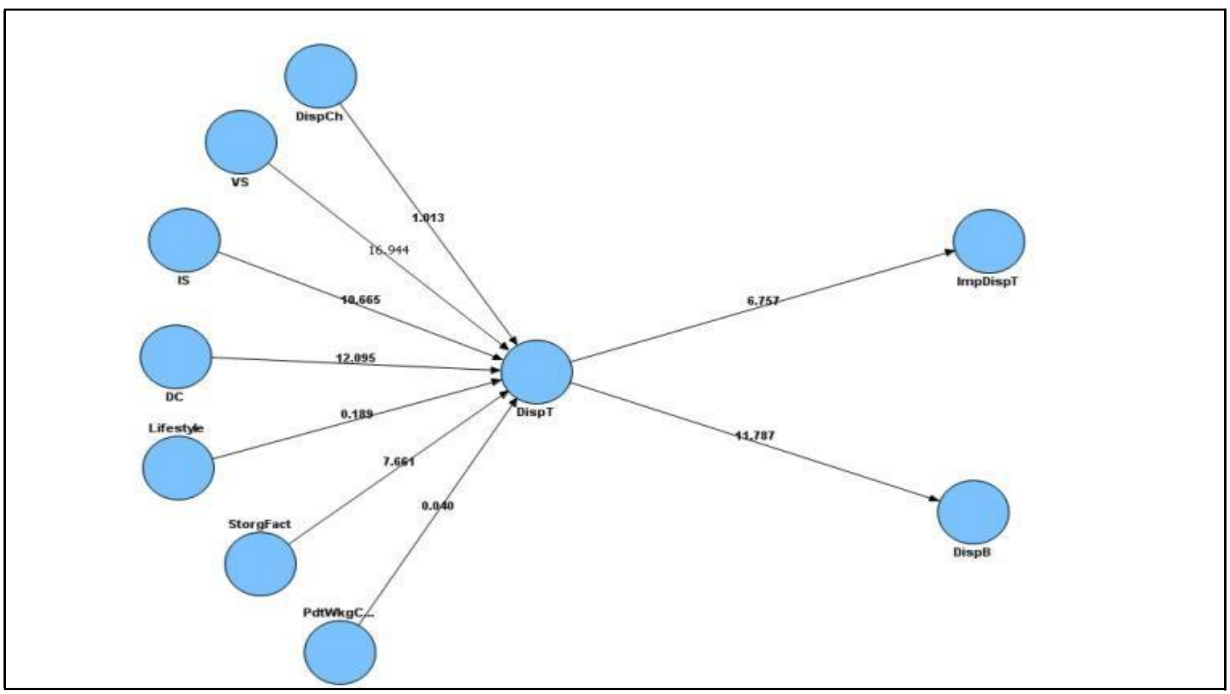

Figure 5.7 Structural Model (Bootstrapping)

5.9.2 Path Coefficients and Hypothesis Testing

The structural model consists of several paths and each path specifies the hypothesized relationship pattern of relationship between two latent variables. The SmartPLS analysis was used to examine whether to accept or reject each hypothesis and also to understand the strength of relationship between predictor and outcome variables. Bootstrapping function was used to derive t-statistics for all paths. This helped estimate the significant level for all hypothesized paths. Table 5.19 provides a summary of the path coefficients, observed t-statistics, and significance level for every path. Using the results from the path assessment, the acceptance or rejection of the proposed hypotheses is determined. The confirmation or disconfirmation of the proposed hypotheses is discussed below.

To validate the proposed hypotheses and the structural model, the path coefficient between two latent variables is assessed. Based on previous studies, the path coefficient value needs to be at least 0.1 to indicate positive effects (Hair et al., 2011). Assessment of the path coefficient (refer Table 5.19) shows that six of the nine proposed hypotheses are supported. Hypotheses H4, H5 and H7 are rejected. From the analysis hypotheses were found to be significant at 0.01 level of significance and consisted of a path coefficient value (β) ranging from 0.2338 to 0.4364 for the accepted hypotheses.

Table 5.19 Path Coefficients and Hypothesis Testing

Hypothesis No.	Hypothesised relationship	Path coefficient	Standard Error	T -value	P-value	Decision
H1	DC -> DisT	0.3167	0.0262	12.0947	0.000	Supported
H2	VS -> DisT	-0.4364	0.0258	16.9439	0.000	Supported
H3	IS -> DisT	0.2939	0.0276	10.6649	0.000	Supported
H4	LS -> DisT	0.0061	0.0324	0.1889	0.425	Not supported
H5	PdtWkgCondtn -> DisT	0.0011	0.0281	0.0405	0.484	Not supported
H6	StorgFact -> DisT	0.1943	0.0254	7.6613	0.000	Supported
H7	DispCh -> DisT	0.064	0.0632	1.0135	0.156	Not supported
H8	DisT -> DisB	0.3657	0.031	11.7867	0.000	Supported
H9	DisT -> ImpDisT	0.2338	0.0346	6.7574	0.000	Supported

Based on the analysis, DisT was seen to be influenced directly by VS (β=0.4364, t=16.9439, $p<0.05$), IS (β=0.2939, t=10.6649, $p<0.05$), DC (β=0.3167, t=12.0947, $p< 0.01$) and Storage (β=0.1943, t=7.6613, $p<0.05$). As a result, hypothesis H1, hypothesis H2, hypothesis H3 and hypothesis H6 are supported.

Further, from the analysis, disposition behavior is influenced directly by disposition tendency (β=0.3657, t=11.7867, $p<0.05$). Meanwhile, impulse disposing behavior is influenced directly by disposition tendency (β=0.2338, t=6.7574, $p<0.001$). As a result, hypothesis H8 and H9 are supported.

5.9.3 Effect Size

Effect size of the model (f^2) measures the strength of the relationship between latent variables by examining the extent to which an exogenous latent variable contributes to an endogenous latent variable's R^2 value. Hence, f^2 values help to measure the overall contribution of the research study. Effect size of 0.02, 0.15 and 0.36 indicates small, medium and large effect respectively. The results from the statistical analysis of the mode indicate medium effects of value seeking tendency, innovation seeking tendency and de-clutter tendency and weak effects of storage, disposition channel, life style and product working condition on disposition tendency (Table 5.20).

Table 5.20 Effect Size on Disposition Tendency

Exogenous Variable	R2incl	R2excl	R2incl-R2excl	1-R2incl	Total Effect
Storage	0.5611	0.5275	0.0336	0.4389	0.077
Disposition Channel	0.5611	0.557	0.0041	0.4389	0.009
Value Seeking Tendency	0.5611	0.4105	0.1506	0.4389	0.343
Innovation Seeking Tendency	0.5611	0.4823	0.0788	0.4389	0.180
Tendency to De-clutter	0.5611	0.4701	0.091	0.4389	0.207
Life style	0.5611	0.5586	0.0025	0.4389	0.006
Product Working Condition	0.5611	0.559	0.0021	0.4389	0.005

5.9.4 Predictive Quality

Blindfolding procedure in SmartPLS can be used arrive at predictive relevance (Q^2) values. Q^2 values below zero indicate lack of predictive quality. It shows how well the data collected empirically can be reconstructed with the help of model. The research data confirmed high predictive quality as all the values were above zero (Table 5.21).

Table 5.21 Predictive Relevance of the Model

Variable	R square	Cross-Validated Communality	Cross-Validated Redundancy
Disposition Tendency	0.561	0.872	0.487
Impulse Disposition	0.055	0.805	0.039
Disposition Behavior	0.134	0.847	0.110

5.9.5 Goodness of Fit

GoF index provides a measure of overall model fit by using the geometric mean of average communality and average R^2. Wetzels et al (2009) suggested the following GoF criteria:

GoF small=0.1, GoF medium=0.25, and GoF large=0.36. These may serve as reference values for validating the PLS model globally. Goodness-of-fit (GoF) of the comprehensive model was estimated using SmartPLS by calculating the geometric mean of AVE and R2 for the endogenous constructs of the model (Wetzels et al., 2009). The GoF value was found to be 0.366. This was well above the cut-off value of 0.36 indicating large effect sizes of R^2 (Table 5.22). So, the result confirms that the disposition tendency model is a parsimonious statistical model that performs satisfactorily.

Table 5.22 Goodness of Fit

Variable	R square	AVE
Disposition Tendency	0.554	0.872
Impulse Disposition	0.0547	0.805
Disposition Behavior	0.1337	0.847
Geometric Mean	0.159	0.841
Goodness of Fit		**0.366**

5.10 Multi Group Analysis

The following subsections explore the moderating influence of demographic variables: age, gender, income, family type, job type and work status on the path relationships: DisT→DisB and DisT→ImpDisB using multigroup analysis. The split sample approach was used to classify respondents based on their demographic characteristics for carrying out moderation analyses (Serenko et al., 2006). 16 hypotheses were proposed and multi group analysis was done for each demographic variable individually. Subsequently, bootstrapping analysis was carried out to derive the path coefficients (β), associated t-values and p-values of both groups on different paths in the model (Tables 5.23, 5.24, 5.25, 5.26, 5.27, 5.28, 5.29 and 5.30). Appendix G provides the structural and bootstrapped models for each demographic variable individually.

Structural Models for Multi Group Analysis

To visually represent the hypothesized relationships and observed group differences, the structural models for the multi group analysis are provided below. These diagrams illustrate the key paths and statistical outcomes for each subgroup analyzed, supporting the interpretation of moderating effects.

Structural Models (Multi Group Analysis)

Female disposers

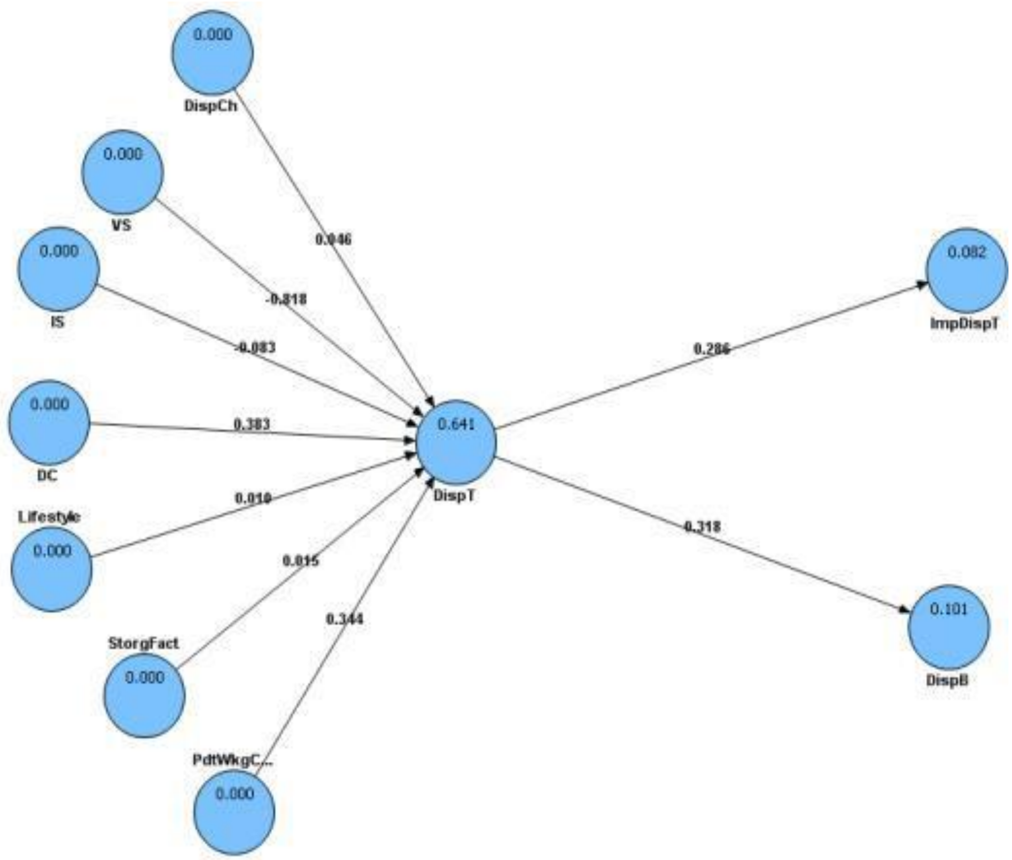

Fig 5.9: Structural Model (Females)

Bootstrapped Model (Female)

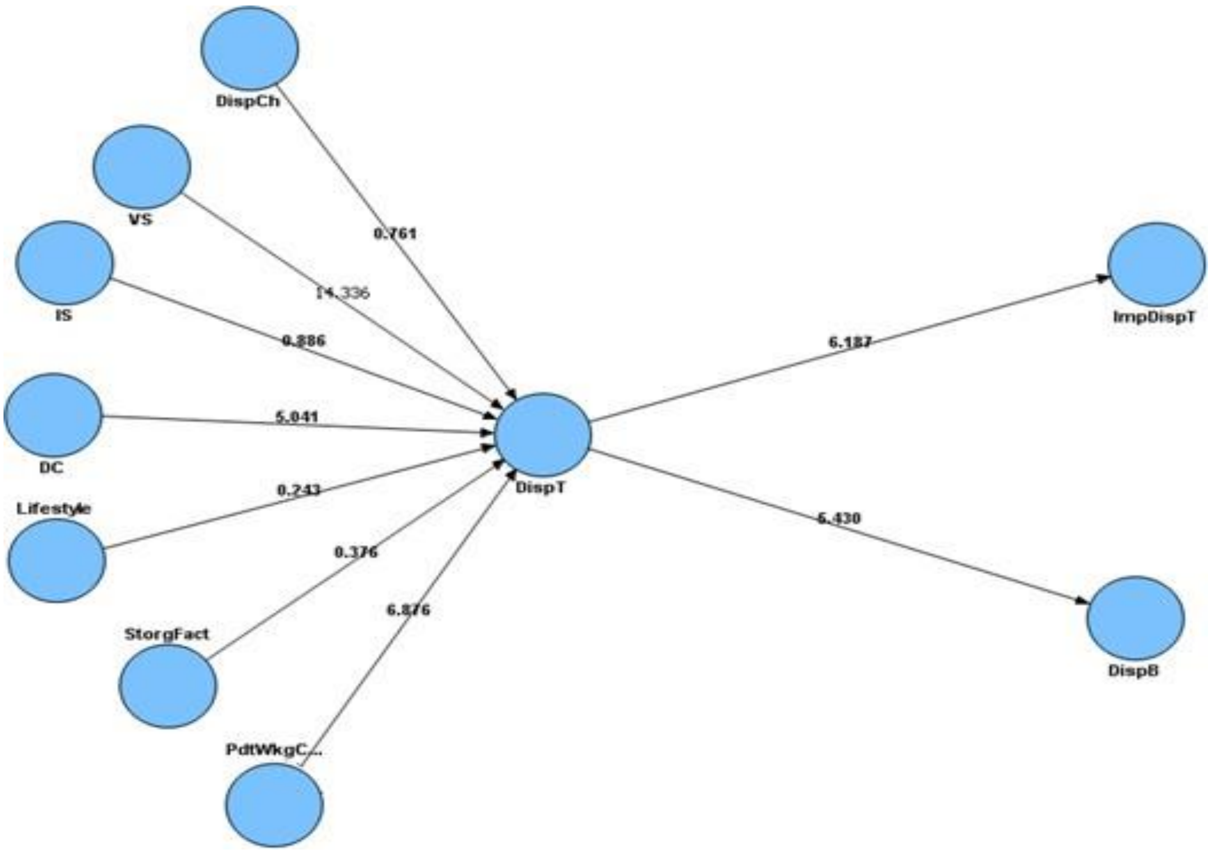

Fig 5.10 Bootstrapped Model (Female)

Structural Model (Male)

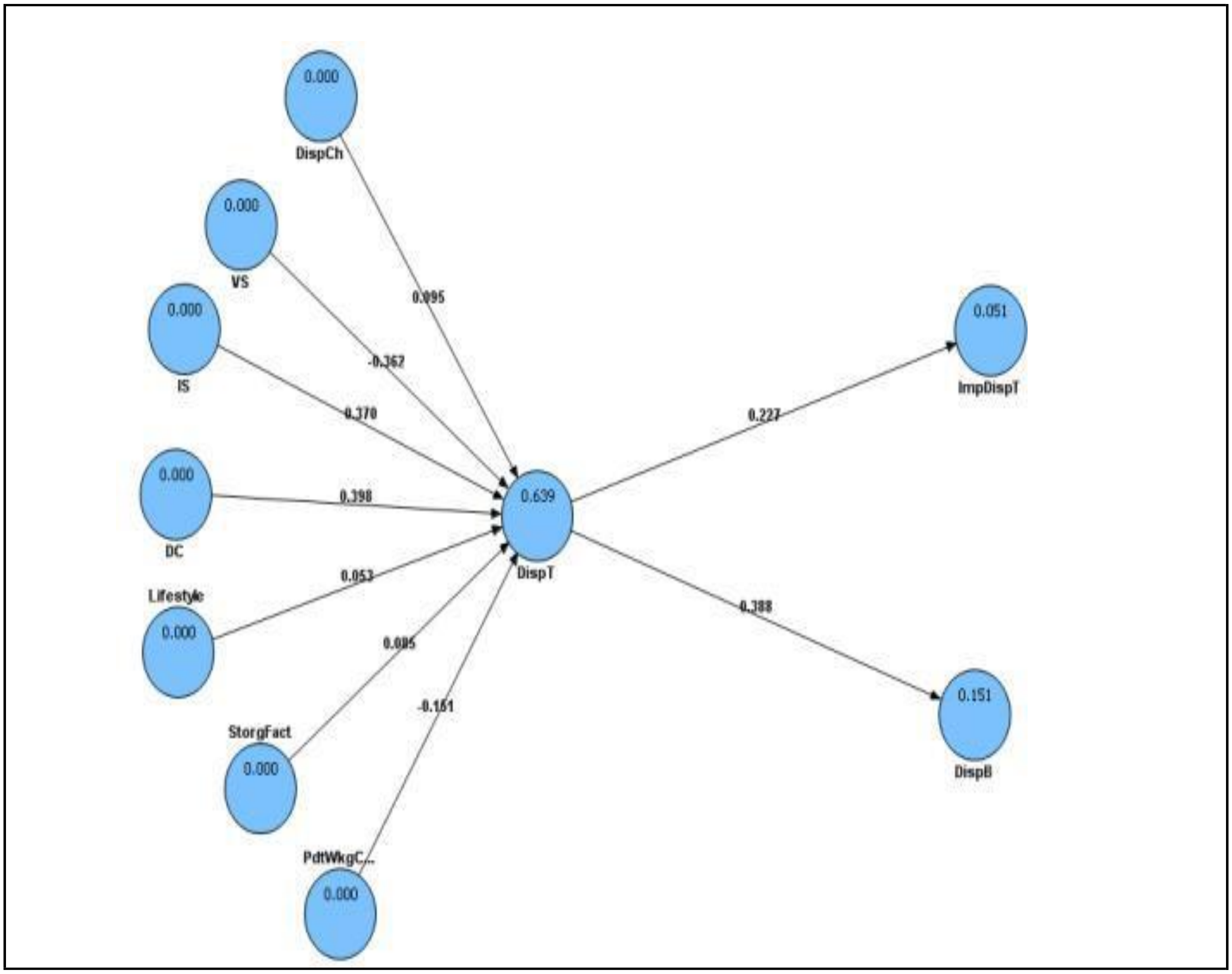

Fig 5.11Structural Model (Male)

Bootstrapped model (Males)

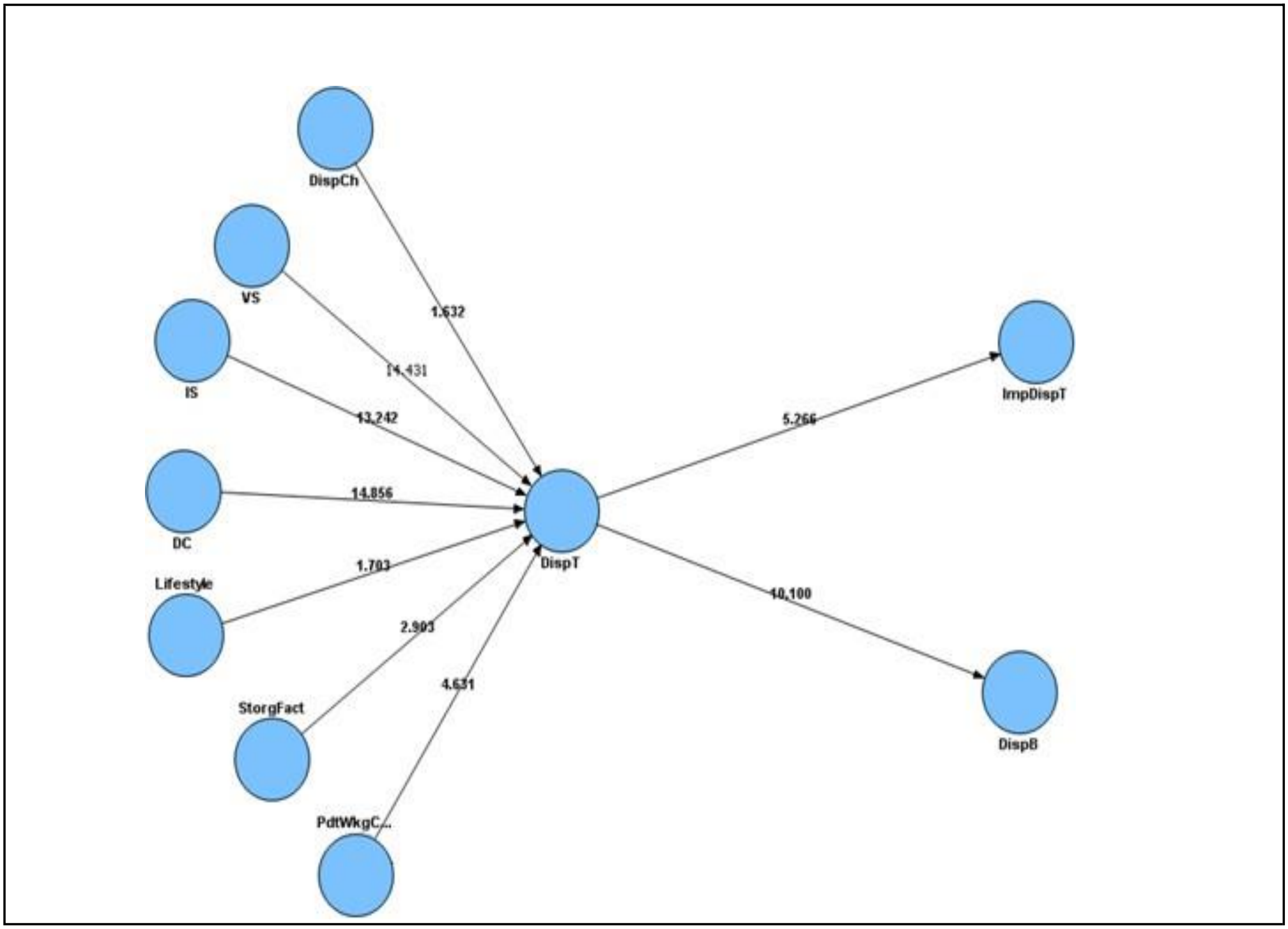

Fig 5.12 Bootstrapped Model (Males)

Structural Model (Low Income)

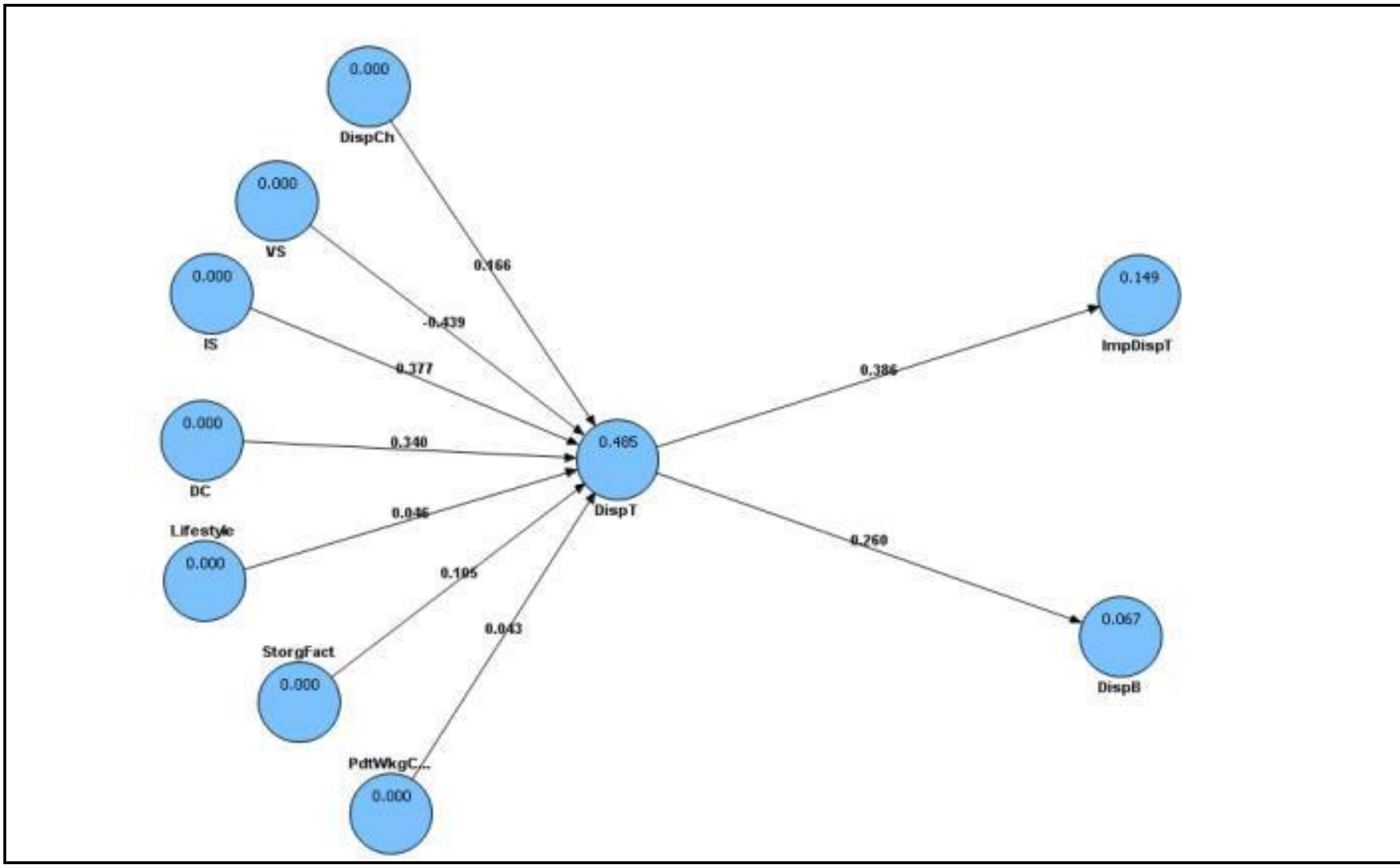

Fig 5.13 Structural Model (Low Income)

Bootstrapped Model (Low Income)

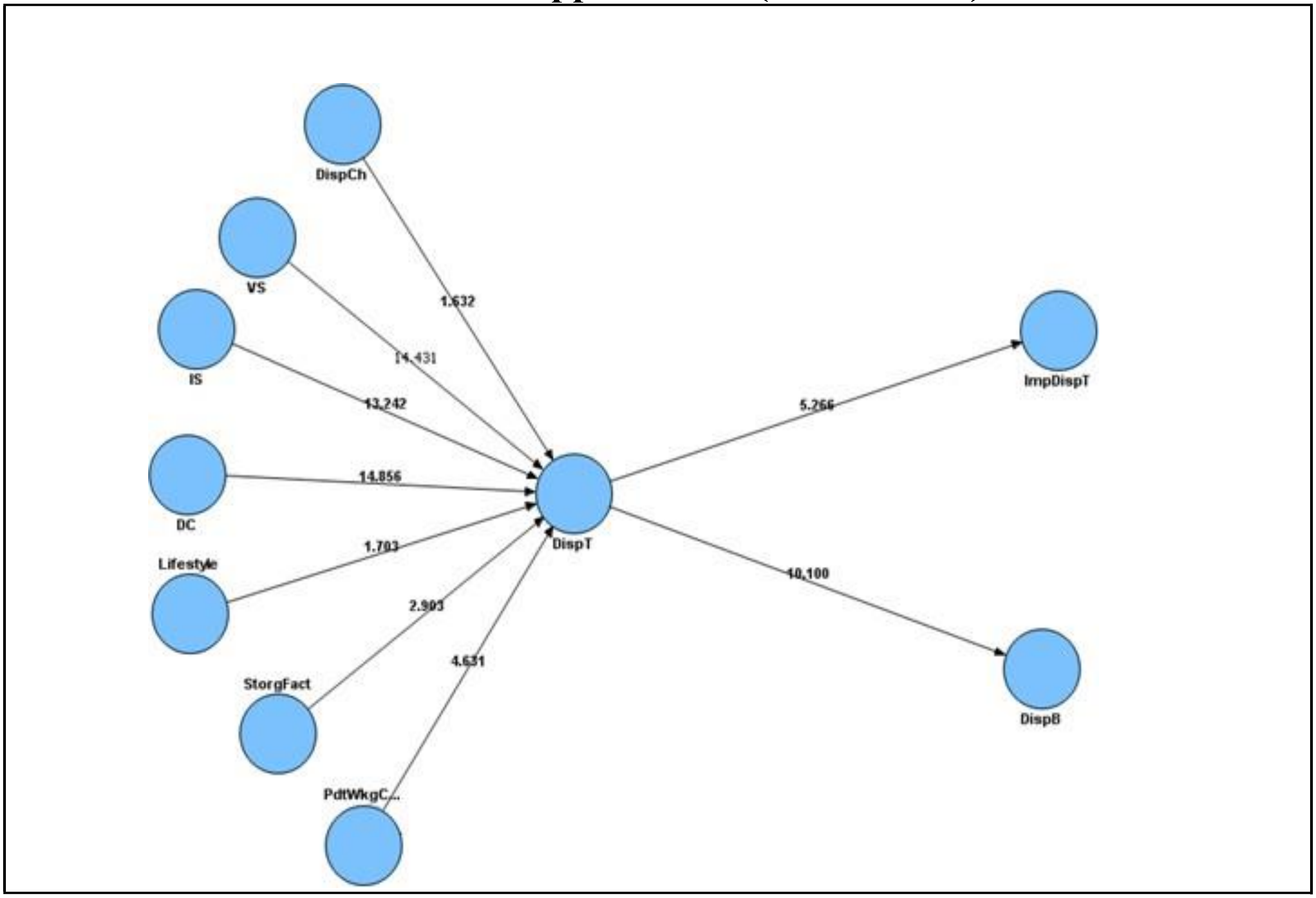

Fig 5.14 Bootstrapped Model (Low Income)

Structural Model (High Income)

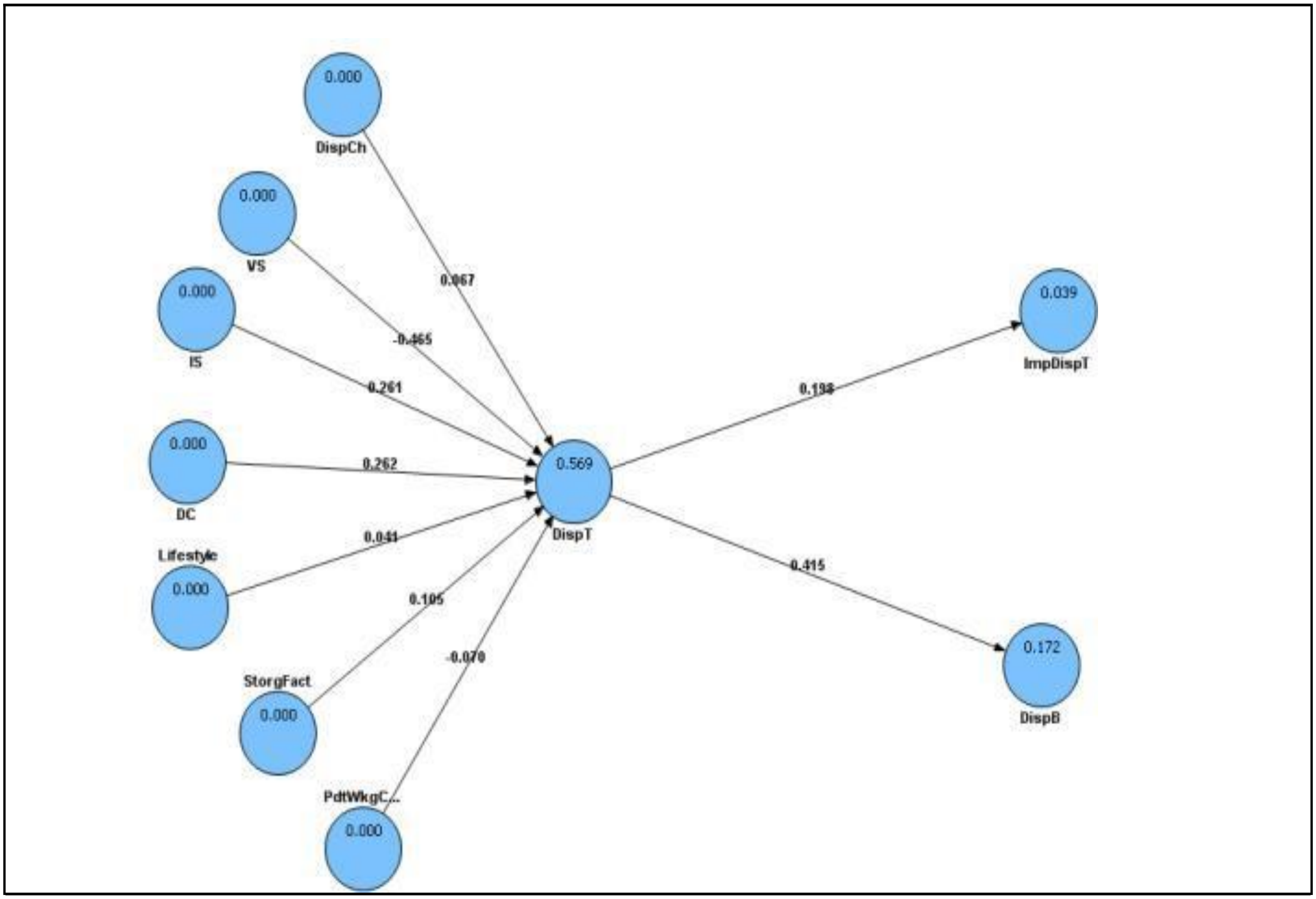

Fig 5.15 Structural Model (High Income)

Bootstrapped Model (High Income)

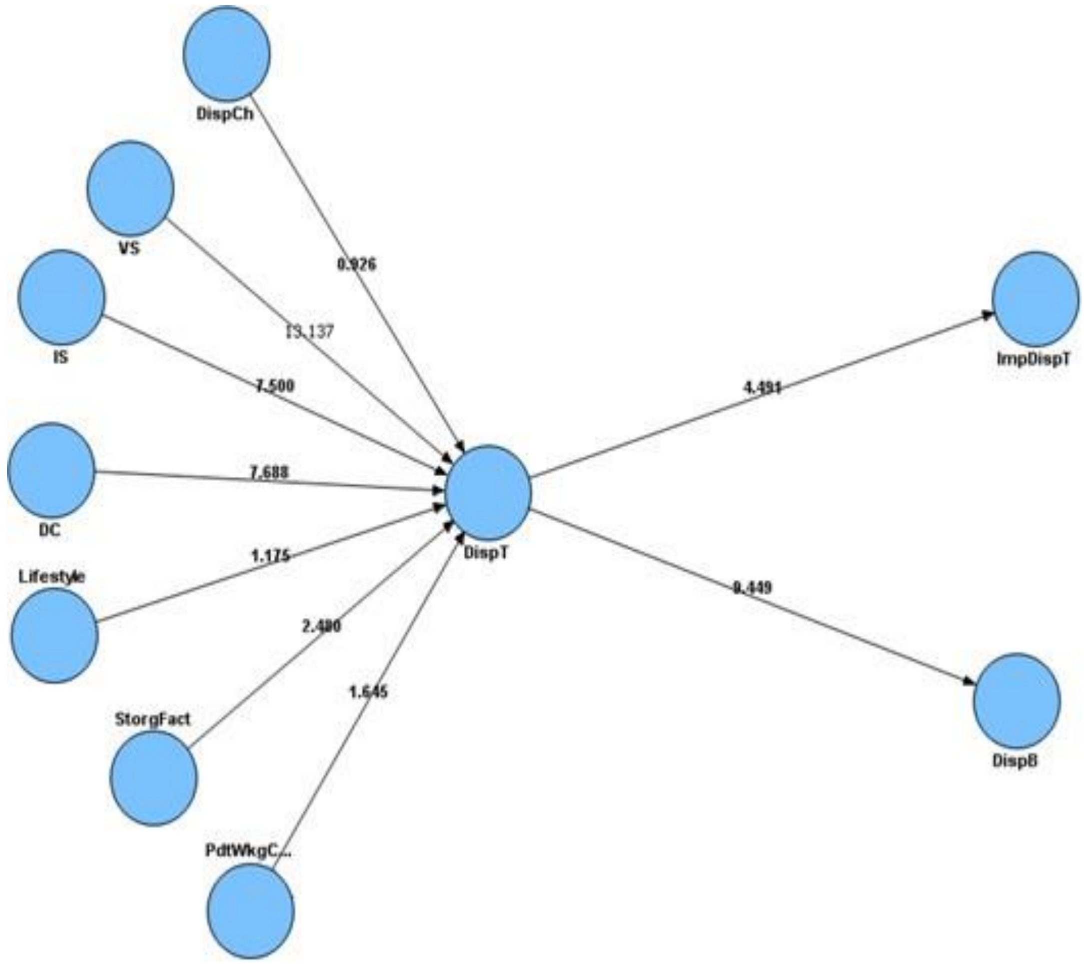

Fig 5.16 Bootstrapped Model (High Income)

Structural Model (Young disposers)

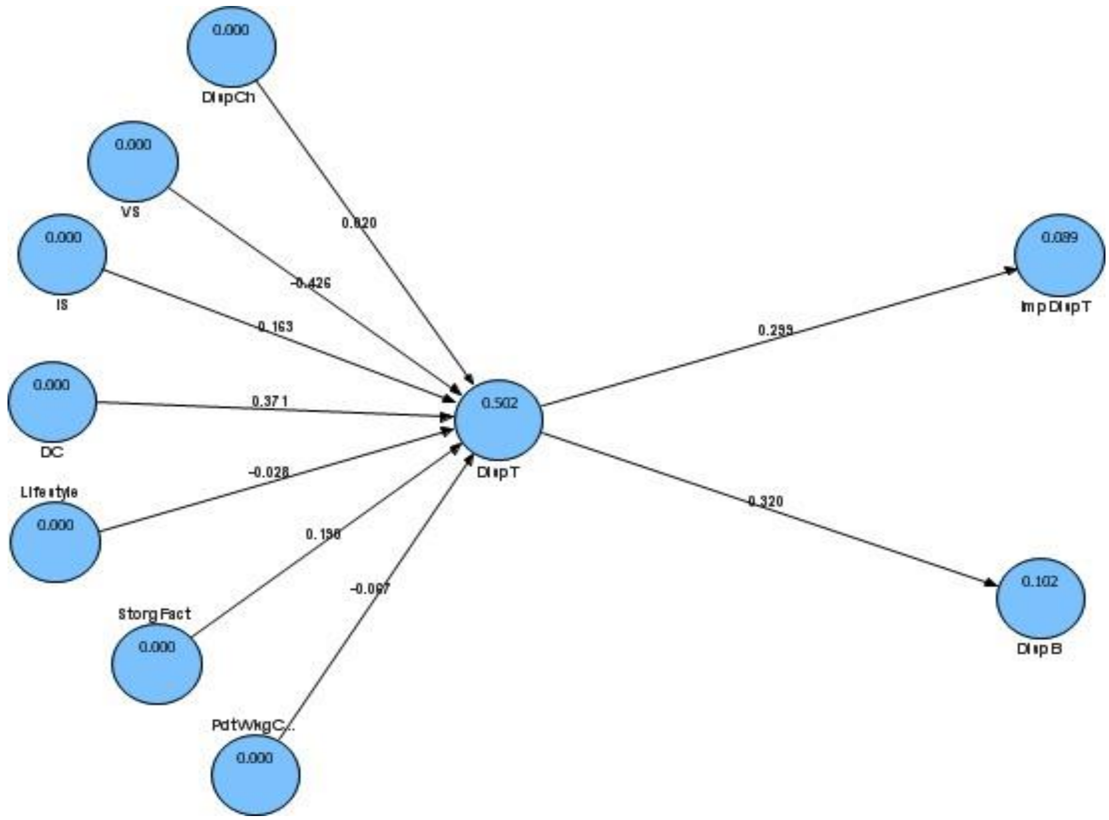

Fig 5.17 Structural Model (Young disposers)

Bootstrapped Model (Young Disposers)

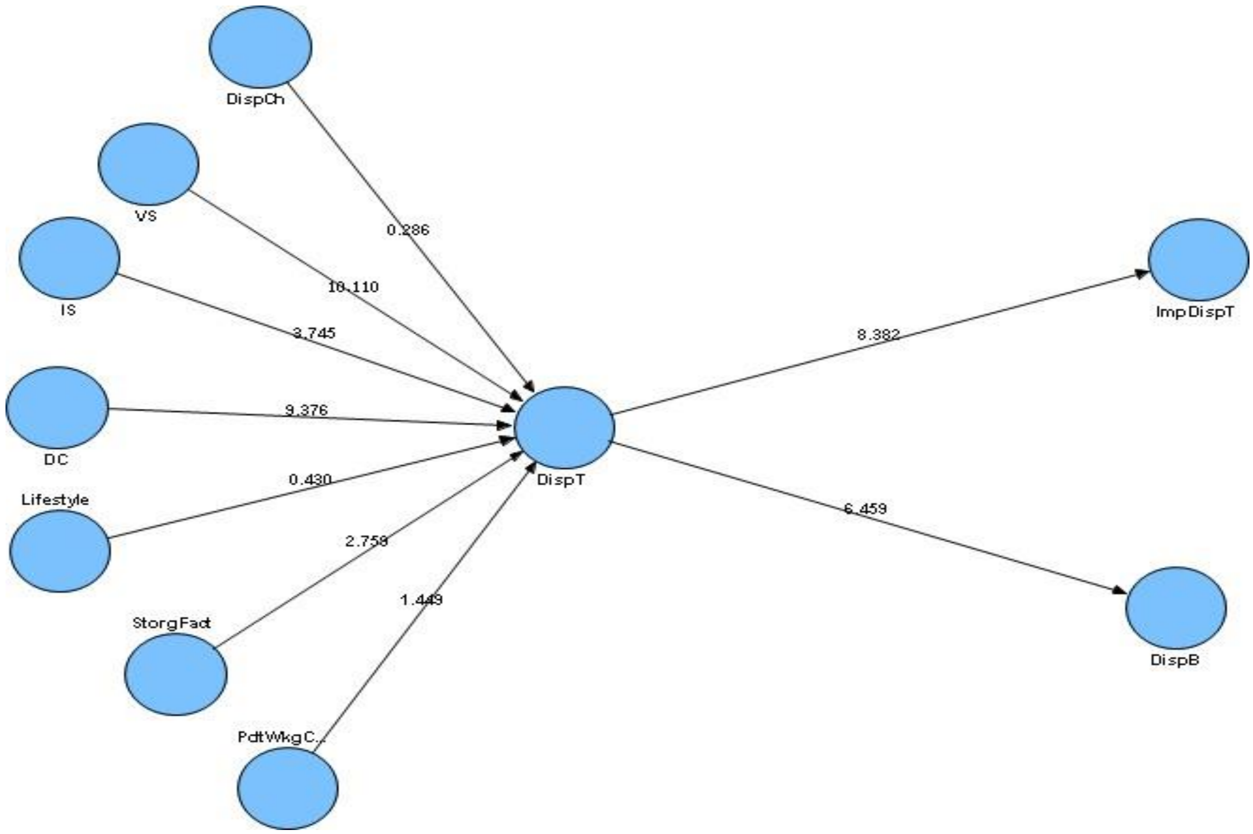

Fig 5.18 Bootstrapped Model (Young disposers)

Structural Model (Middle-aged disposers)

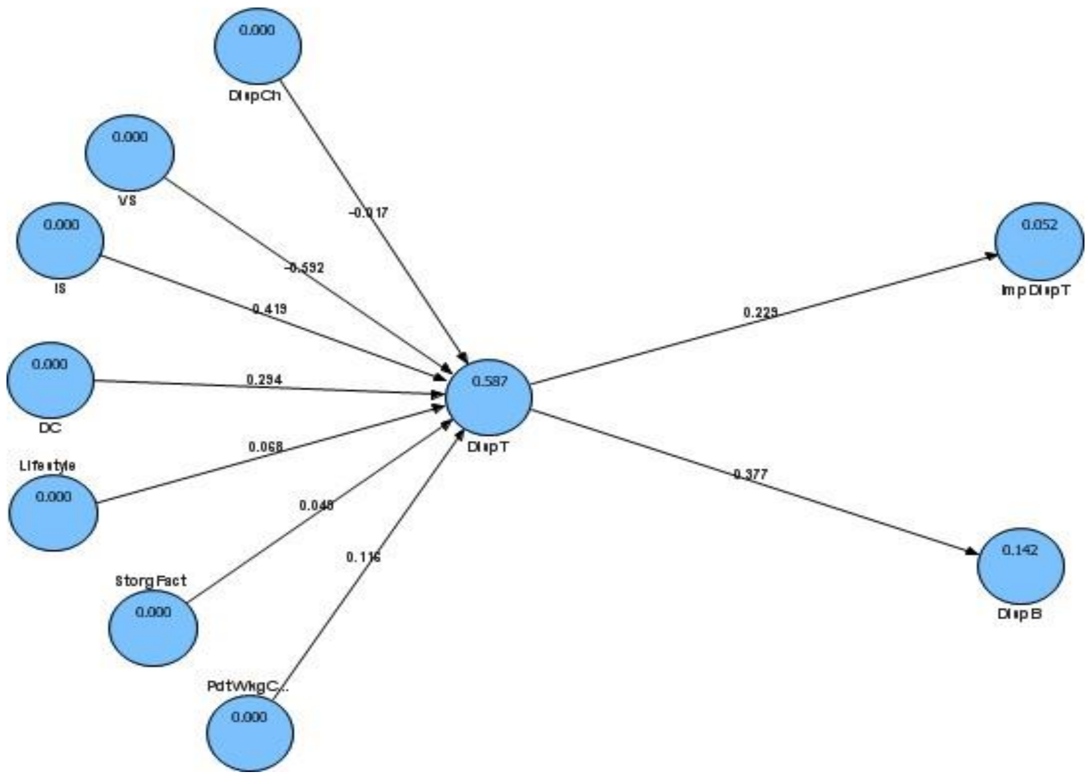

Fig 5.19 Structural Model (Middle-aged disposers)

Bootstrapped Model (Middle-aged disposers)

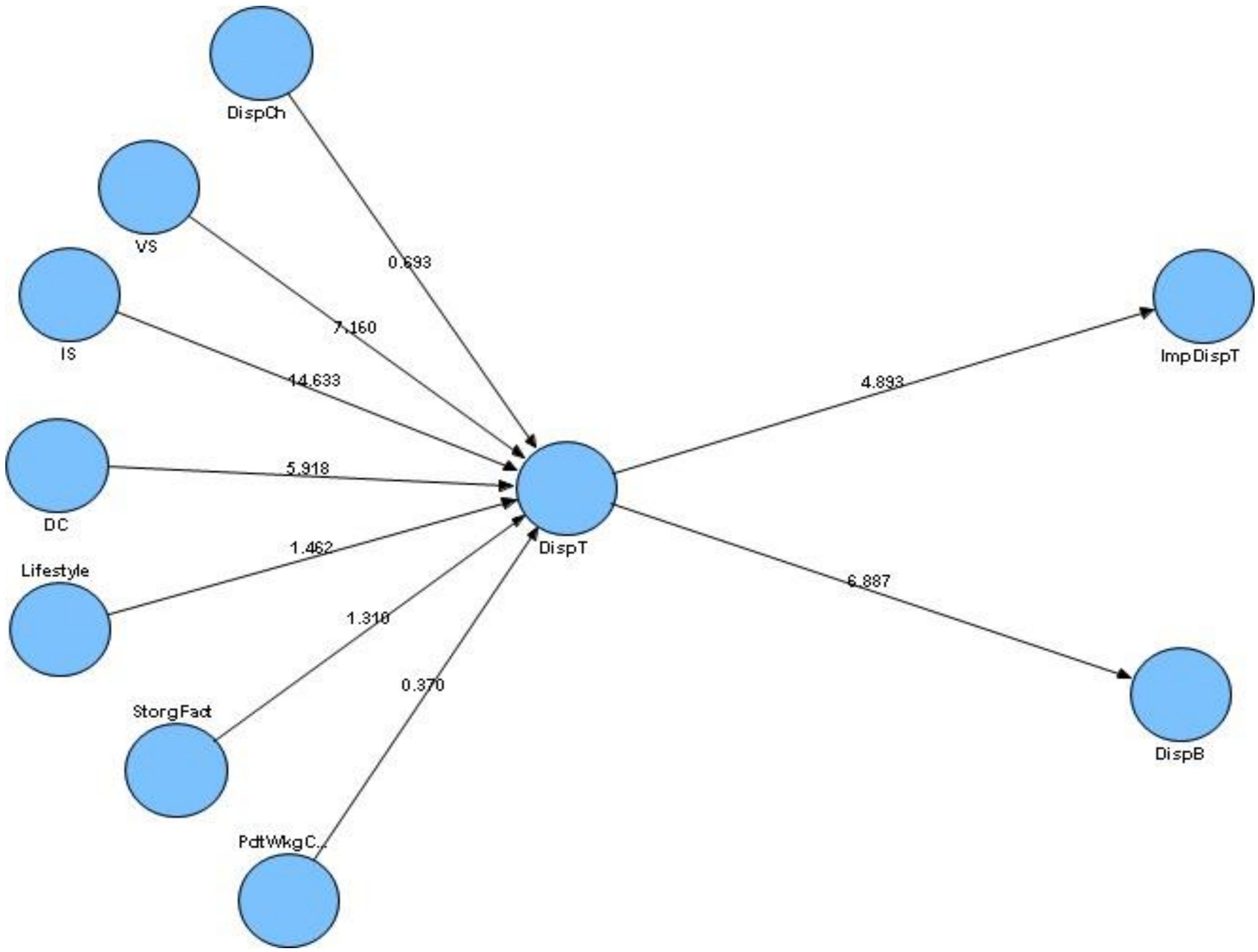

Fig 5.20 Bootstrapped Model (Middle-aged disposers)

Structural Model (Old disposers)

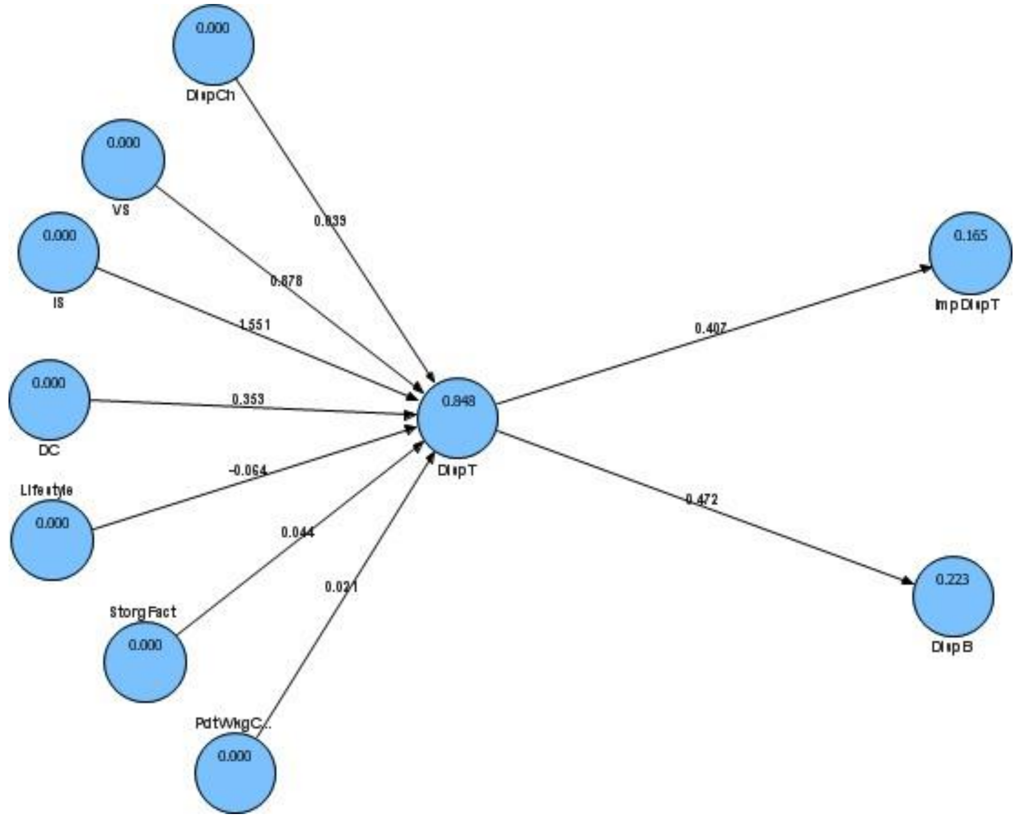

Fig 5.21 Structural Model (Old disposers)

Bootstrapped Model (Old Disposers)

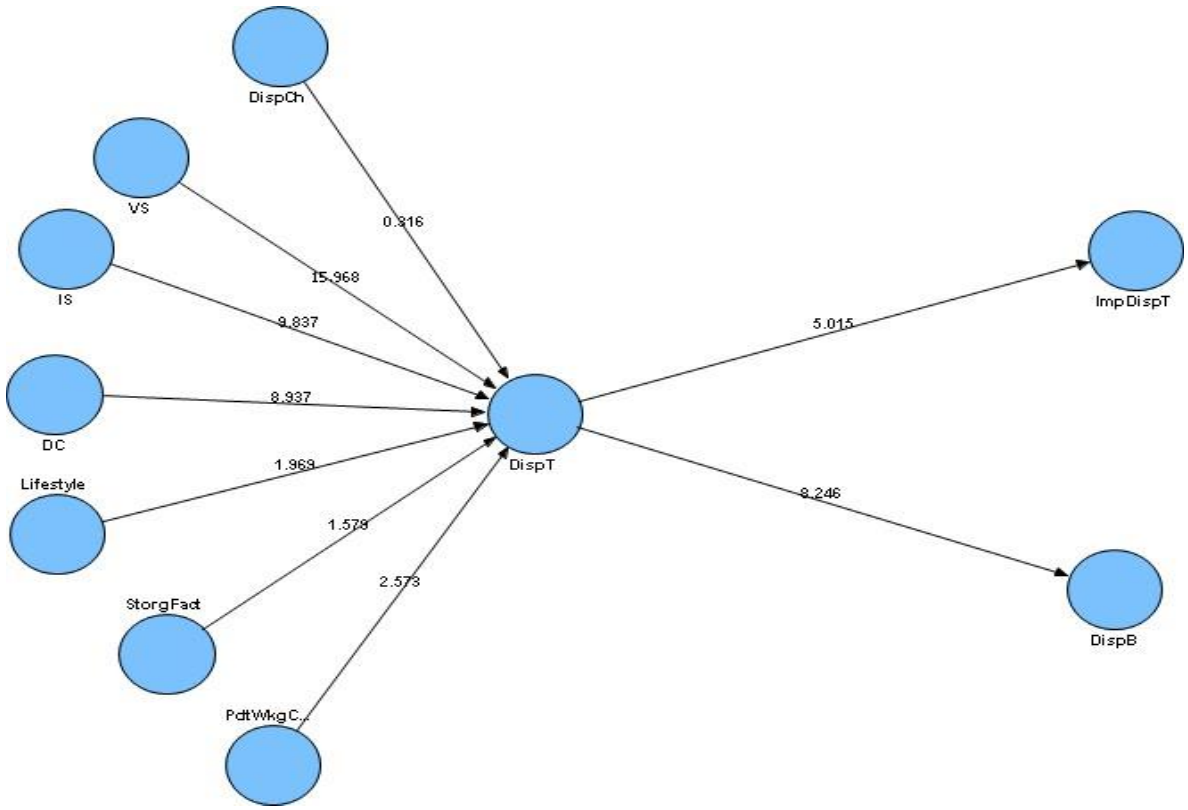

Fig 5.22 Bootstrapped Model (Old Disposers)

Structural Model (Working Disposers)

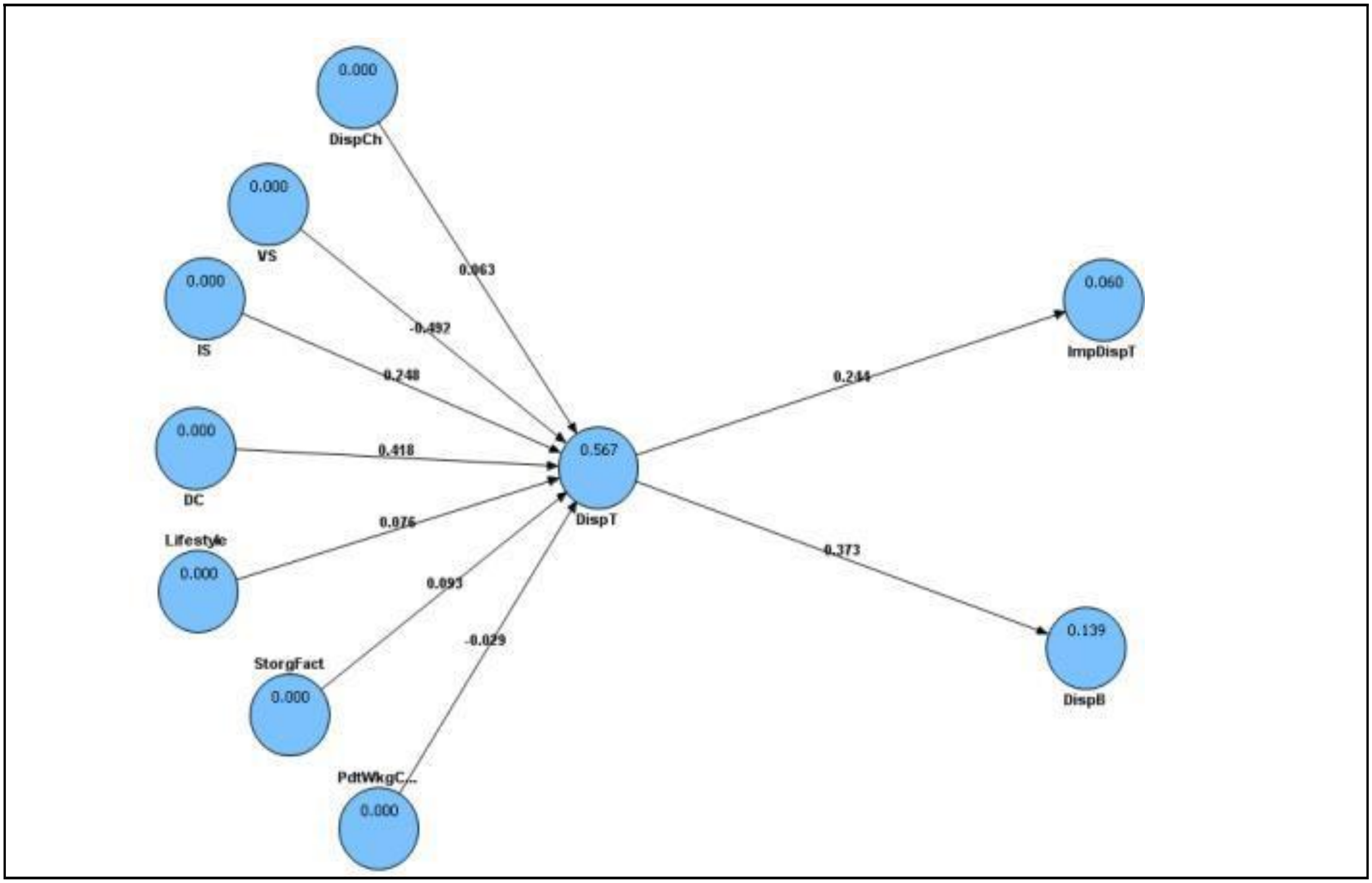

Fig 5.23 Structural Model (Working Disposers)

Bootstrapped Model (Working disposers)

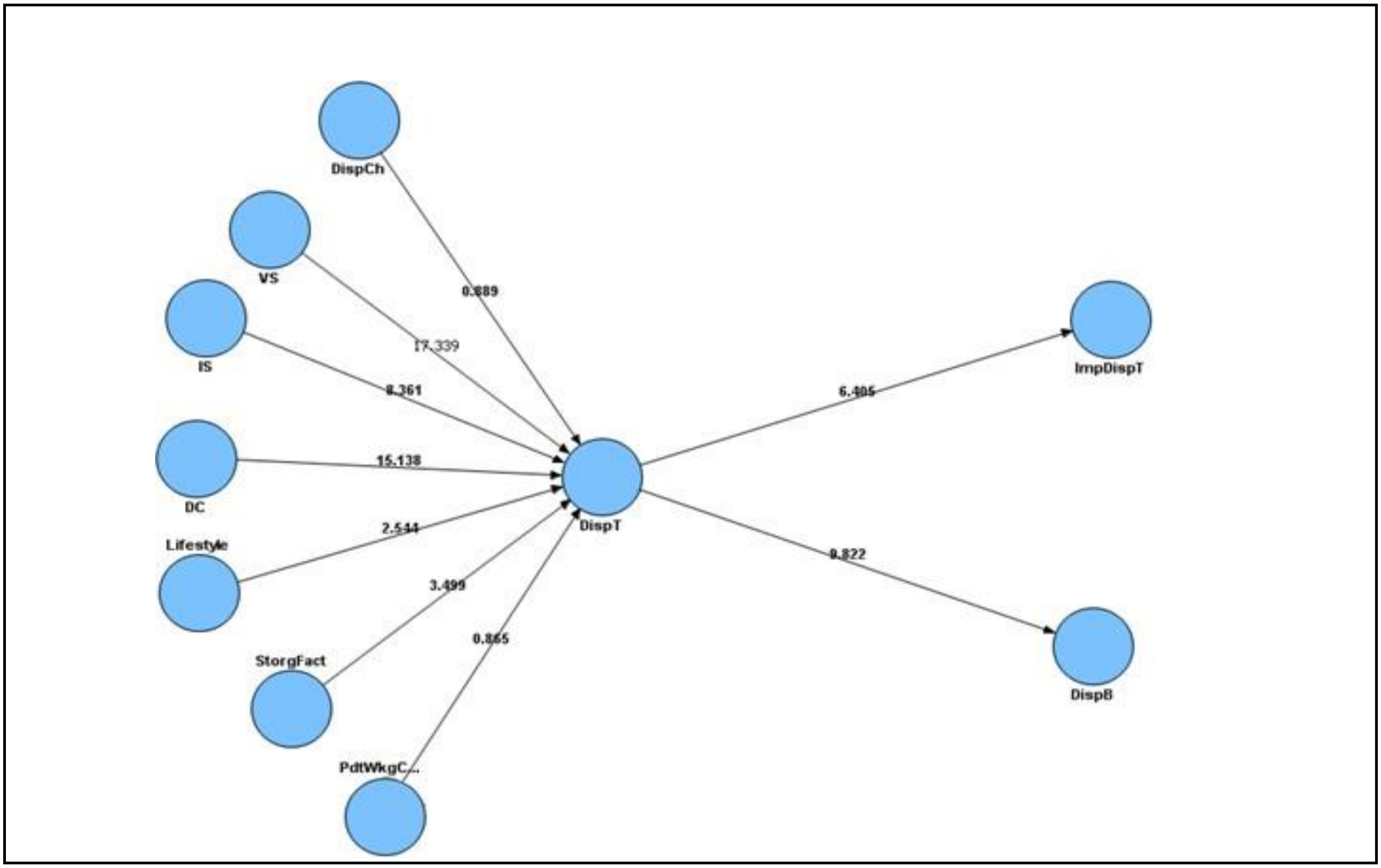

Fig 5.24 Bootstrapped Model (Working disposers)

Structural Model (Non working disposers)

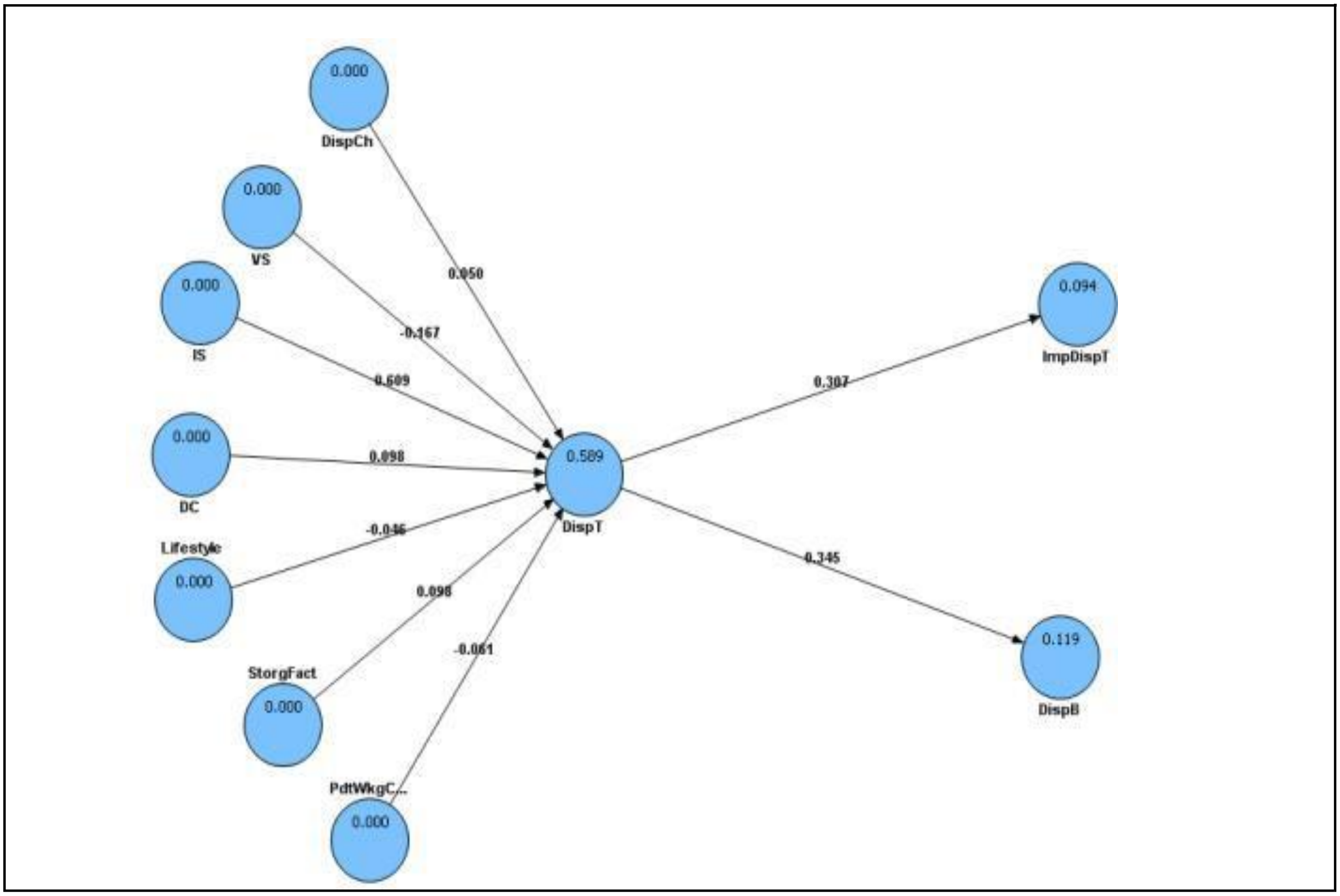

Fig 5.25 Structural Model (Non working disposers)

Bootstrapped Model (Non working disposers)

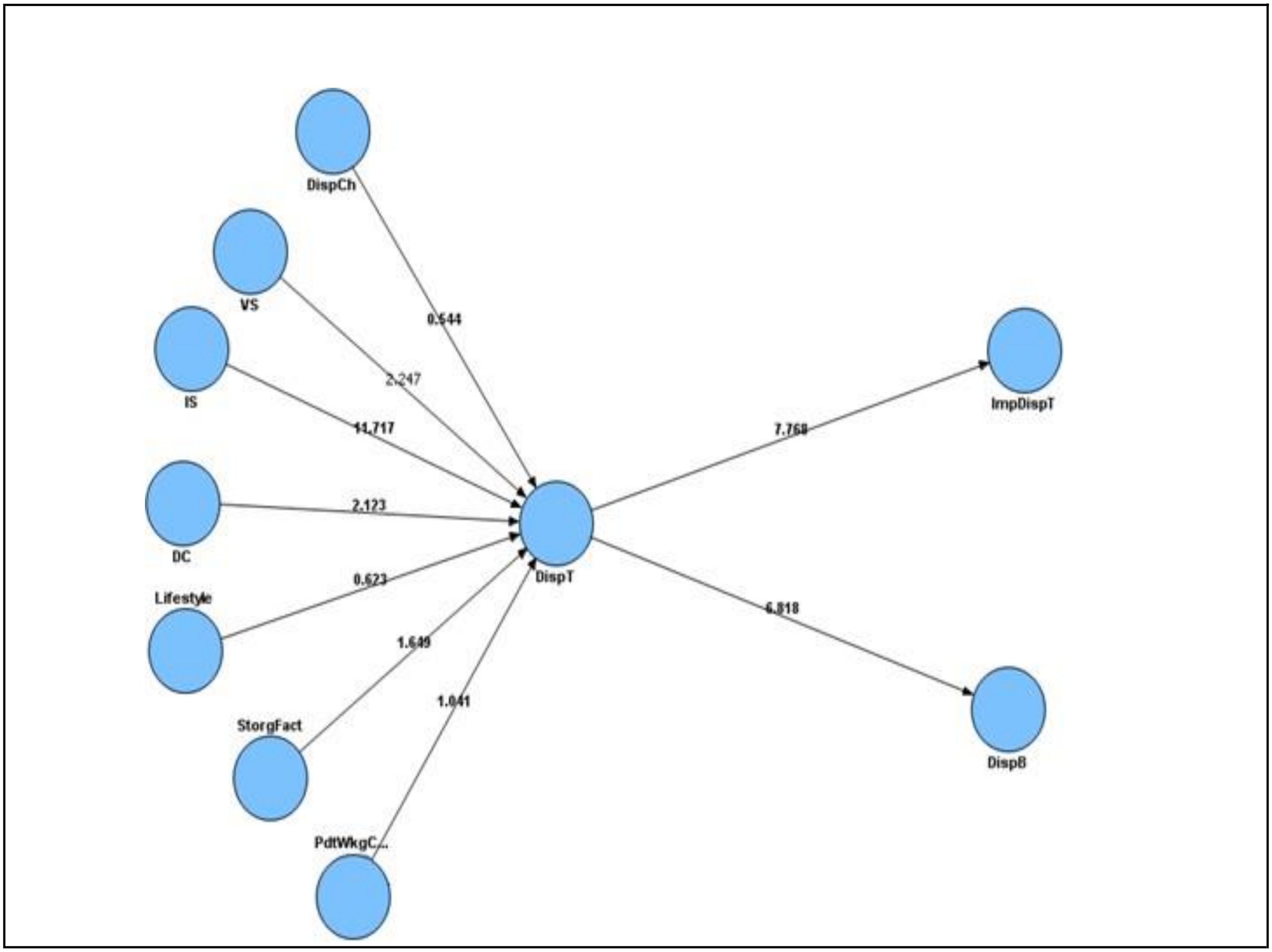

Fig 5.26 Bootstrapped Model (Non working disposers)

Structural Model (Disposers in transferable jobs)

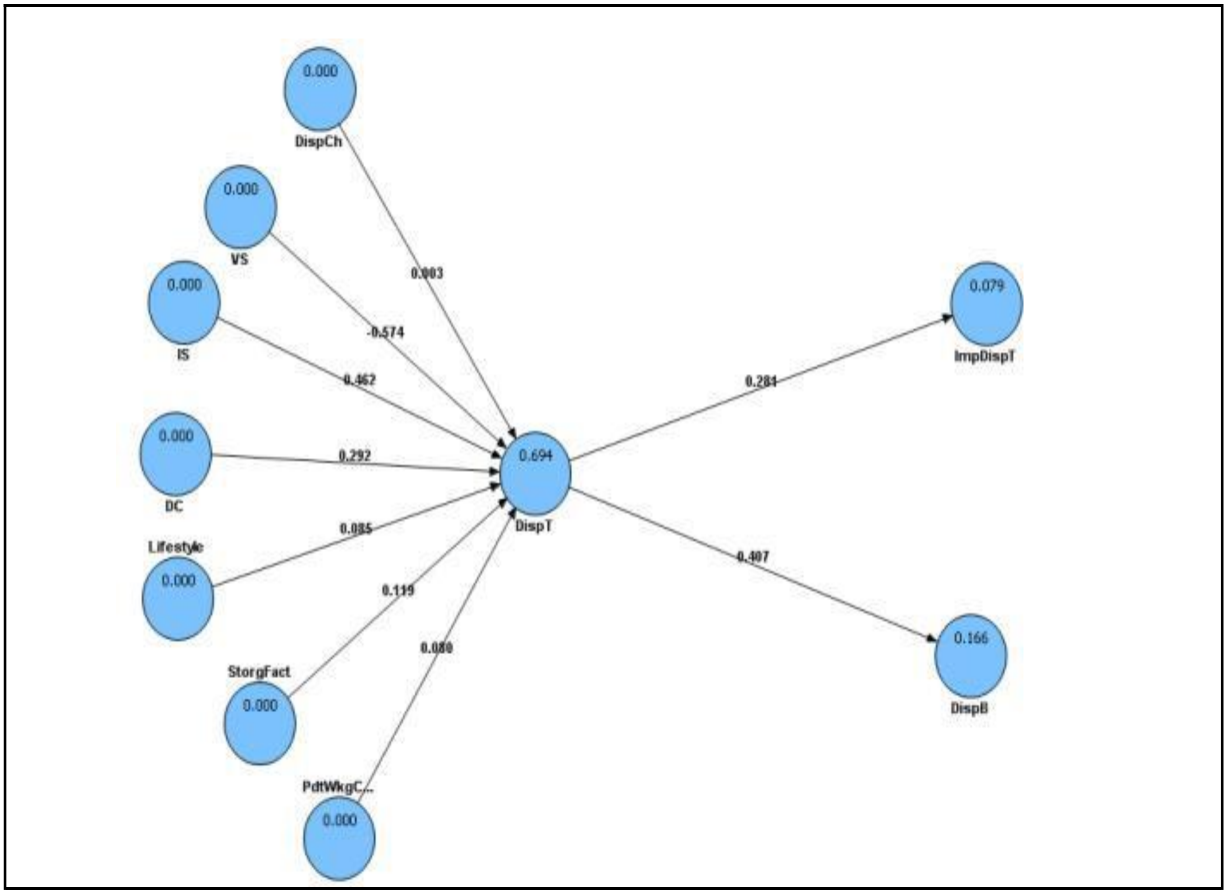

Fig 5.27 Structural Model (Disposers in transferable jobs)

Bootstrapped Model (Disposers in transferable jobs)

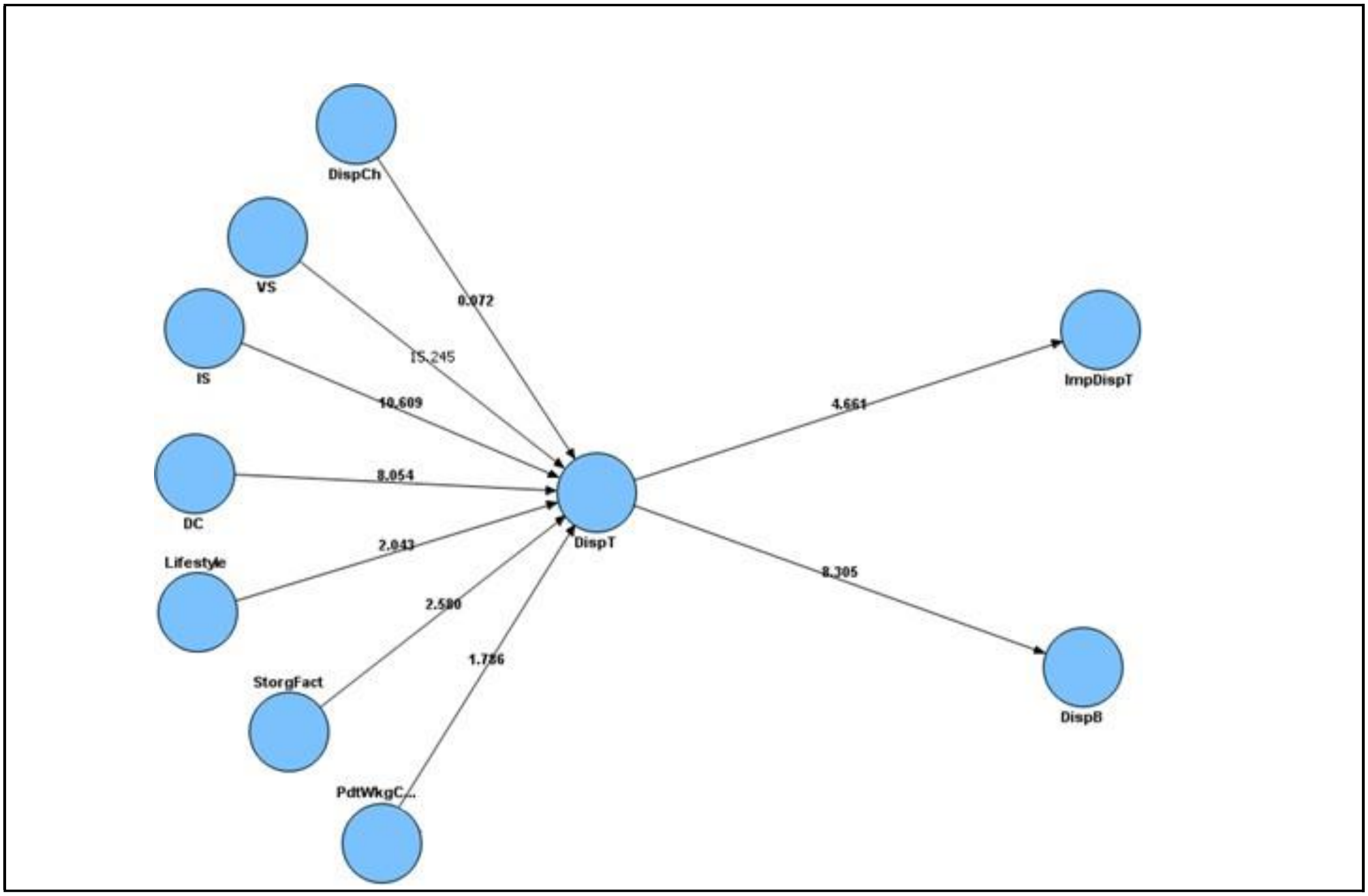

Fig 5.28 Bootstrapped Model (Disposers in transferable jobs)

Structural Model (Disposers in nontransferable jobs)

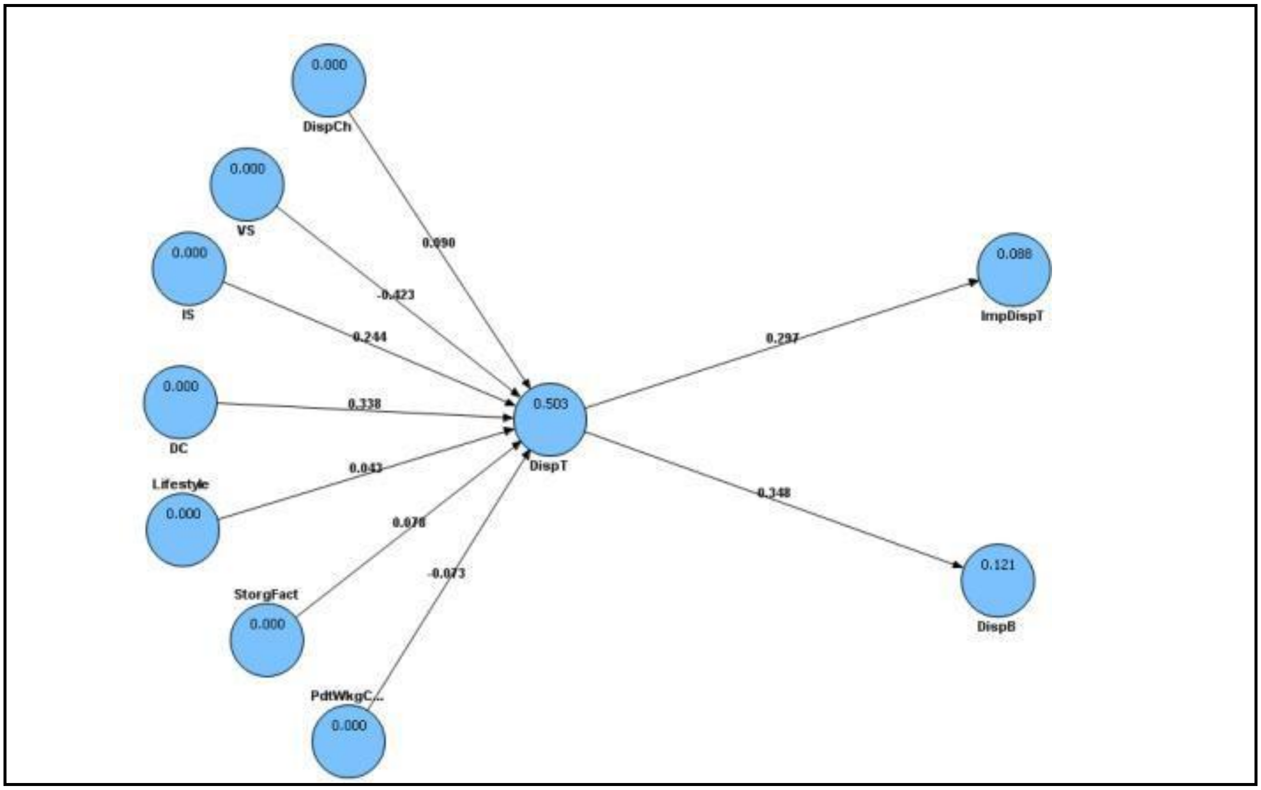

Fig 5.29 Structural Model (Disposers in nontransferable jobs)

Bootstrapped Model (Disposers in nontransferable jobs)

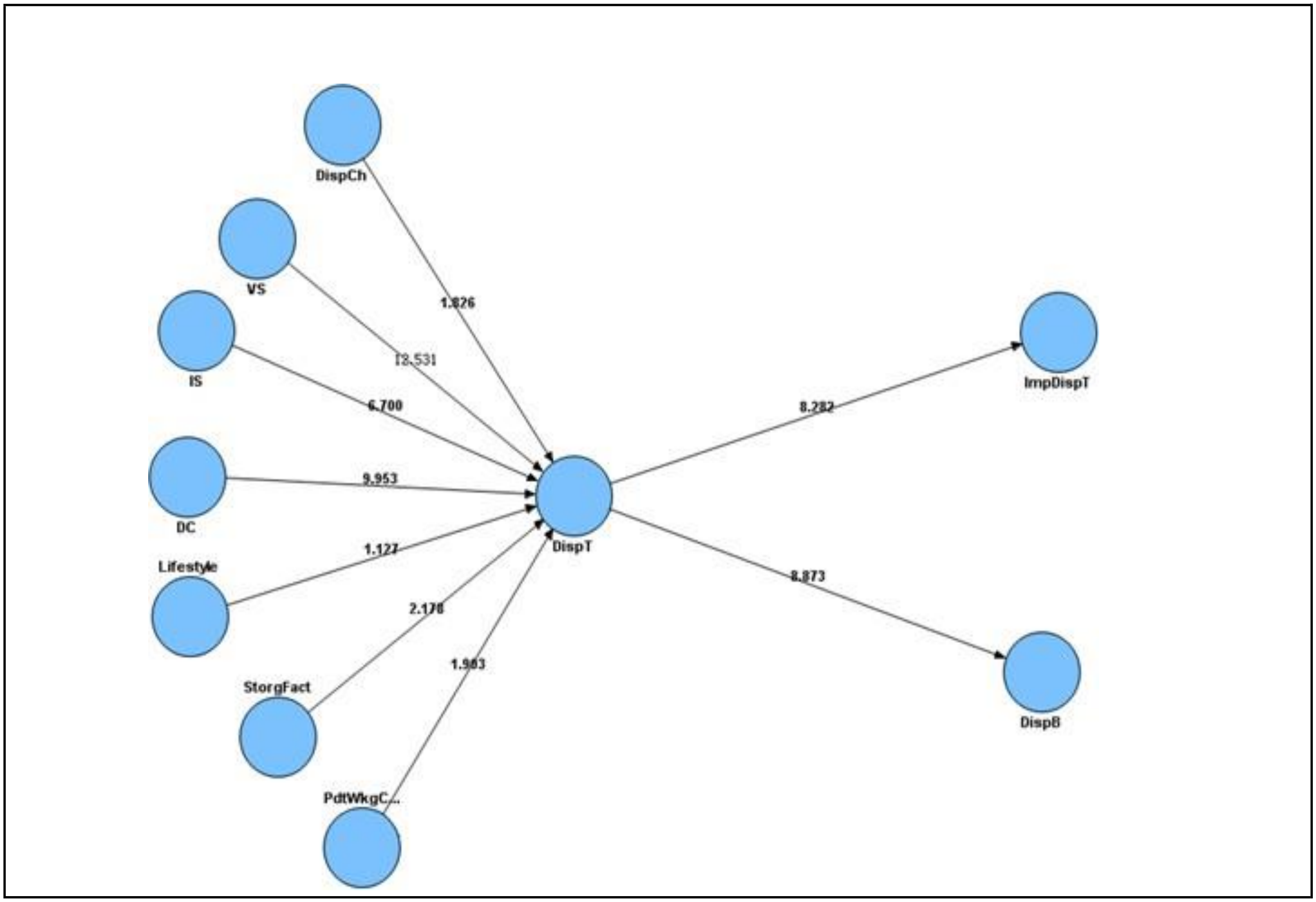

Fig 5.30 Bootstrapped Model (Disposers in nontransferable jobs)

Structural Model (Disposers in Nuclear Family)

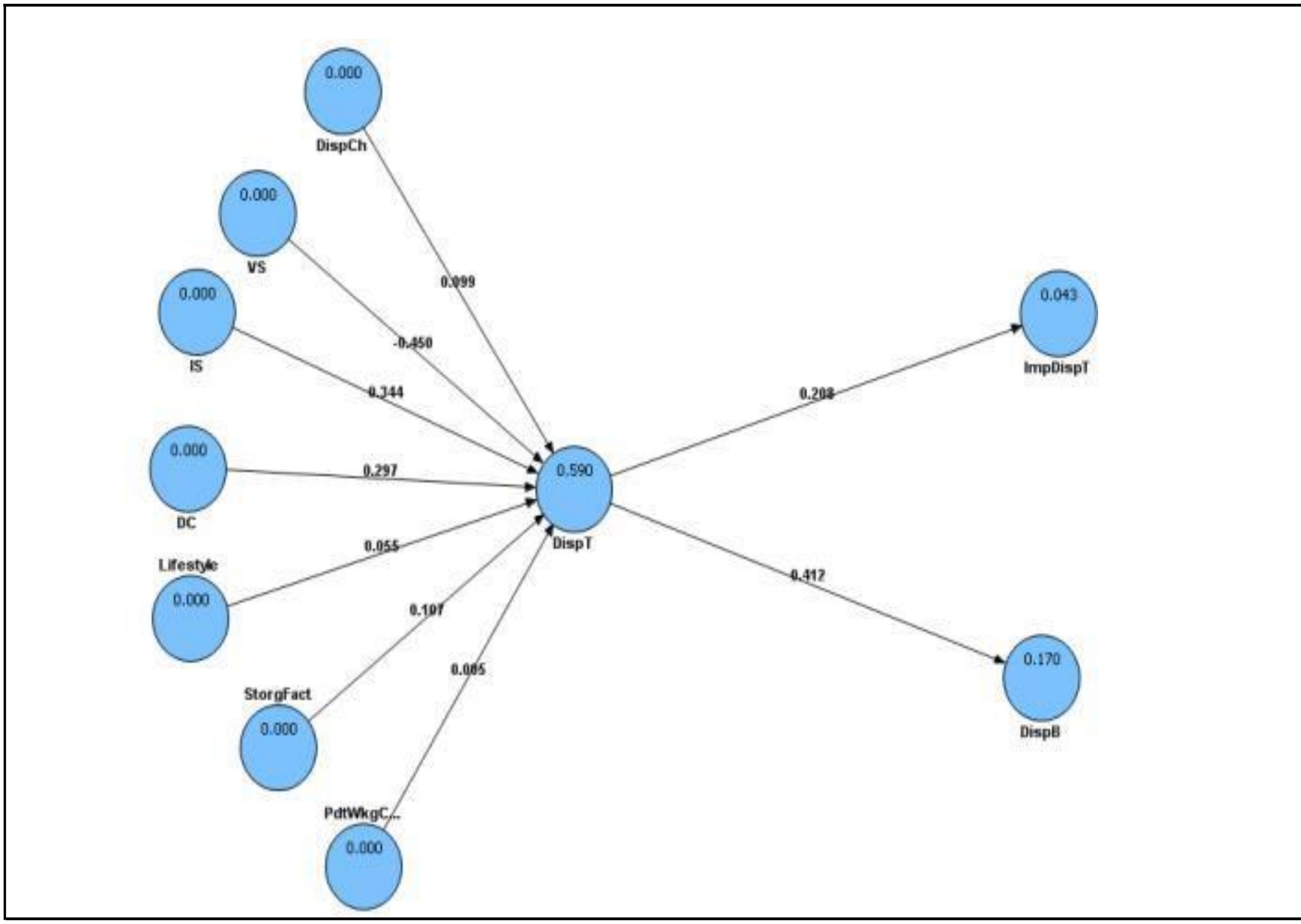

Fig 5.31 Structural Model (Disposers in Nuclear Family)

Bootstrapped Model (Disposers in Nuclear Family)

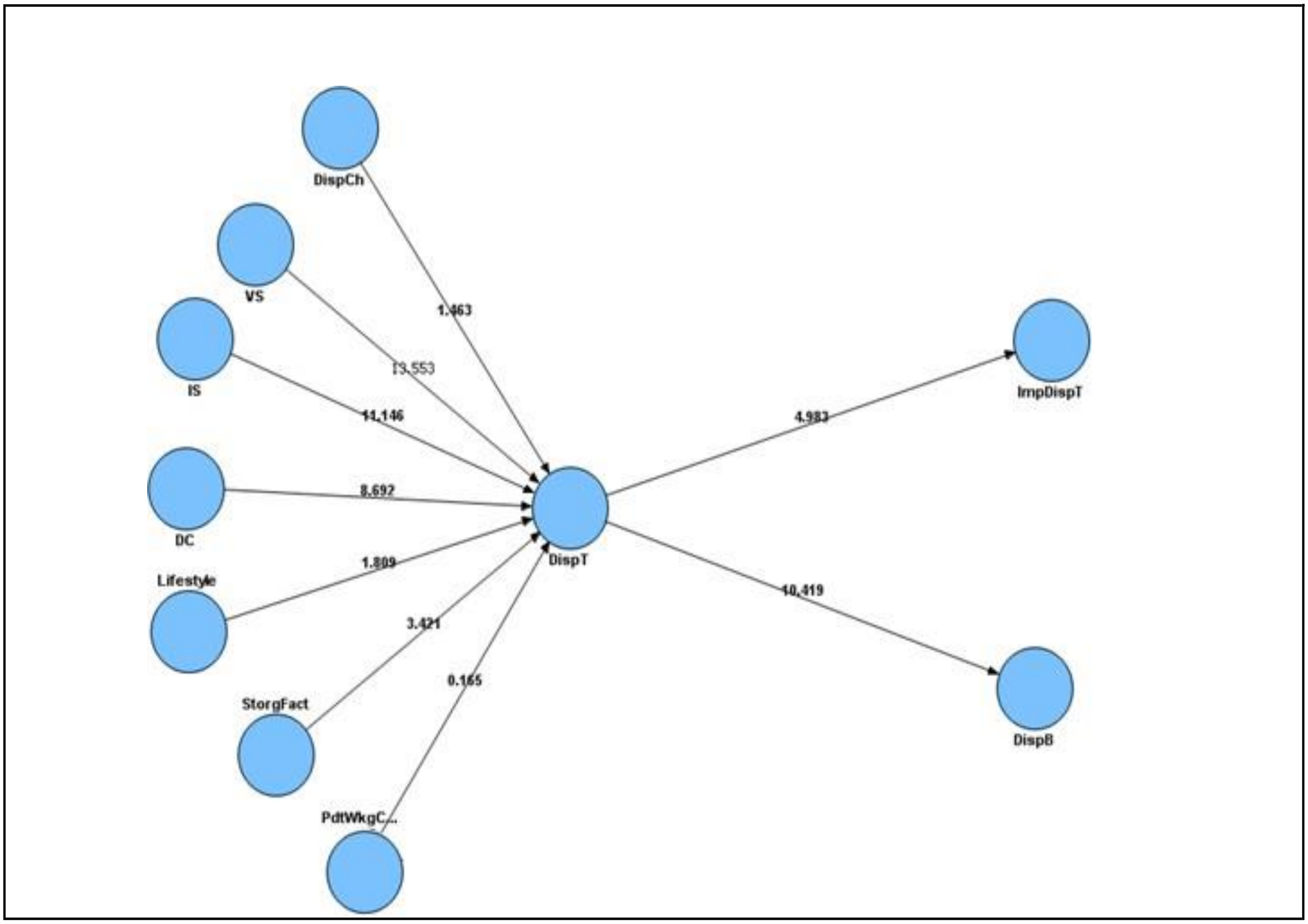

Fig 5.32 Bootstrapped Model (Disposers in Nuclear Family)

Structural Model (Disposers in Joint Family)

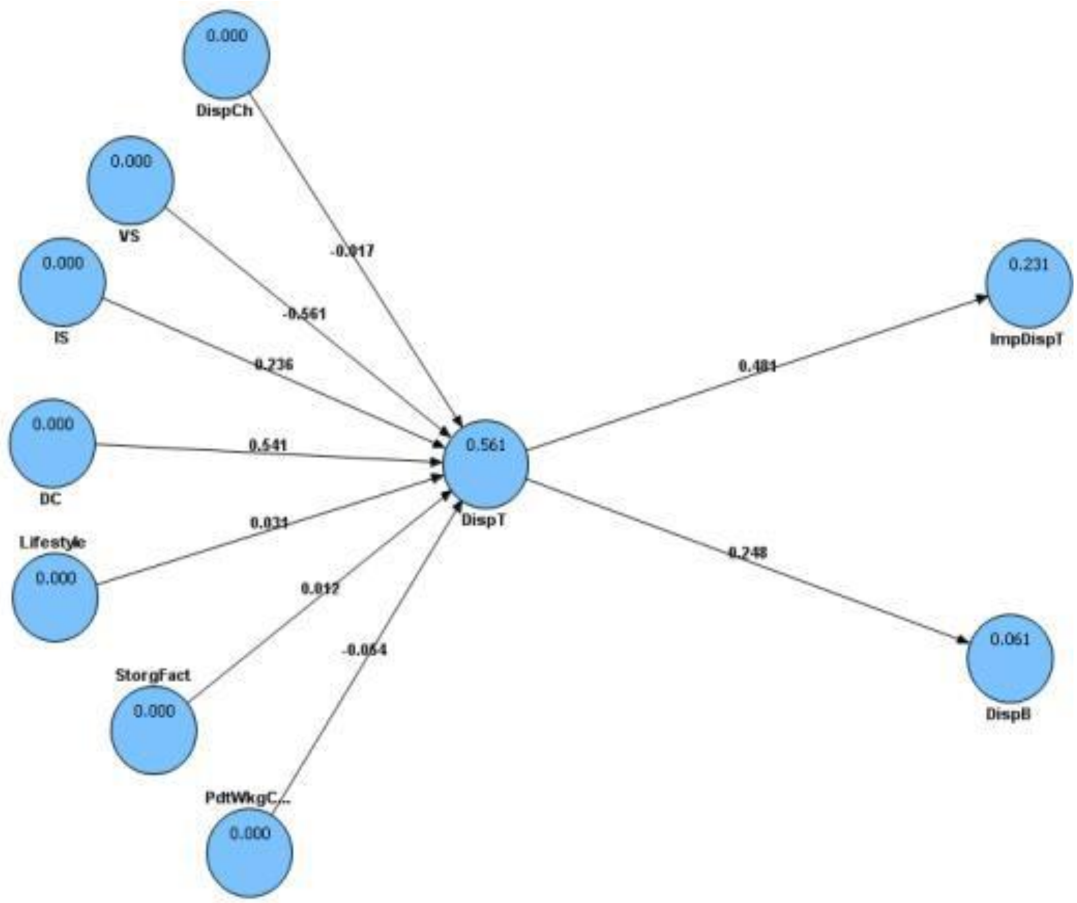

Fig 5.33 Structural Model (Disposers in Joint Family)

Bootstrapped Model (Disposers in Joint Family)

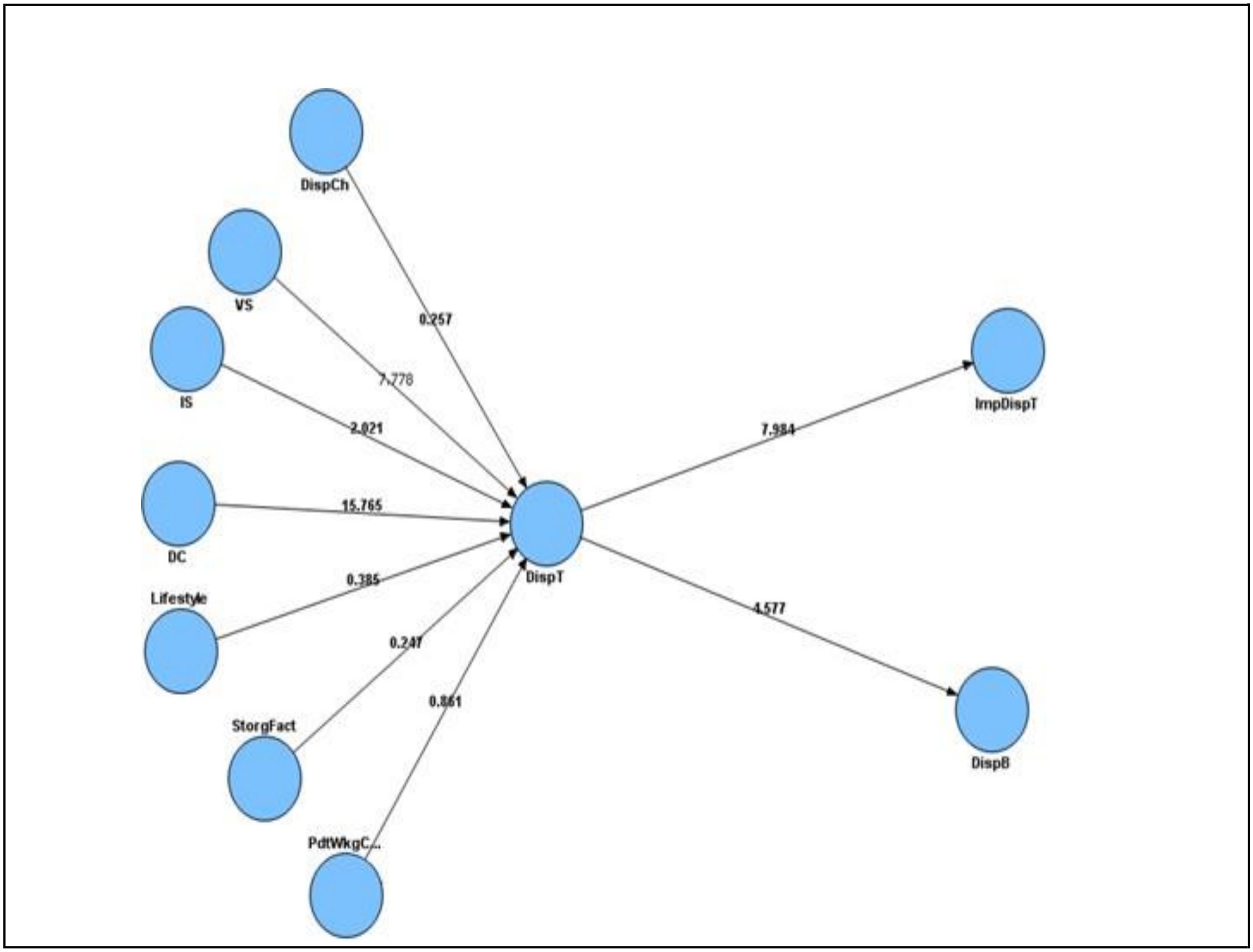

Fig 5.34 Bootstrapped Model (Disposers in Joint Family)

5.10.1 Moderating Effect of Age

The respondents were classified into three age groups (young, middle aged and old). Since SmartPLS computes only multiple pair-wise tests, three age related hypotheses each were framed for DisT→DisB and DisT→ImpDisB respectively. Hence, there were a total of 6 hypotheses (H8a1, H8a2, H8a3, H9a1,H9a2 and H9a3) framed for checking the moderating effect of age (Tables 5.23, 5.24 and 5.25).

The structural models based on age found that path coefficient and R values are different for young and old respondents for the path DisT→DisB. Also, path coefficient and R values are different for middle aged and old disposers for the path DisT→ImpDisB. Thus the finding confirms that there is significant effect among the latent constructs for the path DisT→DisB for young and old disposers and between middle aged and old disposers for the path DisT→ImpDisB in the research model. Hence, hypothesis H8a1 and H9a3 are accepted. The remaining hypotheses H8a2, H8a3, H9a1 and H9a2 are rejected. Hence, age is seen to moderate the paths DisT→DisB and DisT→ImpDisB.

Table 5.23 Moderating Effects of Age (Young Vs Old)

Hyp.No.	Hypothesis	Young (n=204)			Old (n=108)			Moderation	
		Path coefficient	Standard Error	T - value	Path coefficient	Standard Error	T - value	P-value	Decision
H8a1	DisT→DisB	0.320	0.050	6.459	0.472	0.069	6.887	0.070	Moderated
H9a1	DisT→ImpDisB	0.299	0.036	8.382	0.407	0.083	4.893	0.166	Not Moderated

Table 5.24 Moderating Effects of Age (Young Vs Middle)

Hyp.No.	Hypothesis	Young (n=204)			Middle (n=336)			Moderation	
		Path coefficient	Standard Error	T - value	Path coefficient	Standard Error	T - value	P-value	Decision
H8a2	DisT→DisB	0.320	0.050	6.459	0.377	0.046	8.247	0.818	Not Moderated
H9a2	DisT→ImpDisB	0.299	0.036	8.382	0.229	0.046	5.015	0.279	Not Moderated

Table 5.25 Moderating Effects of Age (Middle Vs Old)

Hyp.No.	Hypothesis	Middle (n=336)			Old (n=108)			Moderation	
		Path coefficient	Standard Error	T - value	Path coefficient	Standard Error	T - value	P-value	Decision
H8a3	DisT→DisB	0.377	0.046	8.247	0.472	0.069	6.887	0.286	Not Moderated
H9a3	DisT→ImpDisB	0.229	0.046	5.015	0.407	0.083	4.893	0.057	Moderated

5.10.2 Moderating Effect of Income

With regard to the structural models based on levels of income in the research model, it is found that path coefficient (β) and R2 values are different between disposers with income below Rupees 5 Lakhs and the disposers with income above Rupees 5 Lakhs (Table 5.26). Based on these overall results, it can be said the hypothesized relationships (H8b and H9b) are fully significant.

Hence, income moderates the path relationships: DisT→DisB and DisT→ImpDisB.

Table 5.26 Moderating Effects of Income

Hyp.No.	Hypothesis	High Income (n=360)			Low Income (n=288)			Moderation	
		Path coefficient	Standard Error	T -value	Path coefficient	Standard Error	T -value	P-value	Decision
H8b	DisT→DisB	0.260	0.046	5.623	0.415	0.044	9.449	0.016	Moderated
H9b	DisT→ImpDisB	0.386	0.036	10.768	0.199	0.044	4.491	0.002	Moderated

5.10.3 Moderating Effect of Gender

The gender based structural model found the path coefficients and R values are not significantly different for male respondents and female respondents. As shown in Table 5.27, gender does not moderate either of the two proposed paths model's relationships. It was found that male and female users with a similar disposition tendency display similar disposition behaviour and impulse disposing behaviour. Thus the finding confirms that there is no significant effect among the latent constructs and their path relationships: DisT→DisB and DisT→ImpDisB in the research model based on gender. Hence, hypotheses H8c and H9c are rejected.

Hence, gender does not moderate the path relationships: DisT→DisB and DisT→ImpDisB.

Table 5.27 Moderating Effects of Gender

Hyp.No.	Hypothesis	Males (n=432)			Females (n=216)			Moderation	
		Path coefficient	Standard Error	T -value	Path coefficient	Standard Error	T -value	P-value	Decision
H8c	DisT→DisB	0.388	0.038	10.100	0.318	0.059	5.430	0.302	Not Moderated
H9c	DisT→ImpDisB	0.227	0.043	5.266	0.286	0.046	6.187	0.388	Not Moderated

5.10.4 Moderating Effect of Family Type

The family type based structural model found the path coefficients and R values are not significantly different for disposers in nuclear and joint family set ups. As shown in Table 5.28, family type does not moderate either of the two proposed paths of the model's relationships. It was found that disposers with similar DisT scores in both nuclear and joint families displayed similar disposition behaviour and impulse disposing behaviour. Thus the finding confirms that there is no significant effect among the latent constructs and their path relationships: DisT→DisB and DisT→ImpDisB in the research model across family types. Hence, hypotheses H8d and H9d are rejected.

Hence, family type does not moderate the path relationships DisT→DisB and DisT→ImpDisB

Table 5.28 Moderating Effects of Family Type

Hyp.No.	Hypothesis	Joint family (n=204)			Nuclear family (n=444)			Moderation	
		Path coefficient	Standard Error	T - value	Path coefficient	Standard Error	T - value	P- value	Decision
H8d	DisT→DisB	0.248	0.038	6.463	0.248	0.056	4.425	0.444	Not Moderated
H9d	DisT→ImpDisB	0.481	0.041	11.676	0.481	0.061	7.892	0.864	Not Moderated

5.10.5 Moderating Effect of Job Type

The job type based structural model found the path coefficients and R values are not significantly different for disposers across both transferable and non transferable jobs. As shown in Table 5.29, job type was not found to moderate either of the two proposed paths of the model's relationships. It was found that disposers with similar DisT scores across both job types displayed similar disposition behaviour and impulse disposing behaviour. Thus the finding confirms that there is no significant effect among the latent constructs and their path relationships: DisT→DisB and DisT→ImpDisB in the research model across job types. Hence, hypotheses H8e and H9e are rejected.

Hence, job type does not moderate the path relationships DisT→DisB and DisT→ImpDisB

Table 5.29 Moderating Effects of Job Type

Hyp.No.	Hypothesis	Transferable job (n=228)			Nontransferable job (n=420)			Moderation	
		Path coefficient	Standard Error	T - value	Path coefficient	Standard Error	T - value	P-value	Decision
H8e	DisT→DisB	0.408	0.049	8.305	0.349	0.039	8.873	0.360	Not Moderated
H9e	DisT→ImpDisB	0.281	0.060	4.661	0.297	0.036	8.282	0.810	Not Moderated

5.10.6 Moderating Effect of Work Status

The job type based structural model found that the path coefficients and R values are not significantly different for disposers who were working and disposers who were not working. As shown in Table 5.30, work status was not found to moderate either of the two proposed paths of the model's relationships. It was found that disposers with similar DisT scores irrespective of their work status displayed similar disposition behaviour and impulse disposing behaviour. Thus, the finding confirms that there is no significant effect among the latent constructs and their path relationships: DisT→DisB and DisT→ImpDisB in the research model across work status categories. Hence, hypotheses H8f and H9f are rejected.

Hence, work status does not moderate the path relationships DisT→DisB and DisT→ImpDisB

Table 5.30 Moderating Effects of Work Status

Hyp.No.	Hypothesis	Working (n=456)			Not working(n=192)			Moderation	
		Path coefficient	Standard Error	T - value	Path coefficient	Standard Error	T - value	P-value	Decision
H8f	DisT→DisB	0.373	0.038	9.822	0.345	0.051	6.818	0.672	Not Moderated
H9f	DisT→ImpDisB	0.244	0.038	6.405	0.307	0.040	7.768	0.328	Not Moderated

5.11 Chapter Summary

This chapter has provides the summary of the findings based on the data analysis conducted using SPSS 20.0 and SmartPLS2.0 analysis. The chapter presents the profile of the survey followed by a pre-test summary, a pilot study data analysis and non-response bias test. Next, the details pertaining to the main study are presented. It provides the demographics profile of the respondents and the descriptive statistics of the sample population. The analysis of the data was carried out in two stages. In the first stage, measurement model and structural model are examined. In the second stage, the moderating influence of demographic variables: age, gender, income, family types, job types and work status on two paths: DisT→DisB and DisT→ImpDisB are examined. The next chapter presents the discussion of the results and conclusion.

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