A sample of young female fashion students is used to explore how pure-play retailers can maximise their marketing communications. Prior to this paper, EFA, CFA and SEM hypothesis testing have been undertaken. The focus for this paper begins from the results of hypothesis testing and explores SEM model development to identify meaningful direct relationships between six latent constructs which were not originally hypothesized.

This study is quantitative, following a realist philosophy. This paper discusses an exploratory approach to structural equation modelling using modification indices, model comparison and evaluation. Following a two-step approach to modelling, this paper addresses the second stage of exploratory model development, used in conjunction with substantive theory in order to create the best possible model to fit the collected data set (n=688).

By performing three theoretically and statistically meaningful modifications on the structural model developed during the hypothesis testing phase, a new exploratory model is developed which better fits the data and makes theoretical sense. The fit of the model is checked with $\chi^2$ difference tests, final parameter estimates, squared multiple correlations and model fit statistics. Further testing of this model is needed in the future for validation.
Introduction
The aim of this PhD study is to identify how pure-play fashion retailers can simulate attachment to their websites through the use of different communication mediums, in order to overcome the online environments intangibility. Six latent constructs have been tested in the study using a series of quantitative methods to model relationships between them. These constructs are static product presentation, moving product presentation, expert driven product recommendations, trust, loyalty and purchase intentions. To date a conceptual model has been tested and found to have sufficient model fit and can be said to be tentatively validated. However, a second phase of exploratory modelling has been carried out which attempts to find any more underlying relationships between constructs not originally hypothesized. This paper therefore aims to discuss this small aspect of the PhD. Figure I illustrates the PhD study organisation to date, with this paper focusing on modelling phase #2.

Figure I: PhD Study Organisation

Conclusions of Modelling Phase #1
Modelling phase #1 tested a conceptual model using CFA and SEM via a confirmatory modelling strategy. Twelve hypotheses were tested, developed from an extensive literature review, with nine hypotheses found to be statistically validated. The conceptual model is seen in Figure II in Appendix A, and the results of hypothesis testing (including the structural paths and their p-values) are shown in Table I and Figure III, Appendix A. The measurement model tested in confirmatory factor analysis provided satisfactory evidence to accept the six factor model. Fit statistics indicated a good fit ($\chi^2 = 436.066$, df = 194, p = .000, CMIN/DF = 2.248, GFI = .947, AGFI = .931, RMSEA = .043, NFI = .942, CFI = .967). Factor loadings including all six factors are sufficient with values exceeding .60 apart from one item in the static product presentation construct. Data was checked for reliability, convergent and discriminant validity, which were all present. The data set for structural equation modelling contains 22 observed variables representing 6 latent factors. All latent factors have at least three observed variables. Overall, the fit statistics for the conceptual model indicate a relatively good fit (CMIN/DF = 2.388, GFI = .943, AGFI = .927, RMSEA = .045, CFI = .962, NFI = .937). All of the fit statistics exceed their accepted thresholds. These results from modelling phase #1 give the researcher confidence in moving from a confirmatory modelling strategy to a model development strategy, which will be described in this paper.
**Literature – Structural Equation Modelling**

Structural equation modelling is a family of statistical tools which allows a set of relationships between one or more independent variables and one or more dependent variables to be explored (Hardy & Bryman, 2010). Complex relationships can be examined with structural equation modelling (Hardy & Bryman, 2010) as it uses complete and simultaneous tests of all the relationships between constructs. Different models are used in SEM to represent relationships among observed variables to quantify whether hypotheses stipulated by the researcher are supported (Schumacker & Lomax, 2010). Ultimately the purpose of SEM is to explore the extent to which the theoretical model is supported by the data set (Schumacker & Lomax, 2010). A full structural model is one of the most complex general linear models (Hardy & Bryman, 2010). The structural aspect of a full structural model only concerns the relationships amongst full latent variables and assessing their validity (Byrne, 2010). Latent variables are those which are not directly measurable, being surmised from a set of observable variables present in the data survey (Schumacker & Lomax, 2010). Error in relationships found during SEM is estimated and removed, which only leaves the common variance behind, making the reliability of measurement explicit and relationships free of measurement error (Hardy & Bryman, 2010). CFA is undertaken before full structural equation modelling to test whether the measurement of each latent variable is psychometrically sound (Byrne, 2010). Only after conducting this preliminary analysis can a researcher have confidence in their results.

**Developing a Modelling Strategy**

There are three different approaches towards structural equation modelling, namely a strictly confirmatory approach, an alternative/competing models approach and the model development approach (Hair et al., 2006). When conducting multivariate statistical analysis exclusivity does not exist when applying the techniques (Hair et al., 2006). Structural equation modelling explores relationships which can be fulfilled through multiple strategies. The researcher must decide which is best suited to the studies objectives, and then adopt this approach when modelling.

**Confirmatory Modelling Strategy**

A confirmatory modelling strategy is the most restrictive approach to structural equation modelling whereby one model is specified and SEM is used to assess how well the model fits the data (Hair et al., 2006). This is an all or nothing approach, the model either works or it does not. This does not confirm that the specified model is proven, but rather is it one possibility of many (Hair et al., 2006). This can be an expensive approach as one set of data is used in a restrictive fashion, and if the specified model is not proven then no use has been found for the data.

**Alternative/Competing Models Strategy**

The alternative models strategy is more flexible approach whereby a researcher specifies two or more models and then determines which one is the best fit (Hair et al., 2006). By comparing models a researcher can test competing theories, although there can be a problem in finding two well developed theories in one area which can be tested. With more complex models there is often at least one other model with the same number of parameters, equivalent model fit which differs the portrayed relationships (Hair et al., 2006).
Model Development Strategy
The model development strategy is the most exploratory approach to structural equation modelling. The aim of this strategy is to improve the specified models through modification to the initially hypothesized model (Hair et al., 2006). Caution must be exercised by the researcher not to modify the final model to an extent that it cannot be generalized to other samples or populations (Hair et al., 2006). Theoretical support must always be considered when modifying; the researcher must not just be led solely by the statistics (Hooper, Coughlan & Mullen, 2008). The researcher must try to decide how much fit is enough without over-fitting the model (Byrne, 2010).

Within all three modelling strategies, theoretical insight and judgement must always be exercised by the researcher (Hooper et al., 2008). Within this paper a model development strategy is implemented. Equivalent and alternative models will often exist in over-identified models; it is exceptional to perfectly reproduce the sample variance-covariance matrix so that no other alternatives exist (Schumacker & Lomax, 2010). It is therefore important to understand that there may be more than one plausible model associated with the data. The researcher will therefore attempt to marry the theory with the most appropriate statistical outcome in order to produce an acceptable and plausible model. Modifications will be made according to the modification indices, estimates and theory. As the initial SEM model is of a reasonable fit, some modifications would undoubtedly produce a more appropriate final model.

Methodology
This study is focused on ASOS, the largest independent fashion retailer. ASOS is a pure-play fashion retailer and an industry high standard with 41% profit increase in 2011 to £26.8 million (IMRG, 2011). ASOS will be familiar to the target respondents of this study, their target audience being 16-34 year old fashion-conscious consumers (Mintel, 2011). The sample comprised of young female fashion consumers (specifically fashion retail students, in accordance with Kim and Park (2005) and Kim and Forsythe (2009)). Fashion students are likely to be more innovative than a sample from other disciplines (Workman & Caldwell, 2007).

A cross sectional approach to this study was taken using self administered and online surveys. The survey questionnaire was composed of two sections; demographic and shopping frequency questions and attitude scales. The shopping frequency questions were used as a filter; respondents had to have visited the ASOS online store in the last six months and be female. The second section of the questionnaire used scaled responses to a seven-point likert scale (Goldsmith & Flynn, 2005; Kim et al., 2009) (Strongly Agree- Strongly Disagree). A ‘No Opinion’ box was included (Collins-Dodd & Lindley, 2003) so as respondents who did not use or had not heard of an item would not affect the analysis. 22 items were developed to measure 6 constructs. Items which explicitly measure fashion website variables are limited, and therefore some development and adaptation was needed. However, items originated from academically validated sources. A review of all the item measures used in this study is shown in Table II in Appendix B.

Results
A total sample of 688 was collected for this study, 331 were completed in paper format and 357 were completed online. The average age of respondents is 21 with a range between 16
and 43. 87.9% of the sample is under 24, making this data more applicable to young consumers.

SEM Modification
Several different methods can be used for model modification including elimination of parameters, inclusion of parameters using modification indices (the value that the \( \chi^2 \) would decrease if a parameter were included) and the expected parameter change statistic (approximate value of the parameter if added), examining the standardized residuals and estimates (Schumacker & Lomax, 2010; Tabachnick & Fidell, 2007). A MI value of 4 or more suggests that a significant improvement in the model would be made if a parameter was included (Tabachnick & Fidell, 2007). Parameters can be added to a model one by one, and then redundant parameters can be removed from a model one by one until the researcher thinks there is sufficient fit in the model. Crucial decision making steps during modification concern whether additional parameters are substantively meaningful, sufficient fit statistics and the expected parameter change value is significant (Byrne, 2010). For SEM the modification indices which will be reviewed are the regression weights between latent variables, as it is causal relationships which are being explored. This studies approach to model development is now described. Three modifications were carried out on the initially validated structural model, guided by the modification indices and existing theory. These are shown in Table III.

<table>
<thead>
<tr>
<th>Modification Number</th>
<th>Parameter</th>
<th>MI</th>
<th>Par Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modification 1</td>
<td>Static Product Viewing &gt; Moving Product Viewing</td>
<td>16.501</td>
<td>.418</td>
</tr>
<tr>
<td>Modification 2</td>
<td>Expert Product Recommendations &gt; Moving Product Viewing</td>
<td>13.400</td>
<td>.135</td>
</tr>
<tr>
<td>Modification 3</td>
<td>Static Product Presentation &gt; Guidance</td>
<td>6.590</td>
<td>.225</td>
</tr>
</tbody>
</table>

Model Comparisons
Evaluating whether a model ‘fits’ the data accurately is one of the most crucial steps when performing SEM (Hooper et al., 2008). It is important to look at any progress made during modification to compare the models and determine that the final model is superior. In order to directly compare the modifications made to the final SEM model the ECVI and CAIC statistics will be used to map progress from the initial to the final structural model. The CAIC is a consistent version of Akaike’s information criterion (1987), which assesses goodness of fit and model parsimony (Byrne, 2010), giving three statistics in AMOS output. The CAIC is useful when comparing models and therefore can aid model comparison (Byrne, 2010). Smaller values for this statistic represent better fitting models (Byrne, 2010). By mapping these values the success of modification can be analysed. Moreover, the ECVI will also be examined which also compares models, with small ECVI values being preferred as it indicates a higher chance of replication (Byrne, 2010). ECVI gives three values for saturated, default and independence models.

<table>
<thead>
<tr>
<th></th>
<th>ECVI</th>
<th>CAIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Structural Model</td>
<td>.841</td>
<td>871.198</td>
</tr>
<tr>
<td>First Modified Structural Model</td>
<td>.819</td>
<td>861.698</td>
</tr>
<tr>
<td>Second Modified Structural Model</td>
<td>.806</td>
<td>858.269</td>
</tr>
<tr>
<td>Final Structural Model</td>
<td>.799</td>
<td>859.072</td>
</tr>
<tr>
<td>Saturated</td>
<td>.737</td>
<td>1906.049</td>
</tr>
<tr>
<td>Independence</td>
<td>10.955</td>
<td>7647.773</td>
</tr>
</tbody>
</table>
From the model comparison in Table IV it can be seen that the values for both the ECVI and CAIC both improve as modification is undertaken on the initial structural model. Both statistics show that the final structural model value is smaller than that of both the saturated and independence models. Table V in Appendix C shows that model fit is also improved during modification.

Chi-Square Difference Test
When models are nested (one is a subset of another) then a Chi-square difference test can be performed to determine whether a difference in the $\chi^2$ is significantly improving model fit (Tabachnick & Fidell, 2007; Hair et al., 2006). The Chi-Square difference statistic $\Delta\chi^2$ allows a comparison between a baseline model and a nested model using the following formula (Hair et al., 2006, p. 756):

$$\Delta\chi^2 = \chi^2_{df (B)} - \chi^2_{df (A)}$$

$$\Delta df = df(B) - df(A)$$

When the $\Delta\chi^2$ difference value has been calculated it can be tested for statistical significance using the difference in $\Delta df$ (Hair et al., 2006). A model with one degree of freedom difference needs a $\Delta\chi^2$ of 3.84 or more to be better fitting (Hair et al., 2006).

Table VI: Chi-Square Difference Test

<table>
<thead>
<tr>
<th>Model B DF</th>
<th>Model A DF</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta df$</th>
</tr>
</thead>
<tbody>
<tr>
<td>471.907 200</td>
<td>454.874 199</td>
<td>17.033</td>
<td>1</td>
</tr>
<tr>
<td>454.874 199</td>
<td>443.911 198</td>
<td>10.963</td>
<td>1</td>
</tr>
<tr>
<td>443.911 198</td>
<td>437.180 197</td>
<td>6.731</td>
<td>1</td>
</tr>
</tbody>
</table>

Table VI shows that all three modifications whereby parameters were added to the model were statistically significant with $\Delta\chi^2$ all above the critical value of 3.84 (seen in bold). The $\Delta\chi^2$ from the initial to the final model is 34.727 with 3 $df$ which shows that the overall $\Delta\chi^2$ was significantly improved and that all modifications are statistically validated.

Conclusions
A model development approach towards SEM can aid the researcher in gaining further insights into enhancing the structure of their final model by the addition of parameters not originally hypothesized. Caution must be exercised in terms of adding parameters which are not theoretically supported, and although this paper has a statistical focus, theory was used to inform all three modifications described. A depiction of the final model is seen in Figure IV. In order to be verified, this model needs to be tested with an independent sample (Hair et al., 2006). Static product presentation clearly drives product viewing in pure-play fashion websites, leading to a more involved viewing process (by watching videos) and to the evaluation of expert driven product recommendations. Significant relationships are found between moving product presentation and loyalty, product recommendations and trust, and between static product presentation and trust and purchase intentions. Simulating attachment to a website without physical interaction can be carried out by using multiple static viewing options of products, moving product videos and expert driven product recommendations as facets of an overall online strategy. The research in this study could be further extended by further development of latent constructs and the development of second order SEM.
References


Harris, L.C., Goode, M.M.H. (2004). The four levels of loyalty and the pivotal role of trust: a study of online service dynamics. Journal of Retailing, 80, 139-158.


**Appendix A**

**Figure II: Conceptual Model**

![Conceptual Model Diagram]

**Table I: Structural Path Estimates**

<table>
<thead>
<tr>
<th>Hypothesis Number</th>
<th>Structural Path</th>
<th>Standardized Regression Weights</th>
<th>P-Value</th>
<th>T-value</th>
<th>Support For Hypothesis?</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>Static Product Presentation &gt; Purchase Intention</td>
<td>0.171</td>
<td>***</td>
<td>4.619</td>
<td>Yes</td>
</tr>
<tr>
<td>H2</td>
<td>Static Product Presentation &gt; Trust</td>
<td>0.260</td>
<td>***</td>
<td>5.723</td>
<td>Yes</td>
</tr>
<tr>
<td>H3</td>
<td>Static Product Presentation &gt; Loyalty</td>
<td>0.020</td>
<td>0.635</td>
<td>.475</td>
<td>No</td>
</tr>
<tr>
<td>H4</td>
<td>Moving Product Presentation &gt; Trust</td>
<td>0.189</td>
<td>***</td>
<td>4.599</td>
<td>Yes</td>
</tr>
<tr>
<td>H5</td>
<td>Moving Product Presentation &gt; Purchase Intention</td>
<td>0.028</td>
<td>0.418</td>
<td>.810</td>
<td>No</td>
</tr>
<tr>
<td>H6</td>
<td>Moving Product Presentation &gt; Loyalty</td>
<td>0.235</td>
<td>***</td>
<td>5.656</td>
<td>Yes</td>
</tr>
<tr>
<td>H7</td>
<td>Product Recommendations &gt; Trust</td>
<td>0.305</td>
<td>***</td>
<td>6.761</td>
<td>Yes</td>
</tr>
<tr>
<td>H8</td>
<td>Product Recommendations &gt; Purchase Intention</td>
<td>-0.027</td>
<td>0.470</td>
<td>-.722</td>
<td>No</td>
</tr>
<tr>
<td>H9</td>
<td>Product Recommendations &gt; Loyalty</td>
<td>0.147</td>
<td>***</td>
<td>3.303</td>
<td>Yes</td>
</tr>
<tr>
<td>H10</td>
<td>Trust &gt; Loyalty</td>
<td>0.389</td>
<td>***</td>
<td>8.143</td>
<td>Yes</td>
</tr>
<tr>
<td>H11</td>
<td>Trust &gt; Purchase Intention</td>
<td>0.272</td>
<td>***</td>
<td>6.503</td>
<td>Yes</td>
</tr>
<tr>
<td>H12</td>
<td>Loyalty &gt; Purchase Intention</td>
<td>0.539</td>
<td>***</td>
<td>11.379</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Note: *** = p<0.001*
Figure III: Final Model Path Estimates from Model Phase#1

Standardized Regression Weight Estimates

***p<0.001
**p<0.01
## Appendix B

Table II: A review of the constructs and items

<table>
<thead>
<tr>
<th>Construct</th>
<th>About</th>
<th>Items used in this study</th>
<th>Source (adapted from)</th>
</tr>
</thead>
</table>
| **Static Product Presentation** | Static product presentation includes elements such as 2D or 3D view, back view, viewing a product on a model or a mannequin and zoom capabilities. | Back view on ASOS provides in-depth information  
Zoom feature on ASOS provides in-depth information  
Detailed view on ASOS provides in-depth information  
3D view/Model on ASOS provides in-depth information | Wolfinbarger and Gilly (2003)  
Wolfinbarger and Gilly (2003)  
Wolfinbarger and Gilly (2003)  
Wolfinbarger and Gilly (2003) |
| **Moving Product Presentation** | Such as video. In a recent content analysis of 97 women’s apparel websites, video presentation was only available in 5.2% of cases (Kim et al., 2011). | ASOS has visually appealing catwalk videos  
The catwalk video on ASOS is beneficial  
The product videos on ASOS are lifelike | Kim, Kim and Kandampully (2009)  
Mukherjee and Nath (2007)  
Schlosser (2003) |
| **Expert Driven Product Recommendations** | Expert systems (such as recommender systems) have been found to be the most influential recommender source (Senecal and Nantel, 2004). | ASOS recommended relevant products to me which I had not thought of or did not know ASOS makes purchase recommendations which match my needs “We Recommend” feature on ASOS makes purchase recommendations which match my needs | Demangeot and Broderick (2007)  
Srinivasan, Anderson and Ponnavolu (2002)  
Srinivasan, Anderson and Ponnavolu (2002) |
| **Trust** | Trust is defined as “confidence in or reliance on some quality or attribute of a person or thing, or the truth of a statement” (Wang and Emurian, 2005). | ASOS represents a company or organisation that will deliver on promises made ASOS can be counted on to do what they say they will do ASOS is reliable ASOS puts the customer’s interest first | Bart, Shankar, Sultan and Urban (2005)  
Mukherjee and Nath (2007)  
Verhoef, Franses and Hoekstra (2002) |
| **Loyalty** | Loyal customers are prepared to spend more, buy more, are easy to reach, repeatedly return and are positive promoters of a company (Harris and Goode, 2004). | When I need to make a purchase, ASOS is my first choice I have repeatedly found ASOS better than others I would classify myself as a loyal customer of ASOS I will visit ASOS first when I buy fashion | Srinivasan, Anderson and Ponnavolu (2002)  
Harris and Goode (2004)  
Brady, Knight, Cronin, Tomas, Hult and Keillor (2005)  
Demangeot and Broderick (2007) |
| **Purchase Intentions** | A measure of the claimed level of future consumption of a product or service by target customers | I would purchase an item from ASOS  
I intend to continue using ASOS in the future  
I would recommend ASOS to a friend  
In the future I intend to use ASOS for fashion purchases | Bart, Shankar, Sultan and Urban (2005)  
Demangeot and Broderick (2007)  
Maxham and Netemayer (2003) |
Appendix C

Table V: Comparison of values of model fit during modification

<table>
<thead>
<tr>
<th>Fit Index</th>
<th>Initial SEM</th>
<th>1st Modified SEM</th>
<th>2nd Modified SEM</th>
<th>3rd Modified SEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square</td>
<td>χ² = 471.907 p = .000</td>
<td>χ² = 454.874 p = .000</td>
<td>χ² = 443.911 p = .000</td>
<td>χ² = 437.180 p = .000</td>
</tr>
<tr>
<td>CMIN/DF</td>
<td>2.360</td>
<td>2.286</td>
<td>2.242</td>
<td>2.219</td>
</tr>
<tr>
<td>RMR</td>
<td>.152</td>
<td>.129</td>
<td>.099</td>
<td>.090</td>
</tr>
<tr>
<td>GFI</td>
<td>.944</td>
<td>.945</td>
<td>.946</td>
<td>.947</td>
</tr>
<tr>
<td>AGFI</td>
<td>.928</td>
<td>.930</td>
<td>.931</td>
<td>.932</td>
</tr>
<tr>
<td>TLI</td>
<td>.957</td>
<td>.959</td>
<td>.960</td>
<td>.961</td>
</tr>
<tr>
<td>PGFI</td>
<td>.745</td>
<td>.743</td>
<td>.740</td>
<td>.737</td>
</tr>
<tr>
<td>CFI</td>
<td>.963</td>
<td>.965</td>
<td>.966</td>
<td>.967</td>
</tr>
<tr>
<td>NFI</td>
<td>.937</td>
<td>.939</td>
<td>.941</td>
<td>.942</td>
</tr>
<tr>
<td>RMSEA</td>
<td>.044</td>
<td>.043</td>
<td>.043</td>
<td>.042</td>
</tr>
<tr>
<td>ECVI</td>
<td>&gt;S</td>
<td>&gt;S</td>
<td>&gt;S</td>
<td>&lt;S</td>
</tr>
<tr>
<td>&lt;1</td>
<td>&lt;1</td>
<td>&lt;1</td>
<td>&lt;1</td>
<td></td>
</tr>
<tr>
<td>Hoelter’s CN</td>
<td>341</td>
<td>352</td>
<td>359</td>
<td>363</td>
</tr>
</tbody>
</table>
Appendix D

Figure IV: Final Structural Model

Standardized Regression Weight Estimates

*** p < 0.001
** p < 0.01
* p < 0.05

X² = 437.180
DF = 197
X²/DF = 2.219
RMSEA = 0.042
AGFI = 0.932
PGFI = 0.737
GFI = 0.947
NFI = 0.942
CFI = 0.967