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# Improving prediction with POS and PLS consistent estimations: An illustration☆

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ABSTRACT

Recent advances (Dijkstra and Henseler, 2015a, 2015b) have introduced methods that provide consistent PLSc estimates. In parallel, Becker et al. (2013) propose a novel prediction oriented segmentation (POS) approach which by taking into account unobserved heterogeneity increases the predictive power with regard to the dependent variables. Hence, the main objective of this paper is to show how the complementary use of PLSc and POS can increase the overall predictive ability of the PLS approach. A concrete example, carefully following the presentation guidelines provided by Henseler et al. (2016), in a Moroccan context demonstrates the plausibility of such a proposal and concretely shows the existence of three different groups of people with different reactions toward counterfeiting. The stability of this segmentation is verified as well as the causal asymmetry of data. Managerial implications with respect to these three groups are highlighted, thanks also to a complementary importance–performance matrix analysis.



## 1. Introduction

For many years, structural equation modeling (SEM) has been the choice for research in management when researchers want to test for causal relationships between unobservable concepts. Nowadays, most researchers still focus on justifying their choice when selecting covariance-based structural equation modeling (CB-SEM) or partial least squares structural equation modeling (PLS-SEM). Most of the time, they try to assess the differences in terms of model estimation and to explain how PLS-SEM is able to mimic CB-SEM. However, this is quite an outdated practice, since renowned researchers in the field actually recommend distinguishing between common factor models and composite models (Henseler et al., 2014).

Factor models state that the variance of a given number of indicators is perfectly explained by the existence of one latent variable (the common factor) and individual random error. In contrast, composite variables are formed as perfect linear combinations of their respective indicators with correlated residuals being a distinguishing characteristic of composite measurement. More broadly speaking, this distinction relates to the overall goal pursued by the researchers, structure or prediction. Indeed, as outlined many years ago (Jöreskog and Wold, 1982), the primary purpose of CB-SEM is to study the structure of the observables whereas "the primary purpose of the PLS approach is to predict the indicators by means of the components expansion" (Jöreskog and Wold, 1982; p. 266). Nonetheless, recent advances (Dijkstra and Henseler, 2015a, 2015b) have introduced methods that provide consistent PLS-SEM estimations. Consequently, researchers can also rely on PLS consistent (PLSc) estimates which mimic CB-SEM for analyzing and testing a model structure. However, from theoretical as well practical reasons, one might want to compare the predictive power of the PLS and PLSc approaches. This is hence our first research question.

Besides the previous advances, researchers (Becker et al. 2013) have also recently shown that unobserved heterogeneity biases parameter estimates, thereby leading to Type I and Type II errors in parameter estimates. As explained in their seminal paper, Becker et al. (2013) show how taking into account unobserved heterogeneity increases the predictive power with regard to the dependent variables. Moreover, and according to Dijkstra (1983), traditional PLS leads to overestimated loadings along with attenuated inter-construct correlations whereas PLSc corrects the original latent variable correlations for attenuation. The contribution to $R^2$ for each independent latent variables being the product of the correlation and the path coefficient for the corresponding dependent variable, we are expecting that relying on PLSc estimates, once the POS approach has found out the appropriate number of segments, will globally increase the $R^2$ within each segment. This is our second research question.

As for the field study, we chose to focus on the study of consumers' reactions when their luxury brands are counterfeited within a Moroccan context. Morocco seems to be particularly relevant for our theoretical as well empirical investigation, since several luxury brands are available in

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both legitimate and counterfeited variants and are present in many Moroccan shops. In addition and according to the National Committee for the Industrial Property and Against Counterfeiting (CONPIAC), the Moroccan counterfeiting market has been estimated to be between 8 and 16 million dollars in 2012, which represents 1.3% of GDP of the country.

Brand loyalty which has been recognized for most than fifteen years (e.g. Oliver, 1999), as a key concept leading to greater market share and to a higher relative price for the brand (Chaudhuri and Holbrook, 2001) which is the focal dependent variable in our research model. Our model encompasses counterfeiting resistance, brand experience, perceived risk and attitude toward the brand as antecedents of brand loyalty toward luxury brands. Hence, we introduce the concept of "counterfeiting resistance", which represents "the tendency to keep and defend the luxury brand in the context of counterfeiting". Besides this introduction and definition of counterfeit resistance, we postulate that contrary to previous studies, brand loyalty cannot be conceptualized as homogeneously distributed within the sample but has to be checked for potential sub-segments with contrasted loyalty orientations.

Hence, our contribution is threefold. First, we prone the use of a consistent PLS estimation procedure recently introduced by Dijkstra and Henseler (2015a, 2015b) along with a PLS-orientated segmentation procedure (POS) recently put forward by Becker et al. (2013) in order to get a better prediction of the dependent latent variables, in our example, luxury brand loyalty. Second, and besides testing for causal asymmetries (Woodside, 2013, 2015a,b), we carefully test for predictive validity of PLS using holdout samples, showing that PLSc outperforms PLS classical approach. Third, we offer practical guidelines in order to assess the plausibility of the segments put forward by the POS methodology, mainly with regard to a simple cross-validation linear discriminant analysis procedure.

Hence, we first provide a short overview of the theoretical background we rely on as for the causal model used as an example. We then detail the different stages involved in the subsequent analyses. The article then details the brand luxury loyalty example results and concludes with a discussion of further research avenues that warrant attention.

## 2. Theoretical development

All in all, our proposed causal model supposes that consumer's resistance to counterfeiting affects the attitude toward the luxury brand, brand experience and perceived risk which in turn predict brand loyalty.

### 2.1. Consumer's resistance to counterfeiting

First of all, and in order to better delineate how consumer reacts to counterfeiting, we have focused on Commuri's study (2009), where the consumer of a particular trademark adopts one of the three following strategies:

(1) Flight: For the individual adopting this strategy, when the preferred brand is counterfeited, the consumer abandons it for a new brand that has not been counterfeited, lest others confuse the consumed product with a counterfeit article.
(2) Reclamation: Consumers from this group are defensive concerning counterfeiting. Because they are loyal customers of the counterfeited brand, they deplore the loss of exclusivity and absence of recognition.
(3) Abranding: These consumers do not want to be imitated. They want to be unique in what they wear, drive and do. Abranding is a state of consumption in which the brand may carry high personal meaning, but neither its identity nor the meaning is readily accessible to others.

Nevertheless, Commuri (2009) describes these different reactions toward counterfeiting without suggesting a measurement scale. Consequently, we have developed the concept of counterfeiting resistance that represents "the tendency to keep and defend the luxury brand in the context of counterfeiting". More precisely, counterfeiting resistance manifests the importance of counterfeiting when choosing a brand and is composed of two main facets:

(1) Counterfeiting debate: the choice for the legitimate brand is supported with relevant arguments. Consumers believe in the relevance of the purchase of genuine luxury products. For them, counterfeiting can never equal the consumed luxury brands.
(2) Counterfeiting emotional rejection: the presence of counterfeiting disconcerts luxury brand consumers who regret and reclaim this situation especially when the consumed product is counterfeited. Consumers with a high level of counterfeiting emotional rejection turn down all counterfeited brands including their brands.

According to Banikéma and Roux (2014), resistance is a matter of combatting the influences exercised on consumers. Therefore, we can consider counterfeiting resistance as a psychological variable that may affect attitudes. Therefore, we suggest the following hypothesis:

**H1.** Counterfeiting resistance positively influences the attitude toward the luxury brand.

### 2.2. Brand experience

Brand experience represents "subjective, internal consumer responses (sensations, feelings, and cognitions) and behavioral responses evoked by brand-related stimuli that are part of brand's design and identity, packaging, communication, and environments" (Brakus et al., 2009). According to Yoo and Lee (2009), experience brought by legitimate products does not affect the consumer preference for counterfeited products because this consumer is a rigorous prospector (Mason, 1998) that deliberately exclude counterfeit in his product selection. This is due especially to a possible negative social impact of counterfeiting purchase and because this category of consumers has sufficient financial wealth to buy expensive products. For their future purchases, these consumers will continue buying genuine products as long as they are looking for a social self-accomplishment through an ostentatious consumption.

In this study, we assume that luxury brand experience is so relevant that it cannot be affected by counterfeiting. Counterfeiting has no impact on brand experience as well as experience generated by luxury brand cannot be deteriorated by the presence of other products. Therefore, counterfeiting resistance may positively affect brand experience.

**H2.** Counterfeiting resistance positively affects luxury brand experience.

### 2.3. Perceived risk

In addition, we suggest that perceived risk also plays a role in counterfeiting context. Indeed, perceived risk is a key factor that affects consumers' evaluations and purchasing behaviors. In this research, we will be interested in the effects of perceived risk on legitimated purchase intention in counterfeiting context.

In this research, we will consider both social and psychological risks to study the effects of perceived risk. Social risk can be defined as the potential loss of esteem, respect, and/or friendship offered to the consumer by other individuals, whereas psychological risk is the potential loss of self-image or self-concept as the result of the item purchase (Stone and Gronhung, 1993). Counterfeited product associated with perceived risk leads consumer to regret their purchase, since other consumers may discover that this product is non-legitimate.

According to perceived risk concept, consumers will prefer genuine products that offer a lower level of potential loss compared to counterfeited product. In the consumer's point of view, legitimate products are less risky compared to counterfeited items. Therefore, consumer tendency to resist counterfeiting may strengthen the perceived risk:

**H3.** Counterfeiting resistance positively affects perceived risk.

### *2.4. Brand loyalty*

The effects of counterfeiting on luxury brand loyalty have not been undertaken in previous research. Sridhar (2007) evokes negative effects of counterfeiting on brand loyalty on the basis of the literature review without making an investigation on this subject. Therefore, we briefly describe three complementary hypotheses. First, and since attitudes are useful in predicting consumer behavior (Mitchell and Olson, 1981) including brand loyalty, we assume that brand loyalty is influenced by the attitude:

**H4.** Attitude toward the luxury brand positively affects brand loyalty.

Second, and according to previous research, brand experience positively affects consumer satisfaction (Brakus et al., 2009; Oliver, 1997), brand associations and brand personality (Brakus et al., 2009) or brand loyalty (Brakus et al., 2009; Reicheld, 1996). Therefore, we suggest the following hypothesis:

**H5.** Brand experience positively affects brand loyalty.

Finally, perceived risk is presumed to have an influence on brand loyalty. Indeed, and according to Cunningham (1967), when there is a perceived risk, brand loyalty plays a smaller role in the risk reduction process. Moreover, Sheth and Venkatesan (1968) studied these concepts and conclude that perceived risk is a necessary condition for the development of brand loyalty. Therefore, we suggest the following hypothesis:

**H6.** Perceived risk positively affects brand loyalty.

All in all, counterfeiting resistance is assumed to directly affect attitude toward the brand, perceived risk and brand experience. All these expected connections will be tested in the empirical study presented in the next paragraphs. Fig. 1 displays the corresponding structural equation model.

## 3. Methodological and practical implementation

### *3.1. Fuzzy-set Qualitative Comparative Analysis (FsQCA)*

As structural equation modeling in general is based on the assumption of symmetric statistical relationships between variables (Woodside, 2013) we have first to assess if this is the case with the data set at hand. Consequently, in order to evaluate the nature of the causal relationships between the variables encompassed within this research, we plot the luxury brand loyalty as the dependent (Y) variable against the set of all the independent variables (X) (namely, brand experience, brand attitude and perceived risk). The corresponding XY plot displayed in Fig. 2 shows that, according to Woodside (2015b), we are in the case of a sufficient asymmetric solution with a high overall solution consistency of 0.96 and moderate solution coverage of 0.30. Being behaviorally loyal to the brand might not be consistently related to positive pattern of brand experience, brand attitude and perceived risk. Therefore, we have to rely on a finer analysis which will enable evaluating the degree of consistency between the independent and dependent variables.

Hence, applying the direct calibration method suggested by Ragin (2008), this research transforms the variables into fuzzy sets using three thresholds: full membership, the cross-over point (i.e., the ambiguity point) and full non-membership, coding each of them with 1, 0.5 and 0, respectively. In this study, the calibration process is based on the original scales for all the reflective measures. In order to assess the results, and by analogy with the coefficient of determination, raw coverage indicates the degree of overlap of causal and target sets relative to the size of the set representing the outcome (Woodside, 2013). Following Ragin (2008), causal models are informative when their raw coverage is between 0.25 and 0.65.

Corresponding results are displayed in Table 1. In our case, they show evidence of a rather established causal symmetry since the patterns of variables explaining high loyalty are exactly the opposite of those explaining low level of loyalty. Being behaviorally loyal to the brand is consistently related to high patterns of the predictive variables and vice-versa. In other words, the relationships between the predictive variables and brand loyal intentions are nonetheless rather symmetric and fully warrant the use of a structural equation modeling approach.

Ultimately, to test for predictive validity, the sample was randomly divided (fifty–fifty split) into a modeling sample and a holdout sample of observations. Then, we performed fsQCA for the modeling sample and used the two resulting configurations, by the way identical to those obtained on the full sample, to assess their consistency and coverage in the holdout sample. Configurations in the holdout sample show highly similar consistency and raw coverage as in the modeling sample (highly consistent model (.98) with high raw coverage (.49)). Interested readers can get all the results from the authors upon request.

### *3.2. Implementing the POS approach*

As stressed by Becker et al. (2013), it might often be the case that unobserved heterogeneity could hide some different relationships between the latent concepts encompassed within one given causal model. Indeed, recent researches have called for the routine application of latent class techniques for evaluating the PLS path models (e.g. Becker et al., 2013; Rigdon et al., 2010). Hence, we need to apply some kinds of latent response-based segmentation that allow identifying unobserved

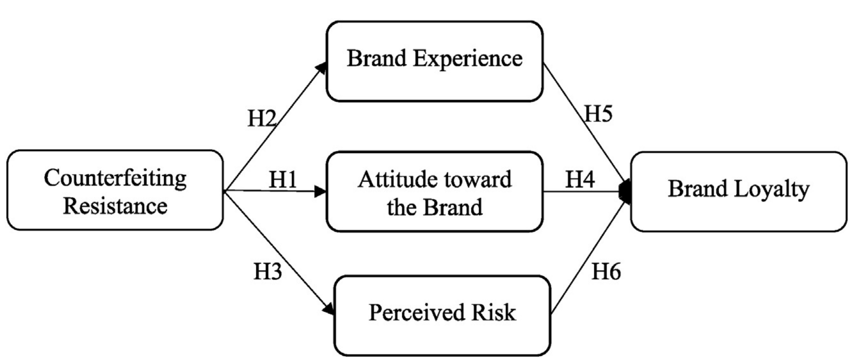


**Fig. 1.** Structural equation model and hypothesis.

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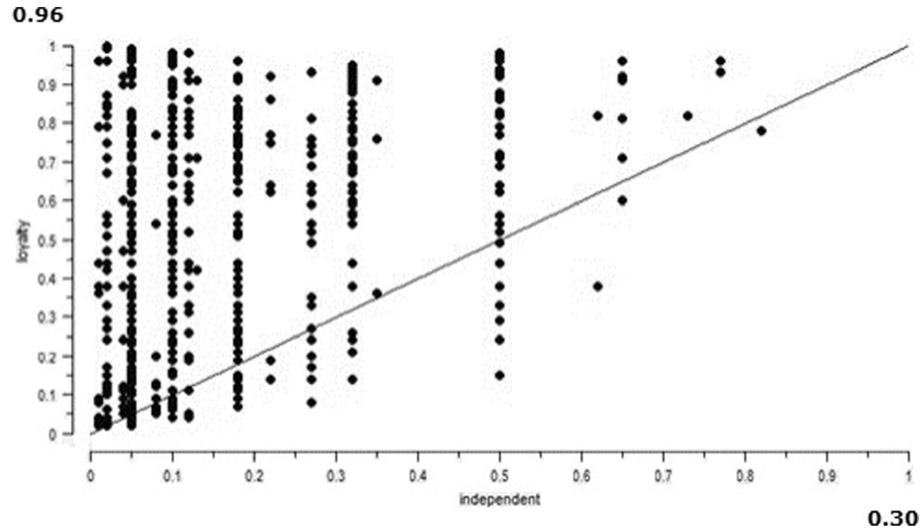


**Fig. 2.** XY-plot for loyalty = f (counterfeiting resistance, brand experience, brand attitude, perceived risk).

heterogeneity. Among the available recent techniques, the hill-climbing method (e.g. Becker et al., 2013) seems very promising due to its distribution-free measurement approach to PLS-SEM. Contrary to the FIMIX approach (e.g. Hair et al., 2016), the POS methodology doesn't provide any indices such as the BIC, AIC or CAIC in order to choose the "best" number of segments. The main disadvantage of the FIMIX approach being that it relies on the assumption of a multinormal distribution at the latent variable level, which is very unlikely to hold, we did rely on the POS distribution-free allocation method. Since we have to specify in advance the number of unknown segments, we have to rely on some heuristics in order to determine which solution is supposed to be the "best one". We hence have to compromise between the size of the groups, the validation of the number of segments by means of discriminant analyses (split-half cross validation), the predictive validity of the PLS path models using holdout samples, the final labeling of the groups and their cross-tabulation with descriptive variables.

### 3.3. Assessing the validity of the POS solutions

In order to evaluate the overall quality of the retained segmentation, we have to propose a strategy enabling to assess both its validity either from a statistical point of view or a managerial one. Consequently, we suggest the following three steps:

- Firstly, the PLS-SEM approach being linear in its relationships between latent variables, it is possible to assess the overall quality of the obtained classification by means of a linear discriminant analysis based on the latent scores of all the constructs, but the loyalty one, encompassed within the model. In addition, randomly splitting the sample into two parts permits to cross-validate the results by cross-tabulating the predicted class membership issued from the discriminant analysis and the affection got from the POS analysis.
- Secondly, we have to evaluate the predictive validity within each segment using holdout samples. To do so, we recommend following the 8 step procedure put forward by Cepeda, Henseler, Ringle and Roldán (in press). To sum up, the 8 steps are: (1) create a training sample (randomly drawing 2/3 of the observations), (2) estimate model parameters on the training sample, (3) standardize the holdout sample data, (4) create construct scores for the holdout sample as linear combinations of the respective indicators using the weights obtained from the training sample, (5) standardize the construct scores for the holdout sample, (6) create prediction scores or each endogenous construct in the holdout sample using the path coefficients obtained from the training sample, (7) calculate for each endogenous construct of the holdout sample the proportion of explained variance ($R^2$) as the squared correlation of the prediction scores and the construct scores and (8) contrast the $R^2$ values of the holdout sample with the $R^2$ values obtained in the training sample.
- Once the statistical stability of the POS segmentation has been formerly proven, we have to assess its validity in terms of interpretation and managerial relevance. To do so, we suggest three main analyses. The simplest one is just to characterize the groups with regard to the latent score mean differences between groups along with the differences in terms of path coefficients. Then, we can characterize the three groups by means of an importance–performance matrix approach (IPMA) recently put forward within the PLS literature (Schloderer et al., 2014). Ultimately, the last test is to depict the groups with regard to socio-demographics or behavioral variables.

## 4. Main results and discussion

### 4.1. Sample and data collection process

The study was organized as face-to-face questionnaires A filter was used to select only Moroccan residents who have consumed at least one luxury brand during the last twelve months (only fashion wear

**Table 1**
Patterns of predictive antecedents relating to high and low brand loyalty.

| Patterns | Causal conditions: Frequency cutoff | Causal conditions: Consistency cutoff | Solution Raw coverage | Solution Consistency |
|---|---|---|---|---|
| *High brand loyalty* → high levels of: counterfeiting resistance, brand experience, attitude toward the brand & perceived risk | 5.0 | 0.94 | 0.40 | 0.94 |
| *Low brand loyalty* → low levels of: counterfeiting resistance, brand experience, attitude toward the brand & perceived risk | 5.0 | 0.95 | 0.31 | 0.96 |

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and accessories: perfume, bag, jewel, watch, etc.). First, we conducted a pilot survey to make sure that all items are well understood. All questionnaires were written in French as long as targeted interviewers speak this language fluently. Finally, the convenience sample comprised 643 consumers among which 61% are women and 79% are less than 34 years old.

### 4.2. Measures

This research used five-point Likert scales. Perceived risk was measured with the scale of Stone and Gronhung (1993). For attitude toward the brand, we used the scale of Moore and Lutz (2000), Roedder et al. (1983) and Wells (1965). To measure brand experience, the scale of Brakus et al. (2009) has been used. For brand loyalty, the scale of Bozzo et al. (2006) and Mercier et al. (2010) was applied. Concerning the concept of counterfeiting resistance, we used Churchill's paradigm (1979) to create an applicable construct. First, we conducted a qualitative study (20 individual in-depth interviews) in order to generate a large number of items. All the interviews have been content analyzed independently by two experts in order to find out the relevant items used for the surveys in the second and third phases. Second, an exploratory factor analysis was applied on a sample of 158 responses. This exploratory factor analysis gave two main factors, labeled as expected, and retaining above 72% of the total variance. Third, we used a confirmatory factor analysis (convenience sample of 643 responses) in order to assess the reliability and validity of this new construct. This application of Churchill's paradigm led to a new two-dimensional valid scale (reliability of 0.71 and convergent validity of 0.58) called "counterfeiting resistance" with 7 items (see Appendix A for a presentation of the formulations of the questions along with the corresponding loadings):

(1) Counterfeiting emotional rejection (three items) that refers to a negative reaction toward consumed counterfeited brand: regret, reclamation and abandon. This is especially due to a negative opinion toward counterfeiting;
(2) Counterfeiting debate (four items) that concerns consumers who continue believing in the relevance of the purchase of genuine luxury products. For them, counterfeiting can never equal luxury brands.

### 4.3. Adjustment quality, validity, reliability and hypotheses testing

In this research, counterfeiting resistance, brand experience, perceived risk and brand loyalty has been measured as second order constructs in order to mirror the research model displayed in Fig. 1. In addition, we relied on a consistent PLS approach that avoids inflated loadings and gives consistent structural path coefficients (Dijkstra and Henseler, 2015a, 2015b) and used both the SmartPLS software (SmartPLS 3, 2015) and ADANCO software (Henseler and Dijkstra, 2015) to perform the aforementioned analyses.

Carefully following the presentation guidelines provided by Henseler et al. (2016) in their most recent article, we rely on the suggested criteria with respect to the overall model, the measurement model and the structural model. All the assessments are based on bootstrapping with 5000 replications (Chin, 2010; Hair et al., 2014, 2012; Henseler et al., 2012, 2009; Roldán and Sánchez-Franco, 2012) which computes the standard errors of estimates from the standard deviation of the bootstrap estimates:

- As for the overall model, in line with recent advices put forward by Henseler and Sarstedt (2013) and Henseler et al. (2016), we provide the SRMR for the PLS and PLSc estimations, respectively 0.0664 and 0.0597, along with the 95% bootstrap quantiles given by the ADANCO software, respectively 0.0698 and 0.0605. In both estimations, the SRMR are below the cut-off value suggested by Hu and Bentler (1999) and non-significant since they are smaller than $HI_{95}$. Moreover, both the geodesic discrepancy $d_G$ (respectively 0.24 and 0.11) and the unweighted least squares discrepancy $d_{ULS}$ (respectively 0.38 and 0.30) (Dijkstra and Henseler, 2015a), are below their 95% bootstrap quantile estimates. Once again, PLSc estimates are better compared to the PLS ones.
- Once the overall quality of the proposed model has been established, we can assess internal consistency reliability, convergent and discriminant validity. In this study, we report only Dijkstra and Henseler's $\rho_A$ which is the only consistent reliability measure for PLS construct scores (Dijkstra and Henseler, 2015b). As shown in Table 2, indicators of convergent validity and reliability are satisfied: the reliability is greater than 0.7 and the convergent validity is equal to or greater than 0.5. In order to assess discriminant validity, we relied on the heterotrait–monotrait (HTMT) criterion that is inferior to 0.85 (see Appendix C). The discriminant validity is then satisfied (Henseler et al., 2015).
- Finally, we can evaluate the structural part of the model. As displayed in Fig. 3, all $R^2$ are fairly high, except for perceived risk which seems rather unrelated to counterfeiting resistance. This can be explained by the fact that other missing constructs may affect this construct. Our research aims at studying the effects of different concepts, counterfeiting resistance, attitude toward the brand, perceived risk and brand experience on brand loyalty. Fig. 3 solely displays the PLSc estimates since we have seen above that PLSc outperforms the usual PLS approach. All the path coefficients have been evaluated for significance by means of a bootstrapping approach with 5000 bootstrap samples. All path coefficients are statistically significant, with t values greater than 2 and confidence intervals which do not include zero (see Appendix B for the corresponding t values and confidence intervals). Incidentally, a close look at the results displayed in Appendix B reveals that the differences between the original sample and the mean value over the 5000 replications are more important for the pooled data compared to the three groups stemming from the POS approach and further described in the following paragraphs. All in all, the study demonstrates a positive influence of counterfeiting resistance on attitude toward the brand (path coefficient: +0.67), brand experience (path coefficient: +0.37) and perceived risk (path coefficient: +0.25). This leads to acceptance of hypotheses H1, H2 and H3 and to confirm the direct consequences of counterfeiting resistance on: attitude toward the brand, brand experience and perceived risk. Concerning consumers' brand loyalty, our study demonstrates that attitude toward the brand affects brand loyalty (path coefficient of +0.46): favorable attitude toward the luxury brand leads to a greater brand loyalty; H4 is then supported. Second, a positive brand experience leads to positive brand loyalty (path coefficient of +0.26). Hypothesis H5 is then confirmed. Third, our model demonstrates that perceived risk also positively affects brand loyalty (H6 confirmed: path coefficient: +0.22). Consequently, the results of our study conform to the six hypotheses presented above.

### 4.4. Segmentation of responses toward counterfeiting

Despite the validation of all the encompassed hypotheses, as stressed before, it might be the case that unobserved heterogeneity could hide

**Table 2**
Convergent validity and reliability indices.

| Latent variables | Convergent validity | Reliability $\hat{Rho}_A$ |
|---|---|---|
| Counterfeiting resistance | 0.65 | 0.79 |
| Brand experience | 0.67 | 0.82 |
| Attitude vs brand | 0.57 | 0.74 |
| Perceived risk | 0.67 | 0.93 |
| Brand loyalty | 0.70 | 0.72 |

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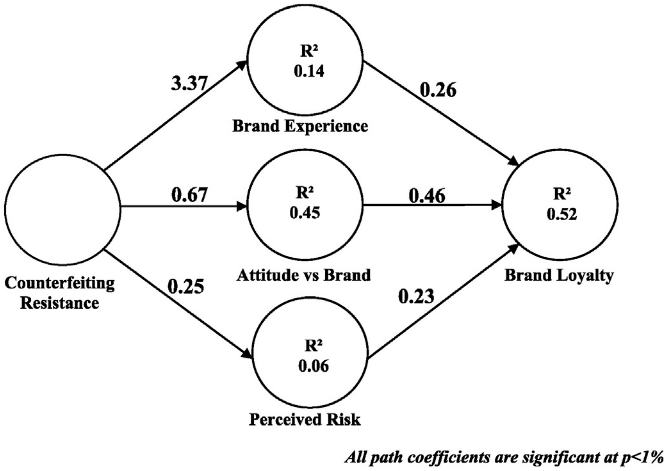


**Fig. 3.** Consistent PLS structural model.

some different causal relationships between the latent concepts. Applying the POS methodology for a different number of segments, led us to retain a 3 segment solution that seems to be the best one with respect to the segment sizes and the overall cross predictive validation which is the best one compared to the 2, 4 and 5 group solutions. The three groups obtained are rather balanced in terms of size, respectively, 31%, 39% and 30% of the total sample. All in all, results give support to the overall stability and quality of the three groups obtained. Even if path coefficients are sometimes different across groups in terms of magnitude, the overall pattern does confirm the hypotheses tested against the aggregated model (see Table 3). In addition, the $R^2$ for the dependent variables have almost always improved compared to the pooled data solution (see Table 4). This result in itself stresses the fact that hidden heterogeneity has to be searched for when studying brand loyalty.

In order to evaluate the overall quality of this segmentation, we had to go for a strategy enabling to assess both its validity either from a statistical point of view or a managerial one. In terms of statistical validation, we have to check: first, whether the classification is satisfactory, second and more importantly, if the prediction, with regard to the dependent variable (in our case, brand loyalty), remains stable when relying on hold-out samples within each segment. If the two aforementioned points are satisfied, we then are ultimately able to label and characterize the three segments.

The PLS-SEM approach being linear in its relationships between latent variables, it is possible to assess the overall quality of the obtained classification by means of a linear discriminant analysis based on the latent scores of all the constructs, but the loyalty one, encompassed within the model. In addition, randomly splitting the sample into two parts permits to cross-validate the results by cross-tabulating the predicted class membership issued from the discriminant analysis and the affection gotten from the POS analysis. Overall, the POS analysis reveals to be quite reliable. A jackknifed discriminant analysis indicates that 93% of the respondents are well affected to the group they belong to. More importantly, a random split of the sample allows assessing the predictive power of the analysis. Form a practical point of view, a discriminant analysis based on the first half of the sample correctly predicts 89% of the affectation of respondents belonging to the second part of the sample. The reverse works well since a discriminant analysis based on the second part of the sample correctly allocates 87% of the respondents belonging to the first part of the sample.

Assessing the predictive validity of the POS segmentation represents the final and crucial test before labeling the segment. Relying on the methodological steps described previously we systematically computed the estimated $R^2$ for the luxury brand loyalty both with the PLS and PLSc parameter estimates. The results displayed in Table 4 systematically show that the PLSc approach outperforms the PLS one. These intriguing results would say that besides being more theoretically grounded, the PLSc approach might as well outperform the usual PLS methodology with regard to prediction. This means that even from a practical point of view the PLSc approach should be preferred. These results can be attributed to the fact that correcting the original latent variable correlations for attenuation leads to higher correlations between the latent variables and consequently to higher path coefficients and coefficients of determination. Once the statistical stability of the POS segmentation has been formerly proven, we have to assess its validity in terms of interpretation and managerial relevance. To do so, we suggest three main analyses. The simplest one is just to characterize the groups with regard to the latent score mean differences between groups along with the differences in terms of path coefficients. Then, we can characterize the three groups by means of the importance–performance matrix approach (IPMA) recently put forward within the PLS literature (Schloderer et al., 2014). Ultimately, the last test is to depict the groups with regard to socio-demographic or behavioral variables.

A simple ANOVA reveals that all the three groups are statistically different with regard to the latent means scores. A supplementary bootstrapped multi-group analysis (Sarstedt et al., 2011) shows that some path coefficients are statistically different between the groups. All in all, this result gives support to the overall stability and quality of the three groups obtained. Even if path coefficients are sometimes different across groups in terms of magnitude, the overall pattern does confirm the hypotheses tested against the aggregated model (See Table 3).

According to the means latent scores across groups displayed in Table 5, we hence have been able to label as follows the three groups: "Resistant and brand attached", "Non-resistant" and "Detached":

(1) Resistant and brand attached: People belonging to this group have a great resistance to counterfeiting. They strongly reject counterfeiting and differentiate their brand comparing to counterfeited items. Furthermore, they are strongly attached to their legitimate brands.
(2) Non-resistant: In this group, people are non-resistant to counterfeiting. They don't reject the presence of counterfeiting because they don't see a real difference between counterfeited and legitimated products. For these people, the purchase of luxury brand is strongly linked to the presence of another alternative of consumption.
(3) Detached: Consumers of this group are indifferent to the presence of counterfeiting. Compared to the other groups, they are neutral to the rejection of counterfeiting or/and the differentiation of the legitimate brand.

**Table 3**
Path coefficients and differences across groups.

| Latent variables | Resistant & brand attached | Non-resistant | Detached |
|---|---|---|---|
| Counterfeiting resistance → perceived risk | 0.39* | 0.19* | 0.51* |
| Counterfeiting resistance → brand experience | 0.34 | 0.32 | 0.27* |
| Counterfeiting resistance → attitude vs brand | 0.65 | 0.68 | 0.66 |
| Perceived risk → brand loyalty | 0.59* | 0.14 | 0.13 |
| Brand experience → brand loyalty | 0.35 | 0.32 | 0.10* |
| Attitude vs brand → brand loyalty | 0.24* | 0.58 | 0.50 |

* Path coefficients are statistically different between groups.

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**Table 4**
$R^2$ and estimated holdout samples $R^2$ for the three segment solution.

| Dependent variables | $R^2$ (%) | Resistant & attached | Non-resistant | Detached | Pooled data |
|---|---|---|---|---|---|
| Perceived risk | PLS | 3.3 | 1.5 | 11.3 | 3.2 |
| | $PLS_c$ | 14.8 | 9.7 | 25.5 | 6.2 |
| Brand experience | PLS | 6.2 | 6.7 | 4.1 | 8.7 |
| | $PLS_c$ | 11.5 | 10.0 | 17.0 | 13.9 |
| Attitude vs brand | PLS | 18.6 | 29.4 | 21.3 | 24.5 |
| | $PLS_c$ | 42.6 | 46.3 | 43.9 | 45.1 |
| Brand loyalty | PLS | 33.4 | 37.5 | 24.0 | 37.1 |
| | $PLS_c$ | 60.2 | 53.8 | 46.4 | 51.7 |
| **Hold-out samples** | **$R^2$ (%)** | **Resistant & attached** | **Non-resistant** | **Detached** | **Pooled data** |
| Perceived risk | PLS | 25.7 | 29.4 | 18.6 | 26.6 |
| | $PLS_c$ | 55.6 | 47.8 | 38.7 | 42.5 |

Nonetheless, a finer analysis has to be undertaken, because besides the impact of the independent variables on band loyalty, the relative importance of the predictors has to be taken into account. One way to do so is to rely on the importance–performance matrix analysis (IPMA), which can be traced back to Slack (1994) and that has been recently popularized within the PLS structural equation modeling approach (e.g. Völckner et al. 2010; Höck et al., 2010). Practically, IPMA builds on the standardized regression coefficients (importance) and adds an additional dimension to the analysis that considers the predictor variables' values, here expressed in terms of a performance index scaled from 0 to 100. This supplementary IPMA exemplifies the differences between the groups. As shown in Fig. 4, the total effect of the independent variables on loyalty has been computed along with a scaling of the latent scores from 0 to 100. On the basis of IPMA mapping, it comes out that brand attitude seems the most valuable variable in order to increase loyalty for all three groups. However, since this variable has already a high performance index value, there is very low potential for further increase. The best choice in terms of importance and performance ratio seems to be brand experience for resistant and attached people, whereas counterfeiting insensitivity appears to be the best compromise in order to influence brand loyalty for non-resistant and brand detached people.

Ultimately, a multiple correspondence analysis between the three POS segments, gender, age class and the type of preferred luxury brand recently bought gives additional support to the managerial validity of the three groups derived from the POS approach. A first glance at the mapping (total explained inertia equals 68%) shows that the three groups are well dispatched on the mapping (see Fig. 5). Importantly, gender differentiates clearly the groups on the horizontal axis. For instance, non-resistant buyers are more connected to female apparel luxury brands (e.g. Dior, Chanel or Prada), whereas resistant & brand attached people are younger clients that are linked to fashionable luxury brands such as Marc Jacobs and Armani. Detached buyers are the oldest and connected to well establish male luxury brands such as Rolex, Hugo Boss or other luxury brands. These results in a sense give *post hoc* further support for the operational validity of the segments found by means of the POS methodology.

**Table 5**
Latent mean profiles and associated F-tests.

| | Resistant & brand attached | Non-resistant | Detached | F test | P value |
|---|---|---|---|---|---|
| Counterfeiting resistance | 3.05 | 2.63 | 2.79 | 16.44 | 0.00 |
| Perceived risk | 2.82 | 1.04 | 1.97 | 382.22 | 0.00 |
| Brand experience | 2.70 | 2.02 | 2.24 | 49.16 | 0.00 |
| Attitude vs brand | 3.39 | 3.14 | 3.11 | 8.20 | 0.00 |
| Brand loyalty | 2.87 | 2.39 | 2.52 | 39.48 | 0.00 |
| Purchase intention | 3.47 | 2.76 | 1.58 | 276.17 | 0.00 |

## 5. Conclusion and discussion

From the outset, this research was designed to answer through a practical example two main research questions aimed at showing that PLSc estimates could lead to higher $R^2$ whether the analysis is performed on the pooled data or on segments got by the POS approach. It comes out that in all cases, PLSc outperforms PLS in terms of prediction with regard to the focal dependent variable. This result is indeed of prime importance in the sense that it could reconcile the two positions regarding PLS either as a prediction oriented method or a structure theoretic one comparable to CB-SEM. In addition, our analysis does confirm that modeling unknown heterogeneity leads to higher $R^2$ and a finer comprehension of the mechanisms under study. In our specific example, the three groups obtained reflect more precisely different consumer's reaction to brand loyalty. This result contributes to the comprehension of consumer's devotion to luxury brand despite the presence of counterfeiting.

In a managerial way, we suggest to counter counterfeiting by focusing on the luxury brand itself. In the Moroccan context, managers may identify the profile of their customers regarding counterfeiting: non-resistant buyers (e.g. Dior, Chanel or Prada), resistant & brand attached people (e.g. Marc Jacobs or Armani) or detached buyers (e.g. Rolex or Hugo Boss). For non-resistant people, managers should focus on brand experience immersion whereas resistant & brand attached and detached people are more receptive to the perception and the attitude toward the luxury brand. Ultimately, in order to improve the managerial implications stemming from the POS segmentation, we computed the purchase intention based on the scale of Cronin et al. (2000) among the three segments. Not surprisingly, all the mean values are different as displayed at the bottom of Table 5, hence giving strong credence to the operational scope of the three derived segments. This result tells managers that the core target should be on the resistant and brand attached since their overall purchase intention is still fairly high as regards the genuine luxury brands. For this specific group, leveraging brand attitude and brand experience are the two levers of choice. Although the detached have the lowest purchase intention, they might be sensitized, along with the non-resistant, by trying to increase their counterfeiting resistance by means of information campaigns extolling the unbeatable overall quality of the genuine luxury brands.

Concerning the limitations of this research, the main one is obviously related to the specific example and model we relied on. Skilled replications and Monte Carlo investigations are deemed necessary in order to precisely validate the pattern shown in this research and formerly prove that, whatever the type of analysis is, PLSc seems to

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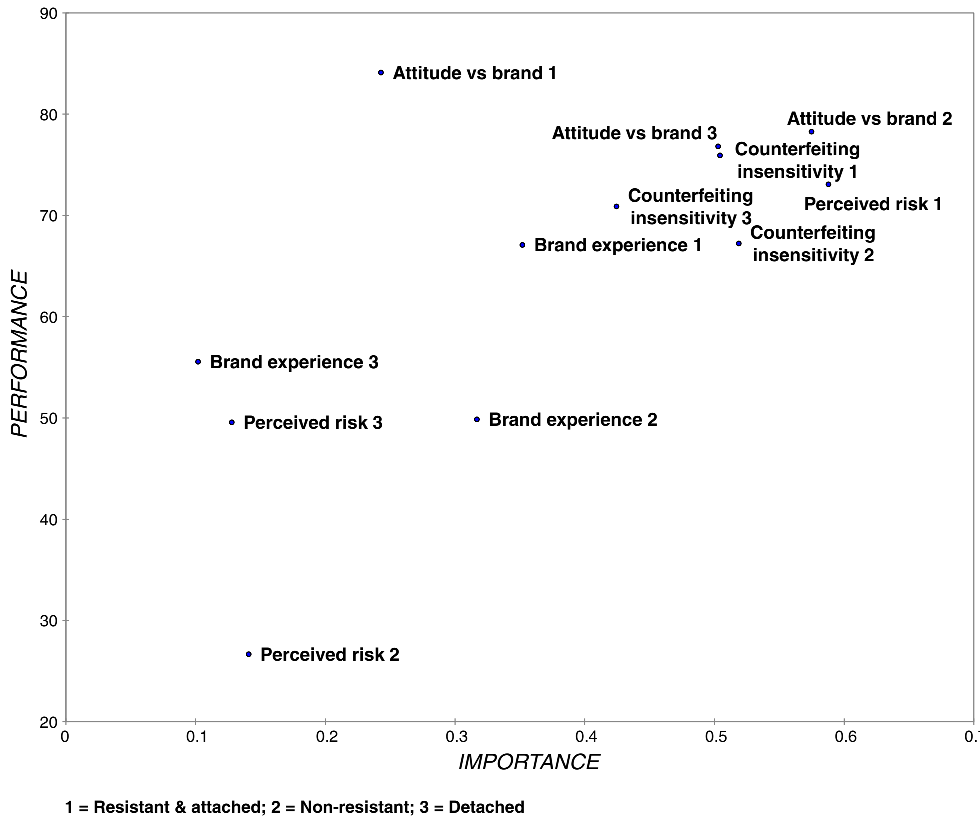


**Fig. 4.** IPM analysis mapping.

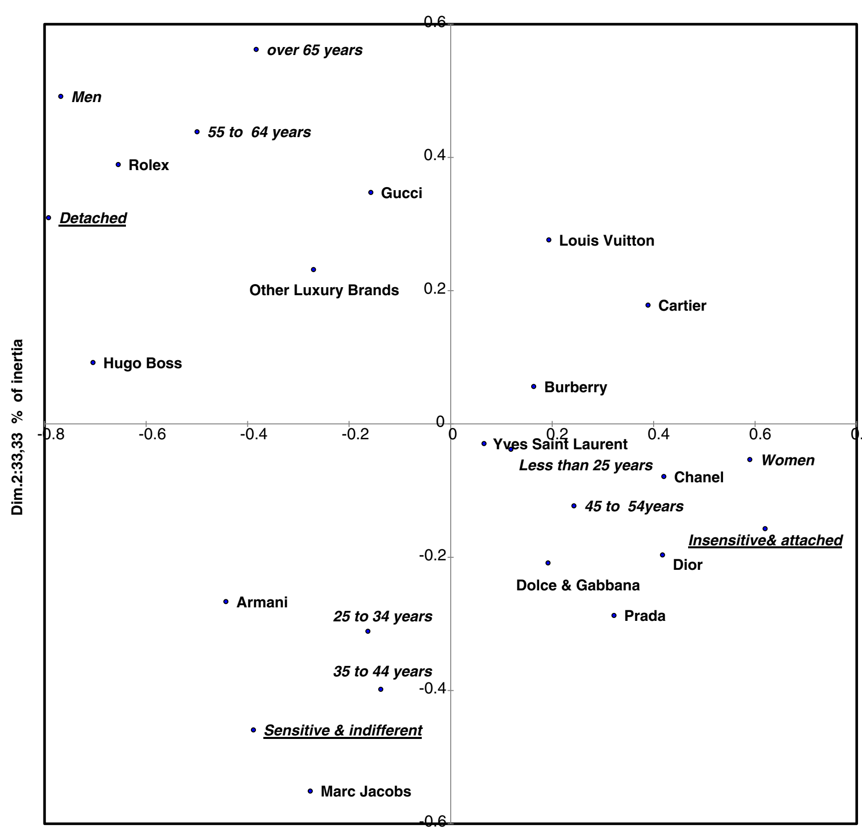


**Fig. 5.** Multiple correspondence mapping.

be the preferred choice also in terms of prediction. From a theoretical point of view, we have overlooked other factors such as personal variables (e.g. personality) or factors related to the product or the brand (e.g. sensitivity to brand). In addition, we have limited the investigation to fashion wear and accessories while consumer's resistance to counterfeiting can fluctuate depending on the category of the product or even the nature of the product (e.g. different kinds of resistance while consuming a perfume or a bag). The limited list of brands used in the survey is another limitation of this research (27 luxury brands).

Regarding research directions, from a methodological standpoint, formal comparisons of the results got with the POS methodology with either the FIMIX or PLS genetic algorithm segmentations (e.g. Ringle et al., 2014) could prove to be very useful. As stated above, intensive simulations have also to be undertaken in order to asses to what extent the PLSc approach leads to higher level of prediction and stability in terms of predictive cross-validation. A more theoretical research direction concerns the study of consumers of counterfeited products instead of legitimate luxury brand. Indeed, the effects of the different concepts discussed above and more precisely counterfeiting resistance could be analyzed in the perspective of this category of consumers. It will be interesting to deepen the profiles developed in this paper. Ultimately, on the managerial side, a characterization with other socio-demographic elements (e.g. profession, matrimonial situation) or live styles will be necessary for brand managers in order to get a finer and better identification of these groups.

## Appendix A. Item labeling and loading of the counterfeiting resistance scale

| Dimension | Item | Loading |
|---|---|---|
| Counterfeiting debate | It's not the same thing, the price makes the difference | 0.73 |
| | Quality has its price | 0.79 |
| | Counterfeiting is not well-founded | 0.75 |
| | Counterfeiting will never equal a luxury product | 0.69 |
| Counterfeiting emotional rejection | It annoys me | 0.83 |
| | I will try to find another brand which is not counterfeit | 0.82 |
| | Luxury should never be subject to counterfeiting | 0.82 |

## Appendix B. PLS & PLSc bootstrapped estimates, t values & confidence intervals (5000 replications)

| Causal paths | Pooled data (PLS) | | | Pooled data (PLSc) | | |
|---|---|---|---|---|---|---|
| | Original sample | Sample mean | t values & confidence intervals | Original sample | Sample mean | t values & confidence intervals |
| Attitude → brand loyalty | 0.36 | 0.36 | 6.07 [0.22–0.49] | 0.46 | 0.51 | 16.83 [0.42–0.58] |
| Brand experience → brand loyalty | 0.30 | 0.29 | 3.24 [0.17–0.34] | 0.26 | 0.27 | 3.07 [0.21–0.39] |
| Perceived risk → brand loyalty | 0.18 | 0.19 | 2.46 [0.14–0.21] | 0.23 | 0.23 | 4.56 [0.17–0.35] |
| Counterfeiting resistance → attitude | 0.50 | 0.49 | 16.85 [0.42–0.57] | 0.67 | 0.67 | 26.92 [0.57–0.74] |
| Counterfeiting resistance → brand experience | 0.30 | 0.29 | 3.27 [0.18–0.36] | 0.37 | 0.37 | 4.32 [0.29–0.43] |
| Counterfeiting resistance → perceived risk | 0.18 | 0.19 | 2.37 [0.15–0.23] | 0.25 | 0.28 | 2.67 [0.19–0.31] |

| Causal paths | Non-resistant (PLS) | | | Non-resistant (PLSc) | | |
|---|---|---|---|---|---|---|
| | Original sample | Sample mean | t values & confidence intervals | Original sample | Sample mean | t values & confidence intervals |
| Attitude → brand loyalty | 0.45 | 0.45 | 9.56 [0.38–0.51] | 0.57 | 0.57 | 11.83 [0.52–0.64] |
| Brand experience → brand loyalty | 0.31 | 0.31 | 8.64 [0.27–0.36] | 0.32 | 0.32 | 9.87 [0.25–0.39] |
| Perceived risk → brand loyalty | 0.07 | 0.06 | 2.07 [0.03–0.10] | 0.14 | 0.13 | 3.23 [0.09–0.19] |
| Counterfeiting resistance → attitude | 0.54 | 0.54 | 12.37 [0.48–0.59] | 0.68 | 0.68 | 19.31 [0.61–0.74] |
| Counterfeiting resistance → brand experience | 0.26 | 0.26 | 4.24 [0.19–0.30] | 0.32 | 0.31 | 9.41 [0.26–0.38] |
| Counterfeiting resistance → perceived risk | 0.12 | 0.12 | 2.74 [0.08–0.16] | 0.19 | 0.19 | 4.55 [0.14–0.23] |

| Causal paths | Resistant & attached (PLS) | | | Resistant & attached (PLSc) | | |
|---|---|---|---|---|---|---|
| | Original sample | Sample mean | t values & confidence intervals | Original sample | Sample mean | t values & confidence intervals |
| Attitude → brand loyalty | 0.22 | 0.22 | 5.23 [0.18–0.27] | 0.24 | 0.24 | 4.15 [0.20–0.29] |
| Brand experience → brand loyalty | 0.34 | 0.34 | 6.75 [0.29–0.39] | 0.35 | 0.36 | 5.63 [0.29–0.41] |
| Perceived risk → brand loyalty | 0.23 | 0.24 | 3.28 [0.16–0.27] | 0.59 | 0.59 | 11.24 [0.49–0.64] |
| Counterfeiting resistance → attitude | 0.43 | 0.44 | 6.27 [0.38–0.49] | 0.65 | 0.66 | 15.82 [0.59–0.69] |
| Counterfeiting resistance → brand experience | 0.25 | 0.25 | 3.22 [0.18–0.31] | 0.34 | 0.34 | 5.25 [0.29–0.38] |
| Counterfeiting resistance → perceived risk | 0.18 | 0.18 | 2.28 [0.14–0.23] | 0.38 | 0.39 | 7.83 [0.32–0.45] |

| Causal paths | Detached (PLS) | | | Detached (PLSc) | | |
|---|---|---|---|---|---|---|
| | Original sample | Sample mean | t values & confidence intervals | Original sample | Sample mean | t values & confidence intervals |
| Attitude → brand loyalty | 0.38 | 0.38 | 9.24 [0.32–0.43] | 0.50 | 0.51 | 10.61 [0.45–0.55] |
| Brand experience → brand loyalty | 0.16 | 0.16 | 3.72 [0.09–0.21] | 0.10 | 0.10 | 2.11 [0.05–0.14] |
| Perceived risk → brand loyalty | 0.11 | 0.11 | 3.18 [0.07–0.16] | 0.13 | 0.13 | 2.83 [0.07–0.16] |
| Counterfeiting resistance → attitude | 0.46 | 0.47 | 10.58 [0.39–0.52] | 0.66 | 0.67 | 13.24 [0.60–0.72] |
| Counterfeiting resistance → brand experience | 0.20 | 0.20 | 5.12 [0.14–0.26] | 0.26 | 0.27 | 4.93 [0.22–0.31] |
| Counterfeiting resistance → perceived risk | 0.34 | 0.34 | 7.93 [0.28–0.38] | 0.51 | 0.50 | 10.98 [0.46–0.57] |

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## Appendix C. Discriminant validity — heterotrait–monotrait ratio (HTMT)

| | Attitude vs brand | Brand experience | Brand loyalty | Counterfeiting resistance |
|---|---|---|---|---|
| Brand experience | 0.45 | | | |
| Brand loyalty | 0.64 | 0.58 | | |
| Counterfeiting resistance | 0.66 | 0.41 | 0.56 | |
| Perceived risk | 0.11 | 0.47 | 0.39 | 0.26 |

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