Partial Least Squares Modeling in Marketing Research: A Tailor-Made Model of Wine e-Commerce Consumers in Switzerland

Bernard Morard and Dimitri Simonin

***Abstract*—The purpose of this study is to present a new approach to consumer behavior analysis by generating a tailor-made consumer behavior model. The study's area of focus is wine e-commerce on the Swiss market. As a design methodology, the authors sent an electronic survey to local wine consumers in Switzerland. They analyzed a final sample size of *n* = 69 by means of the PLS Assistant 3.0 software (Morard and Jeannette, 2007). The software computed the data based on a partial least squares path modeling (PLS-PM) analysis, which selected the four axes that had the highest potential to explain e-consumers' behavior with respect to purchasing wine on the Swiss market. This approach generated an optimal consumer behavior model. The research implication of the study lies in showing how a tailor-made model can be built for a particular market. Moreover, the choice of Switzerland as the field of study creates a more multifaceted challenge. This study is original in demonstrating a different approach toward determining a specific market's consumer behavior. The model's tailor-made aspect comes from using a PLS-PM analysis instead of the normal structural equation modeling (SEM) analysis. The authors created the model from scratch – in other words, without using explicit models to explain the study data. With regard to the study's practical implications, local SMEs active in wine e-commerce would benefit from the recommendations to improve their offers and develop their activities further. The study also shows marketing researchers the utility of using PLS-PM in their market research field.**

***Index Terms*—Consumer behavior, e-commerce, optimal marketing model, partial least squares path modeling (PLS-PM), structural equation modeling (SEM), Swiss wine market.**

I. Introduction

Wine is one of the oldest alcoholic beverages in the world. The persistent ideas of the traditions and emotions associated with wine sharply contrast with current technologies such as online shops. E-commerce appeared only recently and has upended the traditional way of doing business, including the areas of purchasing, shopping, and selling. However, the online wine market is developing slowly. Wine e-companies face a tough marketing challenge to persuade their customers to buy wine online. Moreover, the volumes of global wine production also exceed consumer demand. This is an important issue for the international wine business. Brunner and Siegrist (2011, p. 353) [1] refer to the studies by Beverland (2001) and Hall and Winchester (2000): "Only recently has it been argued that marketing should be taken seriously in the wine industry." Thus, to determine the needs of customers purchasing wine online — a very specific market — with precision, the authors developed the present study.

The main purpose of this article is to demonstrate the interest of using partial least squares path modeling (PLS-PM) for a consumer behavior analysis in a very specific market. Unfortunately, most marketing researchers still cold-shoulder PLS-PM, partially because it is difficult to interpret the results. However, the situation has made positive progress over the past few years. Furthermore, given the advantages of the PLS-PM analysis, the academic community should be open-minded.

There are two main reasons for the authors' choice of target market: First, the authors could not find any specific study using PLS-PM to target the behavior of consumers in Switzerland in the context of the online wine industry in the academic literature. In addition, there are only a few sources of academic research on global wine e-commerce. Lockshin and Corsi (2012) [2] mention ten studies on "segmenting online purchasers," and the study of Stening and Lockshin, a rare analysis on wine buying behavior in 2001. They determined that consumers felt that online wine shopping was expensive, too great a risk, and lacked enough positive elements. Second, in 2014, Switzerland was the seventh-largest consumer of wine (Brunner and Siegrist, 2011) [1]. As a winemaking country, however, it is not as well-known as it deserves to be. This country is a very specific market with three distinctive cultures, each of which has its own type of behavior, which motivated this study.

In summary, the broad outlines of this article are as follows: First, the authors introduce elements of the wine market industry and the wine market in Switzerland. Second, they lay out the different steps of a study based on an SEM analysis for which Bianchi (2015) [3] conducted the research entitled "Consumer Brand Loyalty in the Chilean Wine Industry." Third, the authors theorize the quantitative statistical model PLS-PM, and describe their perception of the advantages of using PLS-PM analysis in the marketing field. Fourth, they explain the methodology of their research that uses PLS-PM. They suggest an optimal model of consumer behavior for the Swiss e-commerce wine market by means of PLS Assistant 3.0 (PLSA) software (first developed by Morard and Jeannette in 2007 and continually updated) [4]. It also helped determine the four most important

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The authors are with the Faculty of Economics & Management, University of Geneva, Geneva, Switzerland (e-mail: bernard.morard@unige.ch, dimitri.simonin@outlook.com).

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elements for consumers purchasing wine online: *The online purchase* (i) *the appetite for the product* (ii), *the in-store purchase* (iii), and *the variety of choice* (iv) (wine, in this case).The findings highlight new ideas for marketing research by showing the potential of PLS-PM. The authors conclude by providing suggestions for further research by means of PLS-PM as the main marketing research tool.

II. Market Specifications

A. Swiss e-Commerce and Consumer Behavior Tendencies

Switzerland is a territory in the heart of Europe but lacks the European sense of community. Its historical and demographic specification is one of the reasons: Switzerland has 8 million inhabitants, three linguistic regions with four national languages, and 26 "cantons." It is essential for companies to have both an online shop and an in-store shop, because the Swiss consumer finds information online but buys through traditional channels. Rigby (2011) [5] calls this strategy an "omni-channel" strategy. More than just providing an online store and an in-store, companies must rethink and reorganize the in-store itself, whenever necessary. The e-commerce part must be an omni-channel experience, and in-store will be used to consolidate the brand (Speer, 2012) [6]. "Omni-channel" promotion is indispensable for the continued survival of the business, especially in Switzerland (Reymondin, Bilan, April 2013) [7]. Reymondin (Bilan, April 2013) [7] argues that cheaper prices, a more flexible timetable, shipping, and the ease of comparing shops and offers with each other motivate the consumer to shop online.

B. Wine Market

In 2014, France was the world's biggest wine producer with a total of 46.2 million hectoliters (Mhl). In comparison, with an average of 1 Mhl per year, Switzerland is considered a small producer (UBS research, 2015) [8]. The latter exports only 1.6 % of its total production (Federal Office for Agriculture, 2015) [9]. Despite its production being relatively stable, national consumption since 1900 has decreased more than 50% (Federal Office for Agriculture, 2010) [10]. At the same time, although the quantities sold online remain marginal, this part of the market more than tripled in size in just five years. Nevertheless, M.I.S Trend (Swiss Wine Promotion, 2013) [11] shows that the quantity of wine purchased online follows the growth of online food purchasing. Swiss consumers buy most (42%) of their wine in supermarkets. On a global scale, people are drinking less wine, distribution takes the form of organized multichannels, and e-commerce has modified consumers' purchase behavior. Based on their most recent studies, Lockshin and Corsi (2012) [2] write that around the world only about 5% of wine is purchased online.

III. Literature Review

A. Consumer Behavior

Bernoulli in the 18th century, later followed by Neumann and Morgenstern, were the first economists to take an interest in consumer decision-making from an economic perspective (Richarme, 2007, cited in Bray, 2008) [12]. In the early 1900s, microeconomic and macroeconomic models were still influencing most marketing theories (Bastels, 1962, cited in Bray, 2008) [12]. Consumers were considered to be objective and rational. Only after the Second World War did marketers begin to consider consumers as people who think less rationally and more emotionally. Cross-discipline analysis appeared to produce a better understanding of the fundamentals of consumer behavior. Managers implemented "strategies more and more on behavior modification and less and less on persuasion strategies for a global consumer" (Sheth, 1985, p. 5-7) [13]. Ever since, the consumer behavior discipline has not followed an exclusively longitudinal process: A whole range of activities is analyzed and taken into account in order to understand the consumer's actions (Bray 2008) [12].

Many different consumer behavior models from a variety of disciplines have emerged over time. The most important models can be classified into three categories: traditional, cognitive, and – most recently – humanistic. Each of these models is a combination of a wide range of tools borrowed from various fields, including economics, psychology, engineering, and sociology. Solomon *et al*. (2002) [14] define the consumer behavior theory as "the study of the processes involved when individuals or groups select, purchase, use or dispose of products, services, ideas or experiences to satisfy needs and desires" (cited in Bray, 2008) [12]. Many different factors influence the consumer in all his decisions and determine how he behaves. Culture, social class, group belonging, social role, and personal factors are a few of these (Kotler *et al*. 2006) [15].

E-commerce has grown steadily every year since the advent of the Internet, and easy access to information has revolutionized consumer behavior. The "pre-Internet" consumer did not have as many channels as the "post-Internet" consumer does. The former evolved in a buying process where information was hard to access, and the range of shopping options was narrow. The latter faces an omni-channel buying process. Consumers use new tech tools – such as mobile phones and social networks – that help them to make decisions. Using these tools accelerates the entire process of buying for consumers and companies: searching, looking for information, making a decision, buying, and selling. Companies had to change their way of doing B2C business in order to meet consumers' expectations, and the whole process efficiency from manufacturing to selling has been improved. Information is delivered faster and is more qualitative and accessible and closer to being complete. Rigby (2011) [5] argues that "[t]he trick will be to identify each segment's unique paths and pain points and create tailored solutions rather than the one-size-fits-all approach that has characterized much retailing in the past." Moreover, consumers themselves play an important role by delivering a big chunk of information through social networks, fora, and blogs (Simonin, 2015) [16]. Consumers pay more attention to other consumers' opinions, called "horizontal information," and less attention to the "vertical information" provided by the company (Mayol, 2011, p. 2) [17]. In one word, the modern consumer became an "experimenter" (Mermet, 2009, cited in Mayol, 2011, p. 3) [17].

According to Falque *et al*. (2011) [18], the e-consumer faces five paradoxes:

The first paradox is between the "physical world" and the "virtual world": The consumer wants to try on and touch the product but also prefers buying it quickly online without having to physically go to the shop. The second paradox concerns the "form" and the "function" of the transaction. The consumer wants a quick transaction and simultaneously expects to have an opulent purchasing experience. The third paradox is the "personalization" of the service and its "confidentiality." The consumer is looking for a customized service but is very sensitive about privacy. The fourth paradox, which also concerns privacy, is about "person" versus "persona," in the words of Falque *et al*. (2011) [18]. The consumer is satisfied when he feels he is known sufficiently well but does not want to reveal any personal information. The last paradox concerns "choice" and "recommendation": During an online shopping experience, the consumer enjoys a large selection of products; nonetheless, he feels lost when the range is too large.

A major issue facing companies is that the consumer runs a risk when making a purchase online, which complicates the management of the consumer behavior during the purchasing process. Hong and Yi (2012) [19] outline two types of risks. On the one hand, an effective purchasing risk comes from an imperfect basic system such as a network security or logistic distribution system, and from "the actual and virtual interface of the network," such as the risks of fakes or threat of net terrorism. On the other hand, a perceived purchasing risk can entail "the financial risk, social risk and psychological risk" (Hong and Yi 2012) [19]. Hong and Yi (2012) [19] argue that the online purchase is perceived to be more risky than an in-store purchase. The cause is essentially the fact that customers cannot check the product before purchasing. Moreover they are also likely to experience other risks, such as those cited above. The authors also note that the perceived risks have become more numerous over time.

In the discussion below, the authors find interesting albeit sometimes contradictory results concerning some of these paradoxes and online risks in the specific e-market of wine in Switzerland.

B. Using SEM Analysis

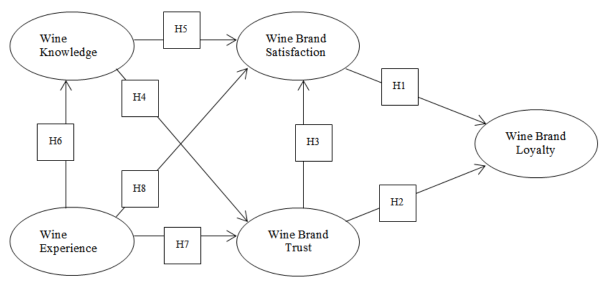
According to DeVault (2007) [20], structural equation modeling (SEM) is quantitative research analysis. Most of the time, researchers use it to confirm a hypothesis and not to explain a situation that has been analyzed. There are five steps for conducting an SEM analysis: (i) specification, (ii) identification, (iii) estimation, (iv) test, and, finally, (v) manipulation of the model. SEM confirms hypotheses by means of a measurable data derivation (Lei and Wu, 2007) [21]. The goal is to predict unmeasurable data from measurable data by using complex computation. Before starting the analysis, the researcher determines the fixed and free parameters depending on a priori hypotheses. From a technical point of view (Maclean and Gray, 1998) [22], SEM builds an estimation of unknown coefficients by linear structure equations computations. Two types of variables are considered in the model: observed variables and unmeasured latent variables. They are correlated with each other (Maclean and Gray, 1998) [22]. SEM anchors its computation in a hypothesis, namely that causality links the unmeasured latent variables.

Helped by computers and adapted software, it has become commonplace to use SEM in most academic fields, including marketing research. For instance, Selnes and Sallis (2003) and Steenkamp and Baumgartner (2000) apply SEM in their B2B relationship analysis, while Luo and Bhattacharya (2006) use it in a B2C customer satisfaction analysis (cited in Iacobucci, 2009) [23].

C. Illustration of SEM in Marketing Analysis

A recent academic article, "Consumer Brand Loyalty in the Chilean Wine Industry" (Bianchi, 2015) [3] is a perfect example of how to process an SEM analysis. Her research helps to understand "the driving forces of wine brand loyalty in a new wine producer country context" (Bianchi, 2015, p. 444) [3]. Bianchi's study provides an opportunity to compare SEM and PLS-PM analyses with each other, because the study is quite new and close to the field that the authors are focusing on: the wine market.

First of all, Bianchi (2015) [3] lays out eight hypotheses of correlation between six constructs. The following figure (Fig. 1) represents the model of consumer brand loyalty for Chilean wine she proposes:

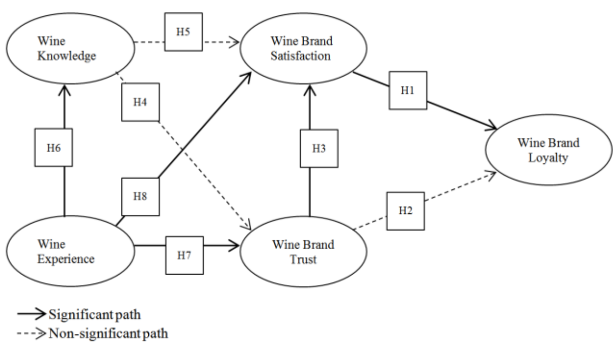


Source: Bianchi (2015) [3]

Fig. 1. Proposed conceptual model of consumer brand loyalty in the wine sector.

Second, Bianchi used a survey to collect data from wine consumers. Having data from 300 cases means the results had relatively good reliability. An exploratory factor analysis and a standardized regression validated the measures.

Bianchi used "structural equation modeling (SEM) in AMOS 19 […] to test the proposed model and the hypothesized paths" (Bianchi, 2015, p. 452) [3]. The following figure (Fig. 2) represents the model of consumer brand loyalty for Chilean wine found after SEM analysis:



Source: Bianchi (2015) [3].

Fig. 2. Final model of consumer brand loyalty in the wine sector.

The hypotheses are validated/dismissed in order to determine significant correlations between them. It must be noted, however, that all the different terms used to determine the hypotheses (product knowledge, brand satisfaction, brand trust, etc.) come from previous marketing theories.

D. Limits of SEM

DeVault (2007) [20]recalls the "sample size rule of thumb". In order to ensure that the model is reliable enough, SEM requires ten to 20 times more observations than variables. Medsker *et al*. (1998) adds that "200 may be required to produce valid fit measures and to prevent making inaccurate conclusions" (cited in Morard *et al*., 2012, p. 23) [24]. By contrast, PLS-PM requires a more flexible sample size and allows a smaller N. DeVault (2007) [20] explains that SEM cannot prove the "directionality" of the variables' relationships. Indeed, the model is not made for testing the causality direction. Hox and Bechger (1994) [25] rightly point out that causality in the correlation of the analyzed data already exists before the analysis is performed. This means that SEM will not create the causality, nor does it test the existence of causality, because causality is implicit. Furthermore, SEM will always be an approximated reality, as it uses mathematical linear relations in the computation (DeVault, 2007) [20]. Working on models development in accounting and controlling, Morard *et al*. (2015) [26] add another layer. They say that any researcher could make collected data fit with any generated model if he wanted to. In other words, depending on the chosen model, the estimation will always be considered correct. The authors conclude that a model will always only be a representation of the reality: a generalization of a multiplicity of realities.

E. Partial Least Squares Path Modeling

Partial least squares path modeling (PLS-PM) is a sub-part of structural equation modeling (SEM). A complete data analysis of this study is analyzed with PLSA (Morard and Jeannette, 2007) [4]. The software is based on the PLS-PM model. Hair *et al*. (2011, cited in Hair *et al*., 2012, p. 321) [27] have called the PLS-PM method "'a silver bullet' in many research situations – if correctly applied." "The method is a family of alternating least squares algorithms, or 'prescriptions,' which extend principal component and canonical correlation analysis" (Henseler *et al*, 2009, p. 284) [28]. PLS-PM is quite a recent statistical tool and works with a small sample size. A principal component analysis (PCA) generates axes. Then, PLS-PM selects some of the axes with the highest potential for explanation by summing up the variance of the data. The model comprises a structural part that represents the relationships between latent variables (LVs). The other part is the measured part, which represents the relationships between the measurable variables (MVs), i.e. the observed variables, and the latent variables (LVs), i.e. the unobserved variables (Russolillo, n.d.) [29]. MVs are used to generate a model of statistic relationships between LVs. PLS-PM is perfectly adapted to predictive causal analysis in a complex situation that has little theoretical information (Jöreskog & Wold, 1982, cited in Fernandes, 2012) [30]. For instance, "in-variables" and "out-variables" make up many managerial and industrial issues. In these cases, the goal is to understand the relationships between these two types of variables without any theoretical model. Most of the time, the "in-variables" are much larger in number than the observations. In that kind of situation, the most common methods of linear regression cannot solve the problem, and therefore PLS-PM regression is used (Tenenhaus, 1998) [31]. As Morard *et al*. (2005, p. 6) [32] argue, PLS-PM has "its inherent limitations, most notably, that it is a limited information technique, designed to maximize prediction, rather than fit." However, PLS-PM showed a potential use for statistical analysis in management, because it is able to make an optimal prediction without a large sample of data (Morard *et al*., 2005) [32].

Morard *et al*. (2012) [24] lists five chronological steps to build a powerful model using PLS-PM: First, the researcher *collects* all the historical data and the numerical elements. Second, the researcher *cleans* the collected data to avoid the possibility of any data errors. Third, a number of axes are generated. *Filtering* keeps only those axes that have useful information and high correlation. Fourth, the researcher uses the PLS-PM regression to *verify* the actual situation of the analyzed reality. Finally, PLS-PM equations will be *applied* "to study and forecast the relation for the long term" (Morard *et al*., 2012, p. 33) [24]. This last step allows the researcher to analyze the variance on the entire model, forecast future changes in the present situation, determine the optimal changes that must be made, and then determine how these changes will be effected. PLS-PM has an advantage over the other models, because it determines the structure of the most viable model regarding the present situation (Morard *et al*., 2012) [24].

F. PLS-PM in Marketing

Recently, several researchers in the field of marketing have started to use PLS-PM, particularly because of the unique strengths of the analysis. Indeed, PLS-PM is able to build a model and determine whether it is stable. It is good at predicting, which allows marketing researchers to use PLS-PM at the beginning of a study. Hence, it saves a precious time to compete a valid analysis (Henseler *et al*., 2009) [28]. Then, according to Henseler *et al*. (2009) [28], prediction-oriented function of PLS-PM is a great advantage in a marketing study. Indeed, it helps to develop the theoretical part of an analysis that is still lacking theory. Also, most of the time, researchers are not able to collect enough data to apply SEM analysis. In fact, collecting data is always complicated in the field, with a shortage of answers and wrong completion of surveys being the most common issues. In that case, PLS-PM is very convenient to use. It offers "excellent capabilities for work with small samples and formative measurement, as the methodology is sufficient for most success factor (cause indicator) analyses" (Henseler *et al*., 2009, p. 311) [28]. Finally, Henseler *et al*. (2009) [28] argue that sometimes it is impossible to use a method such as SEM in a case of incompatibility of distribution or model identification. In these situations, PLS-PM offers a substitute solution for a rigorous analysis.

IV. HYPOTHESIS AND METHODOLOGY

A. Hypothesis and Research Question

Current consumer behaviors models consist of theoretical elements that generalize consumer behavior. These models do not consider place, market, or type of industry; instead, they mainly focus on how consumers generally react to stimuli. Thus, as in Bianchi's study (2015) [3], marketing researchers collect data, compare it with different existing models, and then find a model that best corresponds with the study's perspective. The conclusions are mainly adapted to 'what we want to show.' The aim of this present study is to demonstrate that the process of market research is tackled from the wrong angle, by asking, 'why not find the optimal model that best explains consumer behavior regarding the analyzed market and the collected data?' To reach this objective, the authors suggest PLS-PM analysis using the PLSA (Morard and Jeannette, 2007) [4] instead of an SEM analysis. Morard and Jeannette have been developing this software at the University of Geneva since 2007 [4]. It determines the optimal model by means of PLS-PM analysis. The model is based on a number of axes previously computed by a PCA.

It is important to note that the authors presuppose the existence of an implicit model before starting the data computation. The model explains a specific consumer behavior without relying on a template of an existing model. The authors use PLS-PM to search for the exact model. Thus, the hypothesis is that there is an optimal model. However, they avoid an a priori model.

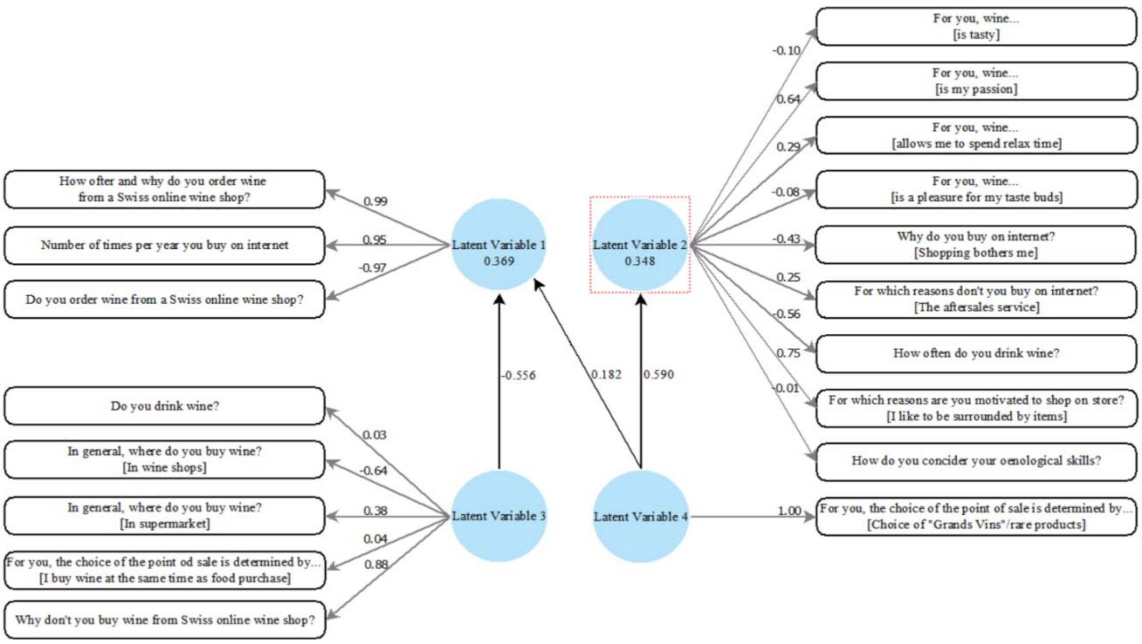
B. Methodology

An online survey was used to collect the quantitative data necessary for a Swiss consumer behavior analysis in wine e-commerce. The survey was available online over Christmas time from the middle of November 2014 until the middle of January 2015. In total, 69 subjects completed the survey. The survey includes five sections: 1. *Online purchase behaviors,* 2. *Wine consumption attitudes,* 3. *Wine purchase,* 4. *Online wine purchase,* and 5. *Personal consumer information.*

V. RESULTS AND DISCUSSION

A. Results

After computing the survey data, the PLSA (Morard and Jeannette, 2007) [4] generated a visual representation of the statistical analysis (Fig. 3):



Source: Simonin (2015) [16]

Fig. 3. Visual representation of the online survey's data analysis.

In the controlling analysis, Morard *et al*. (2012) [24] use this visual representation as a strategic map. Based on this map, they build an optimal balanced scorecard that reflects the optimal strategy the company has to follow. Since the authors use this map in consumer behavior research, they decided to name it the *optimal consumer behavior description* (OCBD). In the studied example, it explains a very specific type of consumer behavior: *the behavior of the Switzerland-based consumer who purchases wine online*.

As demonstrated above, the PLSA (Morard and Jeannette, 2007) [4] generated an optimal model based on four axes. These are the latent variables (LVs): LV1, LV2, LV3, and LV4. The four LVs are related to each other. The three dark arrows indicate the positive or negative correlations (correlation index) between the LVs. These correlations show the (positive or negative) impact of one LV on another.

Moreover, these LVs are also related to variables, namely the measurable variables (MVs). The 18 gray arrows indicate the strength of the positive or negative correlations between LVs and MVs. The authors took into consideration all the MVs related to each LV and their positive or negative correlation sign to name the four axes. Indeed, the LVs' names reflect the theme of the correlated MVs: LV1, *Online purchase*; LV2, *Appetite for the product*; LV3, *In-store purchase*; LV4, *Variety of choice*. In that sense, the OCBD determines relations between LVs and help the authors find cause and effect in the consumer's decisions. First of all, LV3 and LV1 are negatively correlated: The more purchases a customer makes in-store, the fewer purchases he makes online. Second, the positive correlation between LV4 and LV1 shows that the larger the variety of products online (i.e. wine), the more likely the consumer will be to purchase online. Admittedly, LV4 and LV1 are not highly correlated. Still, this information hints at how online wine companies have to adapt their offer: They need a wide range of products. Finally, the relationship between LV4 and LV2 shows that the more there is a variety of choice (e.g. wine), the more it whets the consumer's appetite.

According to Morard *et al.* (2013) [33], the strength analysis (stability) of the entire PLS-PM generated model (internal and external) is made by statistical validation. The table below (Table I) summarizes the model's data, which the PLSA (Morard and Jeannette, 2007) [4] computed:

TABLE I: SUMMARY OF THE GENERATED MODEL'S DATA

LVs	Name	R-square	AVE	CR
LV1	Online purchase	0.369	0.940	0.825
LV2	Appetite for the product	0.348	0.185	0.085
LV3	In-store purchase	-	0.270	0.110
LV4	Variety of choice	-	1.000	1.000

Source: Simonin (2015) [16]

The R-square level tests the statistical stability of the internal model, in other words, the strength. If the value is > 0.67, the model is strong; if the value is > 0.33, the model is moderate; if the value is > 0.19, the model is weak (Chin 1998, cited in Morard *et al*., 2013) [33]. It is notable that only LV1 and LV2 have an R-square value, because LV1 and LV2 do not have an impact on other LVs. From a statistical point of view, the authors assess the internal model of this OCBD as moderately stable (R-square > 0.33). Thus, it is not a perfect situation but good enough to consider the internal model as statistically valid.

The average variance extracted level (AVE) stands for the variance of the MVs explained by the common factor. The composite reliability level (CR) stands for the reliability of a summated scale. Both test the stability of the external model. Chin (1998) says that the external model is statistically valid if AVE value is > 0.5. Wert *et al*. (1974) state that the external model is statistically valid only if CR value is > 0.6 (cited in Morard *et al*. 2013) [33]. In this OCBD, LV1 and LV4 have higher AVE and CR values than required. Hence, the external model is statistically strong for LV1 and LV4. However, LV2 and LV3 have lower AVE and CR values than required, which means the external model for LV2 and LV3 is statistically weak. The authors conclude that the external model is moderately stable from a statistical point of view, because the levels of AVE and CR for LV1 and LV4 were very strong, but those for LV2 and LV3 were too weak. Even if, statistically speaking, the model has only moderate stability characteristics, the authors have defined this OCBD as the optimal model, because it represents the best combination of a cause-and-effect relationship. This optimal model has the best predictability capabilities to picture the behavior of a Switzerland-based consumer purchasing wine online. Moreover, regarding the entirety of the results analysis, this OCBD shows interesting axes with a coherent combination.

The PLS-PM computation process is applicable to determine every specific consumer behavior of each specific market, which is the most interesting aspect of this study. It implies that a different consumer behavior model is generated for each market research on consumer behavior, regardless of the market size. This approach allows for a better understanding of the "true reality" of each analyzed market.

For the first time in a marketing research study, PLS-PM (using the PLSA (Morard and Jeannette, 2007)) [4] was used to perform a data analysis to build a consumer behavior model from scratch. It demonstrates the possibility of generating an optimal model that makes sense. Hence, PLS-PM analysis is also suitable for marketing research analysis and not only in strategic and accounting analysis, which is what it generally used for. Going one step further, it is clear to see that consumer behavior impacts the direction of a company strategy, if the latter wants to seduce and retain customers in the short and long term. Evidently, consumer behavior is related and has an impact on the market strategy that a company follows.

A company benefits greatly from finding an optimal consumer behavior model for every territory, market, product, economic situation, and customer segment. This way of analyzing a market shows the exact decisions required to succeed in a very specific market, which guarantees that all the investments are necessary. Hence, there will be no extravagance in investments and no useless effort to reach a market successfully. Moreover, statistical tools help managers to react quickly despite continuous developments in the markets. Even if important modifications have to be made in a business, a study conducted with restrained analytical material using an OCBD can lead straight to optimal solutions in a very short time. The ease of this analysis method is very powerful in an unstable market because the strategy must often be adapted in such an environment and does not require major financial resources for a standard marketing study.

In the case of Switzerland, it is very important to distinguish between the different territories and adapt the business strategy. Many companies fail in the Swiss market because they are not aware that they have to start from scratch every time they launch operations in another part of the country. This mistake might be due to a lack not only of knowledge of Swiss customs but also of time and money, particularly because a marketing study requires substantial financial investments.

B. Criticism and Limitations

First and foremost, it is logical that the computed model of this study is not applicable to any market other than the Swiss online wine market. Obviously, a different model has to be computed for each analyzed market, because the models are tailor-made for each analyzed market. The model can be used only in the analyzed market, which limits the utility for a company to make a financial investment in this kind of marketing study using PLS-PM. However, while it is an advantage that this method is tailor-made, it can also be a disadvantage in the sense that every distinct market must be analyzed separately. The risk for the company is to apply results and solutions too widely and therefore miss the important part of the method's purpose. Yet, being specific could lead to bloated marketing research budgets if investigations are carried out into markets that are too limited in scope. In these cases, the market analysis using an OCBE will be complex, will take time, and will therefore require major financial resources, which is the opposite of the aim of this method. Thus, the authors suggest that a PLS-PM analysis be used when a company makes the decision to enter an entirely new market with specificities that are not well-known, as is the case in Switzerland. However, this analysis is more suitable to companies that evolve in niche markets than for international companies that sell more or less standardized products.

Second, Morard *et al*. (2013) [33] bring up the first limit of the PLS-PM model: The latter could be uninteresting for some research that lacks a technical basis but more interesting to use for "in-the field" research. For the authors of this present paper, a PLS-PM analysis in the field of marketing fits perfectly with a qualitative analysis produced through guided interviews. Morard *et al*. (2013) [33] also consider it idealistic to draw all the conclusions of an analysis based on historical data. Does this model lead to reliable predictions that we can use to propose future moves? Morard *et al*. (2013) [33] say that the only way to plan the future rationally is to analyze the current situation in its entirety, not just one part of it. Indeed, PLS-PM uses the current data to suggest a 'cause-and-effect' model. Hence, it is important to remember that PLS-PM does not resist multicollinearity. In fact, PLS-PM generates internal and external models by means of multiple regression and could cause multicollinearity problems in the PLS-PM estimation. Finally, Morard *et al*. (2013) [33] admit that PLS-PM lacks a theoretical basis, and it would be advisable to work toward "developing a more formal methodology […] while using a simplified model" (Morard *et al*., 2013, p. 73) [33].

Third, in previous research, Morard *et al*. (2005 [32]; 2012 [24]; 2013 [33]; 2015 [26]) performed a PLS-PM analysis on objective data using financial and performance reports. This market research study is based on a survey made with subjective questions and subjective data coding, and the authors decided how to weigh each answer. The PLSA (Morard and Jeannette, 2007) [4] would generate different axes for the same analyzed market with the same survey, using coded data with another subjective point of view, which is impossible with objective data.

VI. Conclusion and Further Research

This study produced a general view of the behavior of the Switzerland-based consumer on the online wine market and his distinctive features. It also provides an overview of the potential of applying PLS-PM to an analysis in marketing research. The authors used a different approach to analyze the consumer behavior of a specific market. Using proof gathered from in-the-field analysis, they showed that PLS-PM is able to determine an optimal consumer behavior model from scratch. Additionally, this study emphasizes the high potential of building an OCBD of a specific market for companies. In fact, they would easily have the opportunities to adapt their future strategic plans by having a better understanding of the targeted market. However, the main limitations of this research study concern the restriction of the use of the results in a single study only, the pertinence of the method in a research case with a lack of technical basis, and the subjectivity in the data encoding.

The authors point out the importance of exploring the interesting possibilities that are opened up by a PLS-PM analysis in marketing research. Being able to use statistics to generate an optimal, tailor-made model helps to understand the reality of the field with greater precision. In practical terms, if poorly done, a consumer behavior market analysis can have a catastrophic financial impact on the company.

As Henseler *et al*. (2009) [28] suggest, using a wide range of statistical analysis methods in a single study is important to create open-mindedness and a variety of points of view. It also helps to confirm or reject some of the results and conclusions. At the same time, however, as Morard *et al*. (2015) [26] point out, researchers using PLS-PM will face a new challenge, namely of reconciling "the pragmatism required by the organizations and the need for a more theoretical framework requested by researchers" (Morard *et al*. 2015, p. 307) [26].

Researchers would be well advised to assess whether PLS-PM generates good, strong, and reliable conclusions from qualitative data. The authors recommend applying a PLS-PM analysis to data collected from semi-structured interviews. The statistical stability should be tested to determine the impact of the qualitative data (compared with quantitative data) on the reliability of the results. Moreover, research could also focus on determining what makes a market specific. First by analyzing consumer behavior for the same product in the same economic context but in different countries and then by modifying the internal parameters, the aim will be to assess the influences on consumer behavior with respect to a specific product. Finally, the authors call for a study into the reliability of the PLS modeling on a larger family of products. Instead of analyzing a very specific market, such as the e-commerce of wine in Switzerland, it would be relevant to test whether the PLS modeling generates coherent results on a larger market, for instance the e-commerce of drinks in Switzerland.

References

[1] T. Brunner and M. Siegrist, "A consumer-oriented segmentation study in the Swiss wine market," *British Food Journal*, vol. 113, no. 3, pp. 353-373, 2011.

[2] L. Lockshin and A. Corsi, "Consumer behaviour for wine 2.0: A review since 2003 and future directions," *Wine Economics and Policy*, vol. 1, no. 1, pp. 2-23, 2012.

[3] C. Bianchi, "Consumer brand loyalty in the Chilean wine industry," *Journal of Food Products Marketing*, vol. 21, no. 4, pp. 442-460, 2015.

[4] B. Morard and C. Jeannette, *PLS Assistant*, 2007.

[5] D. Rigby, "The future of shopping," *Harvard Business Review*, pp. 65-76, 2011.

[6] J. Speer. (2012). How ecommerce is changing the way consumers Shop — And how retailers sell. [Online]. Available: http://apparel.edgl.com/news/How-Ecommerce-is-Changing-the-Way-Consumers-Shop-%E2%80%94--and-How-Retailers-Sell80507

[7] B. Reymondin. (2013). *E-commerce: Les Charmes Cachés Du Marché Suisse*. [Online]. Available: http://www.bilan.ch/node/200432

[8] Ubs. (2015). *UBS Global Topics*. [Online]. Available: http://www.ubs.com/global/en/about_ubs/about_us/research.html

[9] Federal office for agriculture (FOAG). *L'année Viticole 2014, Statistiques Vitivinicoles*, 2015.

[10] Federal office for agriculture (FOAG), *Agricultural Report*, 2010.

[11] Swiss wine promotion, *Etude Sur Le Marché Du Vin En Suisse 2013: Notoriété, Habitudes De Consommation Et d'Achat*, 2013.

[12] J. Bray. (2008). Consumer behaviour theory: Approaches and models. [Online]. University of Bournemouth. Available: http://eprints.bournemouth.ac.uk/10107/

[13] J. Sheth, "History of Consumer Behavior: a Marketing Perspective," *SV - Historical Perspective in Consumer Research: National and International Perspectives*, pp. 5-7, 1985.

[14] M. Solomon, G. Barmossy, and S. Askegaard, *Consumer Behaviour*, Harlow, England: Financial Times/Prentice-Hall, 2002.

[15] P. Kotler, K. Keller, B. Dubois, and D. Manceau, *Marketing Management*, Paris: Pearson Education France, 2006.

[16] D. Simonin, "A new approach of consumer behavior analysis: The use of PLS-Path Modeling in marketing research, the wine e-commerce in Switzerland," Master of Science in Management Thesis, University of Geneva, 2015.

[17] S. Mayol, *Le Marketing 3.0*, Paris: Dunod, 2011.

[18] E. Falque, E. Falque, and S. Williams, *Les Paradoxes De La Relation Client*, Paris: Pearson, 2011.

[19] Z. Hong and L. Yi, "Research on the Influence of Perceived Risk in Consumer On-line Purchasing Decision," *Physics Procedia*, vol. 24, pp. 1304-1310, 2012.

[20] G. DeVault. (n.d.). *Quantitative Research — Using Structural Equation Modeling*. [Online]. Available: http://marketresearch.about.com/od/market.research.techniques/a/Using-Structural-Equation-Modeling.htm

[21] P. Lei and Q. Wu, "Introduction to structural equation modeling: Issues and practical considerations," *Educational Measurement: Issues and Practice*, vol. 26, no. 3, pp. 33-43, 2007.

[22] S. MacLean and K. Gray. (1998). Structural equation modelling in market research. [Online] *Journal of the Australian Market Research Society*. Available: http://www.smallwaters.com/whitepapers/marketing/

[23] D. Iacobucci, "Everything you always wanted to know about SEM (structural equations modeling) but were afraid to ask," *Journal of Consumer Psychology*, vol. 19, no. 4, pp. 673-680, 2009.

[24] B. Morard, C. Jeannette, and A. Stancu, "The relationship between Structural Equation Modeling and Balanced Scorecard: Evidence from a Swiss non-profit organization," *Review of Business and Financial Studies*, vol. 3, no. 2, pp. 21-36, 2012.

[25] J. Hox, and T. Bechger, "An Introduction to structural equation modelling," *Family Science Review*, vol. 11, pp. 354-373, 1998.

[26] B. Morard, A. Stancu, and C. Jeannette, "A comparison between two balanced scorecards: Optimal vs. kaplan and norton model," *Journal of Economics, Business and Management*, vol. 3, no. 2, pp. 302-308, 2015.

[27] J. Hair, M. Sarstedt, T. Pieper, and C. Ringle, "The use of partial least squares structural equation modeling in strategic management research: A review of past practices and recommendations for future applications," *Long Range Planning*, vol. 45, no. 5-6, pp. 320-340, 2012.

[28] J. Henseler, C. Ringle, and R. Sinkovics, "The use of partial least squares path modeling in international marketing," *Advances in International Marketing*, vol. 20, pp. 277-319, 2009.

[29] G. Russolillo, *Algorithme Et critÈres Du PLS Path Modeling*.

[30] V. Fernandes, "En quoi l'approche PLS est-elle une méthode a (re)-découvrir pour les chercheurs en management?" *M@n@gement*, vol. 15, no. 1, pp. 102, 2012.

[31] M. Tenenhaus, *La Régression PLS*, Paris: Éd. Technip, 1998.

[32] B. Morard and A. Stancu, *Structural Equation Modeling in a Rationalization Tentative of Balanced Scorecard*, University of Geneva's Open Archives, Geneva, 2005.

[33] B. Morard, A. Stancu, and C. Jeannette, "Finding your company's optimal balanced scorecard: A new quality criterion," *Economics and Finance Research*, vol. 61, no. 14, pp. 65-74, 2013.

Bernard Morard is a double Ph.D. in both finance and management accounting. He was born on August 6, 1956 in France. He specialized his knowledge in the financial and management accounting field by teaching in prestigious schools like the University of Law, Faculty of Applied Economics in Aix-en-Provence, then the University of Montréal. He is also the author of numerous publications in the specialized field. Since 1990, he is full professor at the University of Geneva, Switzerland.

After being the president of the HEC Business School, he was elected in 2009 the dean of the Faculty of Social and Economic Sciences at the University of Geneva. Using his entrepreneurial approach, he created in the last decade more than 30 economic programs for professionals in various sectors. His two PhDs made him very polyvalent on the research side, his fields of research being focused on specific statistical tools for a better understanding of the performance, both in a macro and micro sector. His favorite computational tools are Matlab, SPSS, Mathematica and Free Basic.

Dimitri Simonin holds a master of science degree with a major in strategy in 2015 from the Faculty of Economics and Management at the University of Geneva (Switzerland), a WSET® Award Level 2 in 2015 in wines and spirits (Fribourg/Switzerland), a wealth management diploma in 2011 from the UBS Business University (Zürich/Switzerland), and a BA degree in business and management in 2009 from the HEC at the University of Geneva (Switzerland).

He has worked as a portfolio advisor assistant at UBS Wealth Management & Swiss Bank (Geneva/Switzerland) and also operated as a strategic marketing consultant in the marketing department of a wine import company (Geneva/Switzerland). He was a substitute teacher at secondary schools in Geneva (Switzerland) for several years. At present, he is looking to pursue a PhD that would focus on the wine business, including e-business, tourism business, and stakeholders' partnership efficiency.