On the Taxonomies and Typologies of e-Customers in B2C e-Commerce

Ilija Hristoski[1] **Olivera Kostoska**[1]

[1] "St. Kliment Ohridski" University – Bitola / Faculty of Economics – Prilep, Republic of Macedonia, {ilija.hristoski, olivera.kostoska}@uklo.edu.mk

Abstract: In the contemporary business surrounding, posed by the new, so-called 'digital economy', the e-Commerce paradigm became a decisive factor for both the survival and successfulness of companies. The whole concept is built on the existence of its two major pillars: the e-Customer and the e-Commerce website. The mutual interaction between these is determined by the e-Customer's online shopping behavior. Despite the fact that various e-Customers exhibit various online shopping behaviors, they can be categorized into classes, or types, by the similarities of their behavioral patterns. In the paper we distinguish between two kinds of online shopping behavior: the one which refers to the e-Customer's behavior prior to entering the virtual store (the aspect that is treated by e-Marketers and e-Retailers), and another kind, which refers to the e-Customer's behavior during online shopping sessions (the aspect that is important to engineers and capacity planners). Both aspects use categorizations of e-Customers into classes or types, sometimes called 'taxonomies', and sometimes 'typologies'. We also shed light not only on the differences between these two terms but also between the two aspects of online shopping behavior. The latter one leads to Customer Behavior Model Graphs (CBMGs) and e-Customer operating profiles. The rest of the paper deals with some of the issues related to the classical view of classification/categorization and ends up with a brief overview and qualitative analysis of some of the known typologies of e-Customer classes. Simultaneously, by analyzing the definition provided for a given e-Customer class, a cataloging of the factors that led to the introduction of particular e-Customer classes, has been conducted. As a result, two groups of factors have been identified: exogenous and endogenous factors, to describe the external and internal factors, respectively, affecting the online shopping behavior prior and after entering the virtual store. This way, the paper contributes to the clarification, systematization, modeling, and specification of e-Customer taxonomies and operating profiles, which makes the basis for building up predictive models suitable for evaluating performability measures.

Keywords: e-Commerce, e-Customers, online shopping behavior, taxonomies and typologies, endogenous and exogenous factors.

1. INTRODUCTION

The way people shop has witnessed a seismic shift in the last three decades. The emergence of the B2C e-Commerce paradigm has radically changed the shopping behavior of millions of people worldwide. The ICTs have totally transformed every aspect of the sales process, including sourcing, browsing, recommending, choosing, comparing, checking, ordering, receiving… As a result, e-Customers have undergone a long way of continuous changes, too. Despite the fact that e-Commerce has offered more opportunities than ever before, the way how e-Customers shop remains to be a very individual process. Every online shopper is different, exhibiting his/her own specific behavior patterns.

The term 'online shopping behavior' has a twofold meaning. From a purely marketing aspect, the term describes the e-Customer behavior outside the virtual shop. In this context, it refers to all socio-economic, demographic, and psychographic factors that could possibly lead towards his/her intention or decision to shop online.

On the other hand, looking from a purely engineering aspect, the term encompasses all specific behavior patterns of an e-Customer from the moment he/she 'enters' until he/she 'exits' the virtual shop. In this context, it refers to the way he/she invokes e-Commerce functions provided by the e-Commerce website: the order, the intensity, and the probabilities of invoking such functions, as well as the average time spent between any two consecutive invocations of e-Commerce functions, also known as 'sojourn time'.

Despite the fact that every online shopper is different, exhibiting his/her own specific behavior patterns outside or inside the virtual shop, it is still possible to organize them into groups by similarities they exhibit regarding one or more criteria. Such groupings are also known as typologies, or taxonomies, of e-Customers.

Often the terms 'typology' and 'taxonomy' are used interchangeably. Yet, there are fundamental differences between the two. According to Smith (2002, p. 381), "there are two basic approaches to classification. The first is *typology*, which conceptually separates a given set of items multidimensionally." "…The key characteristic of a typology is that its dimensions represent concepts rather than empirical cases. The dimensions are based on the notion of an ideal type, a mental construct that deliberately accentuates certain characteristics and not necessarily something that is found in empirical reality (Weber, 1949). As such, typologies create useful heuristics and provide a systematic basis for comparison. Their central drawbacks are categories that are neither exhaustive, nor mutually exclusive, are often based on arbitrary or ad hoc criteria, are descriptive rather than explanatory or predictive, and are frequently subject to the problem of reification (Bailey, 1994)." "A second approach to classification is *taxonomy*. Taxonomies differ from typologies in that they classify items on the basis of empirically observable and measurable characteristics (Bailey, 1994, p. 6). Although associated more with the biological than the social sciences (Sokal & Sneath, 1964), taxonomic methods - essentially a family of methods generically referred to as cluster analysis - are usefully employed in numerous disciplines that face the need for classification schemes (Lorr, 1983; Mezzich & Solomon, 1980)." Put in a more simple way, taxonomies and typologies are both classification structures. The difference lies in the way in which each is developed: empirically (taxonomies) vs. conceptually (typologies).

In general, both typologies and taxonomies divide individuals or objects of interest into groups/categories/classes/types according to their typical behavior or other patterns/properties/criteria/ dimensions/factors and thus contribute to creating a clearer view of individuals' or objects' diversity. According to this perspective, both typologies and taxonomies represent a line-up of groups whose descriptive features are based on a similarity of distances, and in which the individual groups/categories/classes/types represent part of the totality. In this respect, both the typologies and taxonomies can also be interpreted as 'structured totalities' (Hoyer & MacInnis, 2004).

Such division of the totality of e-Customers into clearly distinguishable groups/categories/classes/types of individuals not only provides a clear view on their structure but also helps in determining the causal connection of their personality features and their mapped online shopping behavior.

E-Customer typologies are essential for organizations which are doing business online. The term 'e-Customer typology' can be seen as a collective concept for numerous typological approaches whose objective is the identification of different e-Customer groups/categories/classes/types in order to focus marketing activities on those specific e-Customer segments. It should be notified that some researchers consider customer typologies as being equivalent, or synonymous, to market segmentation (Blackwell et al., 2001; Brehm et al., 2005). According to Wedel & Kamakura (2002), "in market segmentation, one distinguishes homogeneous groups of customers who can be targeted in the same manner because they have similar needs and preferences." One of the most appealing aspects of marketing segmentation is that "it presents segmentation as a conceptual model of the way a manager wishes to view a market." In this context, as a variant of market segmentation, the construction of customer typologies aims at the identification of different types of consumer groups. In a broader sense, the introduction of customer typologies is based on the methodology that customers are being described based on several characteristics, and consequently, persons similar to each other are being grouped into types (Dillon & Goldstein, 1984).

The paper is organized as follows. Section 2 gives a brief overview of some of the most prominent research made in this field. The basic information about the aim, data, and methodology of the research can be found in Section 3. In Section 4, the authors clarify the differences between marketing-oriented typologies (i.e. buying personas) and performability-oriented taxonomies of e-Customers, by putting the focus to online shopping behavior, Customer Behavior Model Graphs, and operating profiles, comprised of a number of e-Customer types/classes. Section 5 elaborates the classical view of classification/categorization and explains the general idea of how it should be conveyed theoretically. Section 6 is devoted to the qualitative analysis of some existing e-Customer taxonomies vis-à-vis the specific criteria/factors/dimensions they are based on, which are then tagged as exogenous and endogenous, depending on whether they can help in building pure marketing typologies or performability-oriented taxonomies of e-Customers, suitable for performing capacity planning activities. Section 7 concludes.

2. RELATED RESEARCH

E-customers' online behavior, as a basis for introducing various e-Customer types/classes, and, consequently, numerous e-Customer typologies and taxonomies, has been subject to an extensive research since the emergence of the e-Commerce paradigm. What follows is just an excerpt from the abundance of related research on this topic.

Li & Zhang (2002) have investigated the current status of studies on online shopping attitudes and behavior, based on the analysis of 35 empirical articles published in scientific journals and conference proceedings. They have proposed a taxonomy representing factors/aspects related to consumer online shopping attitudes and behavior, comprised of ten interrelated factors for which the empirical evidence showed significant relationships. These ten factors are the external environment, demographics, personal characteristics, vendor/service/product characteristics, website quality, attitude towards online shopping, intention to shop online, online shopping decision making, online purchasing, and consumer satisfaction.

Kau, Tang, & Ghose (2003) have examined the online buying behavior of a group of over 3,100 Internet users. They used factor analysis and cluster analysis to classify the respondents into six types of online shoppers ('On-off shoppers', 'Comparative shopper', 'Traditional shopper', 'Dual shopper', 'e-Laggard', and 'Information surfer'), based on their information-seeking patterns, as well as their motivations and concerns for online shopping.

In 2007, Barnes et al. have conveyed a cluster analysis on a data acquired by an online survey being conducted in three countries: France, Germany, and the US. Based on their findings, a marketing segmentation of e-Customers has been done through the identification of distinct, practice-relevant, and addressable clusters of e-Customers by means of selected criteria for constructing typologies, such as psychographics, culturally-specific and purchasing behavior-relevant features. The cluster analysis confirmed the outstanding validity of a three-cluster-solution, comprised of three e-Customer types: 'Risk-averse doubters', 'Open-minded online shoppers', and 'Reserved information-seekers'. In addition, the accompanied discriminant analysis showed that certain constructs, particularly 'neuroticism', 'willingness to buy', and 'shopping pleasure', separate the clusters best.

A research been conveyed by Gaile-Sarkane (2008), who has analyzed the current situation regarding the e-Customer behavior in electronic environment in Latvia and the Baltic states, has shown that today's social and personal motives of e-purchasing are different from those found with the traditional market, and recommends the need of paying more attention to e-Customers and the analysis of their online shopping behavior.

The results obtained by a research study been conducted among experienced e-Customers in Spain have shown that once individuals attain the status of experienced e-Shoppers, their online shopping behavior remains similar, irrespective of their socioeconomic characteristics including age, gender, and income (Hernández et al., 2011).

Based on the results of a hierarchical regression analysis of a data set being acquired by a nationwide online survey of 503 Chinese e-Consumers, Gong et al. (2013) conclude that Chinese e-Consumers' age, income, education, and marital status, as well as their perceived usefulness, are all significant predictors of their intention to shop online.

In their research, Mitrevski & Hristoski (2012) made a contribution to the modeling and specification of operating profiles of e-Customers, as a basis for building predictive models suitable for evaluation of performability measures. Based on their analysis of eight existing e-Customer taxonomies, they propose a taxonomy comprised of five e-Customer classes, including 'Curious', 'Focused', 'Passionate', 'Reluctant', and 'Selective' e-Customers. All of these have been defined both qualitatively and quantitatively vis-à-vis a stochastic predictive model of the online shopping behavior, based on the utilization the semantic power of the class of Deterministic and Stochastic Petri Nets (DSPNs). Furthermore, recognizing the fact that e-Customers' online shopping behavior is largely affecting the conduct of e-Commerce systems, the same authors promote a customer-centric, holistic approach: e-Customers are identified as the most essential 'subsystem' with a number of important, but less well-understood behavioral factors. The proposed taxonomy of customers and the specification of operational profiles was a basis for building a number of hierarchically composed predictive submodels, usable for evaluating a range of performability measures by discrete-event simulations. In addition, a handful of variables are identified in order to turn performability measures into business-oriented performance metrics, as a cornerstone for conducting relevant server-sizing activities (Mitrevski & Hristoski, 2014).

3. AIM, DATA, AND METHODOLOGY

The aim of the paper is to provide a solid background for investigating current and future typologies of e-Customers, in the context of finding suitable ways of mapping particular e-Customer types into their counterparts: e-Customer classes that exhibit specific behavior during online shopping sessions. The method of analysis is based on the identification of the underlying factors/criteria the e-Customer typologies are based on, and their tagging as exogenous or endogenous.

The analysis of some existing typologies of e-Customers in Section 6 has been conducted using secondary data sources found on the Internet, including marketing-related blogs, research papers, and corresponding literature. It belongs methodologically to the group of qualitative analyses, which includes reasoning from a perception of the parts and interrelations of a subject of the analysis. This one aims at identifying the key factors/criteria a given typology is based on. Previously, the analyzed e-Customer typologies are systematized into tables, grouped by the number of e-Customer types included. Based on the analysis of the definition provided for each particular e-Customer type, e-Customer types have been grouped by the similar or identical factors/criteria, regardless of the typologies they come from. In addition, all identified factors/criteria have been tagged as exogenous or endogenous, depending on whether they help in building pure marketing-oriented typologies or performability-oriented taxonomies of e-Customers, suitable for performing capacity planning activities.

4. FROM BUYER PERSONAS TO CBMGs AND OPERATING PROFILES

E-Customers have various socio-economic, demographic, and psychographic characteristics. They come from different countries (geographic locations), all over the world; they have various age, gender, marital status, race and ethnic origin, education, professional occupation, and income background. These are all external characteristics that come from the e-Customer's living and working surrounding and provide an answer to the question 'who' the e-Customer is, i.e. to really understand who is buying what a given e-Commerce website is selling. In addition, each e-Customer exhibits a specific personality, lifestyle, behavior patterns, daily habits, motivations, goals, desires, hobbies, and interests, which all belong to his/her internal characteristics, all needed to provide the answer to the question 'why' the e-Customer is buying online. Known as psychographics, these internal characteristics are the basis of what is called 'marketing psychology'. Both external and internal characteristics are commonly included in the so-called e-Customer profiles, also known as 'buyer personas' or 'marketing personas'.

Buyer personas are fictional or semi-fictional, generalized representations of a specific e-Commerce website's ideal customers. Defining specific buyer personas help e-Retailers in all activities: in marketing, sales of products and services; they help in internalizing the ideal e-Customer a specific e-Commerce website is trying to attract, and relate it to its real e-Customers as real humans. Having a deep understanding of specific buyer persona(s) is critical to driving content creation, product development, sales follow up, and really anything that relates to e-Customer acquisition and retention. Buyer personas help e-Retailers and e-Marketers understand better both their current and prospective e-Customers. This makes it easier for them to tailor e-Commerce website content, messaging, product development, and services to their specific needs, behaviors, and concerns of different groups. In other words, defining different detailed e-Customer profiles help in getting acquainted with the typical backgrounds of the ideal buyers belonging to different groups. This helps to meet the specific needs and interests of the real target e-Customers (Vaughan, 2015; Kusinitz, 2018). As a result, a particular e-Commerce website would be able to attract the most valuable visitors, leads, and e-Customers. It should be also notified that the strongest buyer personas are identified based on market research as well as insights that can be gathered from the real data about actual/existing e-Customer base (through surveys, interviews, etc.).

E-Customer profiles are important to e-Marketers and e-Retailers because they use them as a means to target and attract specific groups of e-Customers, as well as to convert the visitors of a virtual store into buyers. So, the ultimate goal of introducing buying personas is widening the population of current and prospective buyers, in order to increase the volume of online purchases and making a profit.

However, introducing e-Customer profiles is not valuable solely to e-Marketers and e-Retailers. It is also extremely valuable to system engineers who take care of the proper dimensioning of e-Commerce website infrastructure. The reason is of an entirely different nature. E-Customers invoke different e-Commerce functions during their online shopping sessions while interacting with the e-Commerce website. For instance, such e-Commerce functions include functions like BROWSE, SEARCH, LOGIN, REGISTER, SELECT/VIEW_ITEM, ADD_TO_CART, REMOVE_FROM_CART, VIEW_CART, PAY/CHECKOUT, BUY_NOW, etc. All of these are being invoked in a random and unpredictable way. This is the only reason for the occurrence of so-called 'peak rates' or 'bursts' in the Internet traffic being generated towards a particular B2C e-Commerce website, which usually occurs during holiday seasons when an increased number of e-Customers are shopping online. What is more significant, such peaks can exceed the expected traffic levels even ten times or more, which inevitably leads towards significant degradation of the website performances and even functional failures of the systems due to overloading (Banga & Druschel, 1999). In fact, invocation of a single e-Commerce function means that a single HTTP request (a message) is being sent from an e-Customer's browser to a particular e-Commerce website's web server(s). Each HTTP request represents a service demand, i.e. a demand for relevant hardware resources like servers, processors, memory, network resources, hard disk drives, etc. During burst periods, web servers' utilization rate rises because they become saturated with such service demands, whilst the lack of hardware resources considerably slows down the whole system. This usually triggers a series of direct negative impacts on online businesses, because it can incur financial losses, bad reputation, damaged external image of the company, many unsatisfied e-Customers, an increased number of non-loyal e-Customers, lost trustworthiness/credibility and increased e-Customer abandonment rates.

Because of all of these possible outcomes, it is of the utmost importance to continually plan the capacity of the e-Commerce infrastructure, supported by building and evaluating relevant predictive models. According to Menascé & Almeida (2002, pp. 12–13), capacity planning is a relatively new discipline which refers to "the process of predicting when future load levels will saturate the system and determining the most cost-effective way of delaying system saturation as much as possible", whilst "the lack of proactive and continuous capacity planning procedures may lead towards unexpected problems regarding e-Commerce website availability and performances."

Many recent studies point out the importance of analyzing e-Customer online behavior, as a basis for evaluating relevant performability measures, which are needed for proper capacity planning of e-Commerce systems. Performability is a composite measure of how well a given system performs over a specified period of time, in the presence of faults; it encompasses the concepts of performances and dependability; the latter one refers to availability, reliability, safety, and security. This measure is the vital evaluation method for degradable systems, i.e. "highly dependable systems which can undergo a graceful degradation of performance in the presence of faults (malfunctions) allowing continued 'normal' operation" (Jawad & Johnsen, 1995). As such, performability depends not only on the adequate capacity planning, i.e. the proper dimensioning and configuring of e-Commerce website hardware infrastructure but also on e-Customers' online shopping behavior during online shopping sessions. Therefore, the successful management of the concept of e-Commerce systems performability cannot be carried out without a relevant analysis of the e-Customers' online shopping behavior and specifying the operating environment, i.e. determining specific operating profiles. Recognizing the fact that various e-Customers exhibit various online shopping behaviors, some of these can be common for a number of e-Customers, who can be categorized as a specific class. In other words, the majority of e-Customers to a particular e-Commerce website can be classified into two, three, or more classes according to their similar behavior patterns they exhibit during online shopping sessions. Each e-Customer class defines a specific online behavior of a group of e-Customers, which determines both the dynamics (i.e. the frequency) and the structure (i.e. the order) of the invoked e-Commerce functions.

For instance, a specific e-Customer who knows what to buy and is highly determined to make an online purchase could invoke a specific set of e-Commerce functions in the following order:

LOGIN → SEARCH → VIEW_ITEM → BUY_NOW → LOGOUT

On the other hand, another e-Customer, who does not know what to buy, and, therefore, is not determined to make an online purchase, could invoke e-Commerce functions in the following order:

ENTER → BROWSE → VIEW_ITEM → … → BROWSE → VIEW_ITEM → SEARCH → VIEW_ITEM → BROWSE → VIEW_ITEM → … → BROWSE → VIEW_ITEM → EXIT

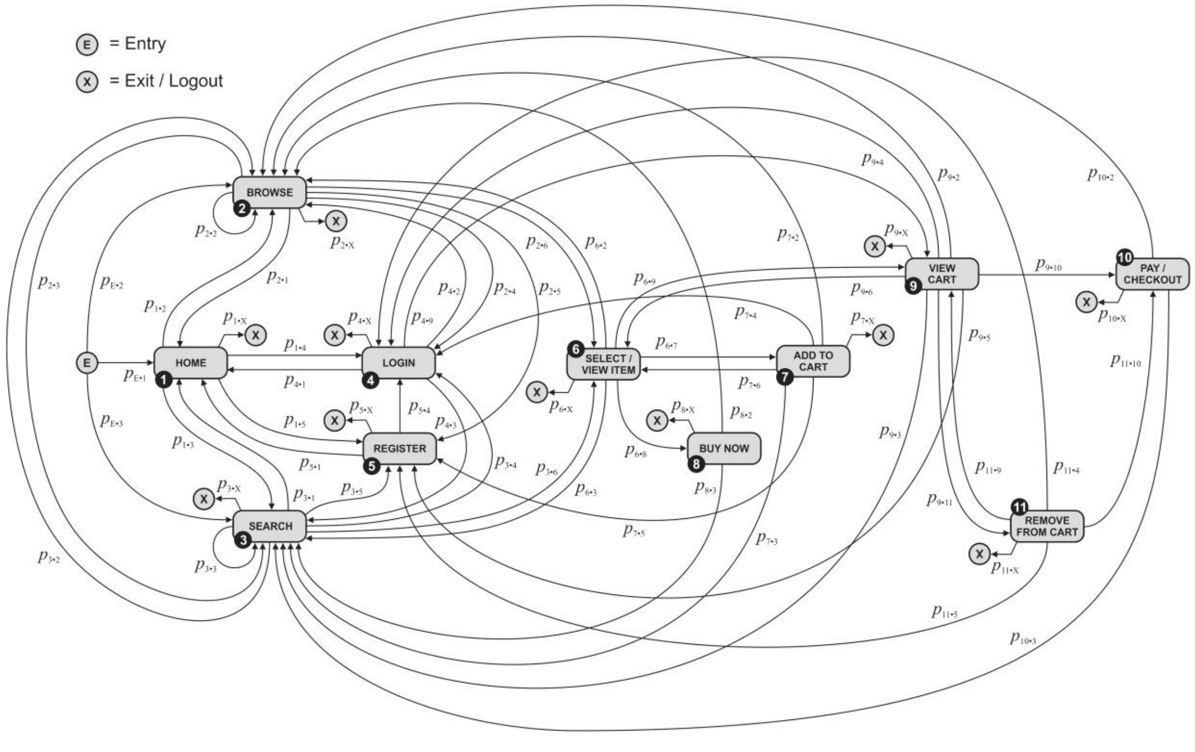
Finally, a third e-Customer, who knows what to buy, but is reluctant, because he/she is not determined to make an online purchase, could invoke a specific set of e-Commerce functions in the following order:

ENTER → SEARCH → VIEW_ITEM → ADD_TO_CART → VIEW_CART → REMOVE_FROM_CART → EXIT

In order to describe the online shopping behavior of various classes of e-Customers, a special type of graphs, known as Customer Behavior Model Graphs (CBMGs) have been introduced (Menascé & Almeida, 2000, pp. 41–59; Menascé & Almeida, 2000, pp. 222–224). CBMGs are graph-based models that characterize Web sessions of e-Customers while they are shopping in a particular virtual store. Put differently, they capture the navigational patterns of e-Customers through a particular e-Commerce website, as viewed from the web server side (Figure 1).

A CBMG is comprised of N states, where state #1 is always the ENTRY state (designated by letter 'E' in Figure 1), and state #N is always the EXIT / LOGOUT state (designated by letter 'X' in Figure 1), whilst the states 2, 3, …, N–1 correspond to the states HOME (1), BROWSE (2), …, REMOVE_FROM_CART (11), respectively. Besides the characteristic set of states, a CBMG is being also described by a set of possible transitions between two particular states i and j, designated by directed arcs from state i to state j. The set of states and the set of possible transitions refer to the static aspect of a CBMG since they reflect the structure of the e-Commerce website and does not depend on the way e-Customers access and use it.

Figure 1. CBMG of a generic B2C e-Commerce website



The $N \times N$ transitional probability matrix $P = p[i, j] = p_{i \cdot j}$, whose elements are the probabilities of transiting from i to state j in one step, represents the dynamic aspect of a CBMG. In Figure 1, such probabilities, which denote, in fact, relative frequencies of invoking specific e-Commerce functions out of each e-Commerce function, are being designated in a form of labels $p_{i \cdot j}$, assigned to each directed arc between some pairs of states in the CBMG.

All e-Customers of a particular e-Commerce website share the same static aspect of the CBMG. However, different groups of e-Customers, who share a similar online shopping behavior, also known as e-Customer classes, can be mapped to a unique transitional probability matrix $P = p[i, j]$, which reflects their unique online shopping behavior. In other words, different classes of e-Customers may be characterized by different, yet corresponding CBMGs in terms of transitional probabilities (Figure 2).

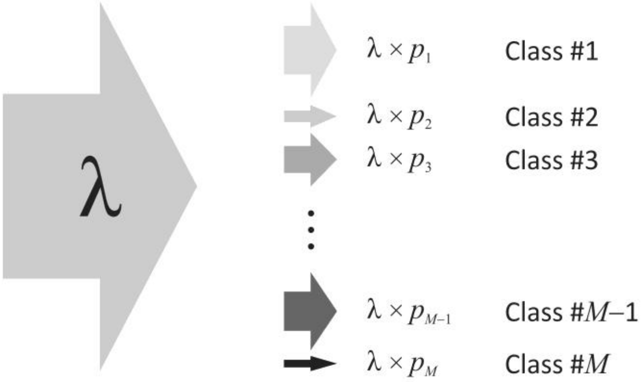
Nonetheless, since it is possible for the same e-Customer to exhibit a rather different type of online behavior during each visit to a particular e-Commerce website, it is more accurate to claim that a CBMG is, in fact, associated to a visit to that website and not necessarily to a specific e-Customer. Still, we assume that the same e-Customer exhibits identical or near-identical online shopping behavior during each visit to a particular e-Commerce website, which reflects his/her personality and attitudes.

Under the assumption that at each instance of time t, a total number of M classes of e-Customers are being identified, and p_k (k = 1, …, M) are the appearance probabilities of the k-th e-Customer class, such that $\sum_{k=1}^{M} p_k = 1$, then the overall arrival rate of the incoming e-Customers (e-Customers' HTTP requests) to a particular e-Commerce website, λ, can be broken down into particular arrival rates $\lambda \cdot p_k$ (k = 1, …, M) of each particular e-Customer class, i.e. $\lambda \cdot p_1$, $\lambda \cdot p_2$, …, $\lambda \cdot p_M$ (Figure 3). This conclusion is being drawn under an assumption that e-Customer HTTP request arrivals at the e-Commerce website follow the Poisson distribution, i.e. their inter-arrival times are exponentially distributed.

Figure 2. The N × N (N = 12) transitional probability matrix $P = p[i, j] = p_{i \cdot j}$, corresponding to the CBMG depicted in Figure 1

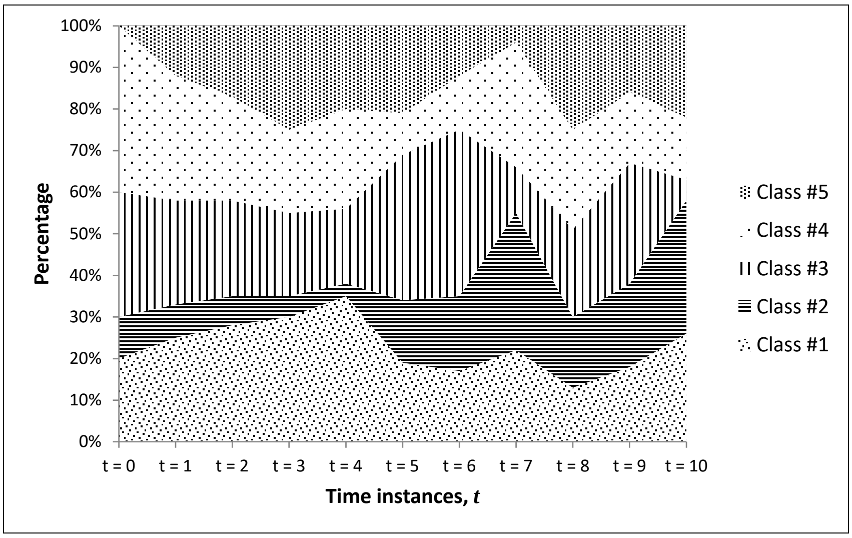
$$P = \begin{bmatrix}
0 & p_{E\cdot 1} & p_{E\cdot 2} & p_{E\cdot 3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & p_{1\cdot 2} & p_{1\cdot 3} & p_{1\cdot 4} & p_{1\cdot 5} & 0 & 0 & 0 & 0 & 0 & 0 & p_{1\cdot X} \\
0 & p_{2\cdot 1} & p_{2\cdot 2} & p_{2\cdot 3} & p_{2\cdot 4} & p_{2\cdot 5} & p_{2\cdot 6} & 0 & 0 & 0 & 0 & 0 & p_{2\cdot X} \\
0 & p_{3\cdot 1} & p_{3\cdot 2} & p_{3\cdot 3} & p_{3\cdot 4} & p_{3\cdot 5} & p_{3\cdot 6} & 0 & 0 & 0 & 0 & 0 & p_{3\cdot X} \\
0 & p_{4\cdot 1} & p_{4\cdot 2} & p_{4\cdot 3} & 0 & 0 & 0 & 0 & 0 & p_{4\cdot 9} & 0 & 0 & p_{4\cdot X} \\
0 & p_{5\cdot 1} & 0 & 0 & p_{5\cdot 4} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{5\cdot X} \\
0 & 0 & p_{6\cdot 2} & p_{6\cdot 3} & 0 & 0 & 0 & p_{6\cdot 7} & p_{6\cdot 8} & p_{6\cdot 9} & 0 & 0 & p_{6\cdot X} \\
0 & 0 & p_{7\cdot 2} & p_{7\cdot 3} & p_{7\cdot 4} & p_{7\cdot 5} & p_{7\cdot 6} & 0 & 0 & 0 & 0 & 0 & p_{7\cdot X} \\
0 & 0 & p_{8\cdot 2} & p_{8\cdot 3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{8\cdot X} \\
0 & 0 & p_{9\cdot 2} & p_{9\cdot 3} & p_{9\cdot 4} & p_{9\cdot 5} & p_{9\cdot 6} & 0 & 0 & 0 & p_{9\cdot 10} & p_{9\cdot 11} & p_{9\cdot X} \\
0 & 0 & p_{10\cdot 2} & p_{10\cdot 3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{10\cdot X} \\
0 & 0 & 0 & 0 & p_{11\cdot 4} & p_{11\cdot 5} & 0 & 0 & 0 & p_{11\cdot 9} & p_{11\cdot 10} & 0 & p_{11\cdot X} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

Figure 3. Schematic representation of the operating profile, comprised of M classes of e-Customers, along with their arrival intensities at a given instance of time



The row-vector $OP(t)=[p_1, p_2, ..., p_M]$, whose elements p_k (k = 1, ..., M), $\sum_{k=1}^{M} p_k = 1$, are the appearance probabilities of the k-th e-Customer class posed to a specific e-Commerce website at a time instance t, is known as an operating profile. Figure 4 illustrates the concept of e-Customer operating profiles. It is a 2D 100% Stacked Area graph, which emphasizes the trend in the proportion of each e-Customer class' probability of appearance over time.

Figure 4. An example portraying the dynamics of an arbitrary operating profile in time consisted of M = 5 e-Customer classes



Knowing the exact number of e-Customer classes for a particular e-Commerce website, M, along with their corresponding transitional probability matrices P_k (k = 1, ..., M), the arrival rate of e-Customers' HTTP requests, λ, and the operating profile $OP(t)$ at each time instance, defines completely the *operational environmen*t of that e-Commerce website. All of these are needed in the process of building a predictive model(s) that would support capacity planning activities vis-à-vis the proper dimensioning and configuring of a particular e-Commerce website.

5. SOME CLASSIFICATION ISSUES

In general, taxonomy is the practice and science of classification/categorization of things or concepts, including the principles that underlie such classification. It is the process in which ideas and objects are recognized, differentiated, and understood (Cohen & Lefebvre, 2005).

Classification and categorization are synonyms; both terms imply that objects of interest are grouped into classes/categories, usually for some specific purpose.

According to the classical view, categories are discrete entities characterized by a set of properties which are shared by their members. Categories should be *clearly defined*, *mutually exclusive* and *collectively exhaustive*. This way, any entity of the given classification universe belongs unequivocally to one, and only one, of the proposed categories.

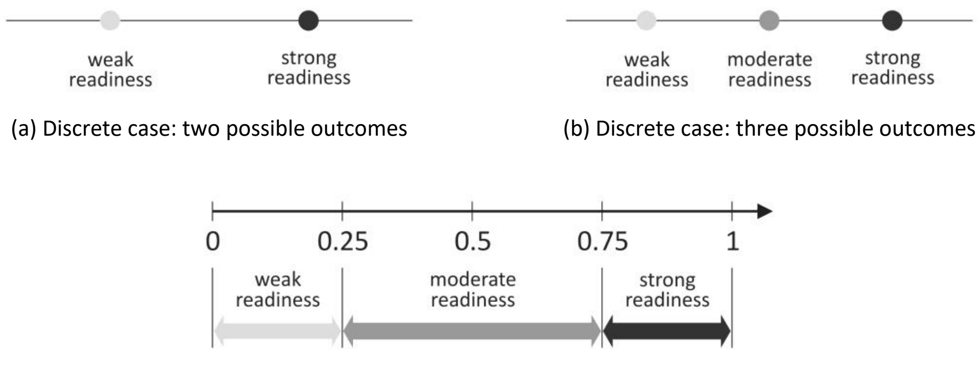
The term '*clear definition*' refers to the sound specification of the property (dimension, criterion or factor) the categorization is made upon. Such specification usually includes some gradation levels, which can be achieved either by specifying categories (e.g. low – medium - high) in a discrete case or by specifying probability ranges (e.g. [0.0, 0.5), [0.5, 1.0]) in a continuous case.

Two events (or propositions) are said to be '*mutually exclusive*' or '*disjoint*' if they cannot both happen or be true at the same time.

A set of events (or propositions) is supposed to be '*jointly*' or '*collectively exhaustive*' if at least one of the events must occur at any time because such set encompasses the entire range of possible outcomes.

For instance, let's consider a single property related to the e-Customers' online behavior: the willingness (i.e. readiness) of making an online purchase. We could distinguish among two possible outcomes, e.g. weak readiness and strong readiness, to distinguish between hesitancy, indifference, reluctance, or uncertainty, and eagerness, speediness, enthusiasm, or promptness, respectively (Figure 6a). Alternatively, we could expand this state-space by including additional outcome: medium readiness (Figure 6b). This criterion can be treated either in a discrete state-space (Figure 6a, 6b) or in a continuous state-space (Figure 6c). In the latter case, it is necessary, as an example, to break down the continuous segment [0, 1], which resembles the entire probability space [0, 1], into three disjoint continuous sub-segments, e.g. [0, 0.25), [0.25, 0.75), and [0.75, 1].

Figure 6. Graphical representation of the property 'the willingness (readiness) of making an online purchase'



(a) Discrete case: two possible outcomes

(b) Discrete case: three possible outcomes

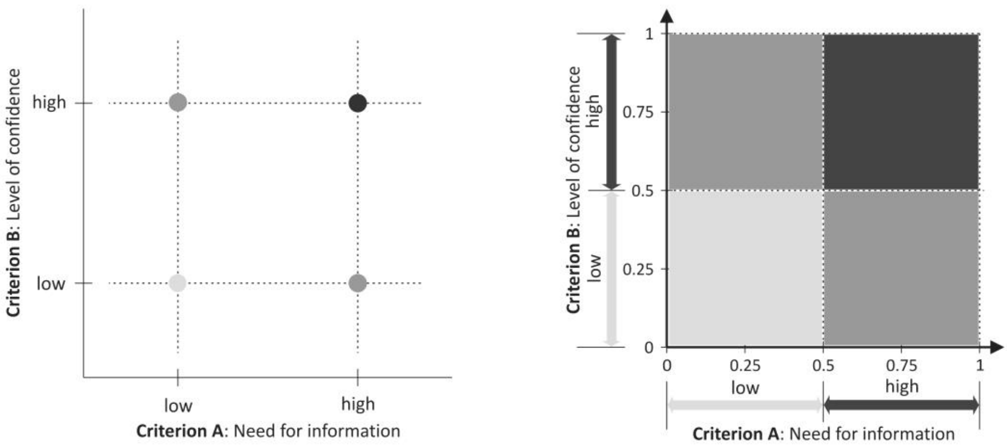
(c) Continuous case: three possible outcomes

In this view, all e-Customers could be classified according to this particular criterion as those who exhibit weak, moderate, or strong readiness to make an online purchase.

Taking into account additional criterion, which is described by its own specific state-space, would enrich the set of possible outcomes, and consequently, the classification. For instance, let's assume that the properties 'level of confidence' vis-à-vis online shopping security aspects, and the 'need for information' about products, both have identical state-spaces, described by the set {low, high}. The Cartesian product of these two sets leads towards a classification comprised of four distinct types of e-Customers, described as {(low level of confidence, low need for information), (low level of confidence, high need for information)}, (high level of confidence, low need for information), (high level of confidence, high need for information)}, depicted in Figure 7.

Including a third, fourth, fifth etc. dimension would make the e-Customer classification more subtle. For instance, let's take into account the following three criteria: the 'level of curiosity' of e-Customer to look around the virtual shop, the 'level of determination' to buy online, and the 'level of trendiness' to buy novel products, all exhibited by a particular e-Customer. Let's assume that each of these criteria has a state-space including three outcomes, e.g. {low, medium, high}. The resulting classification would, therefore, enumerate theoretically a total of $3 \times 3 \times 3 = 27$ different e-Customer types (Figure 8).

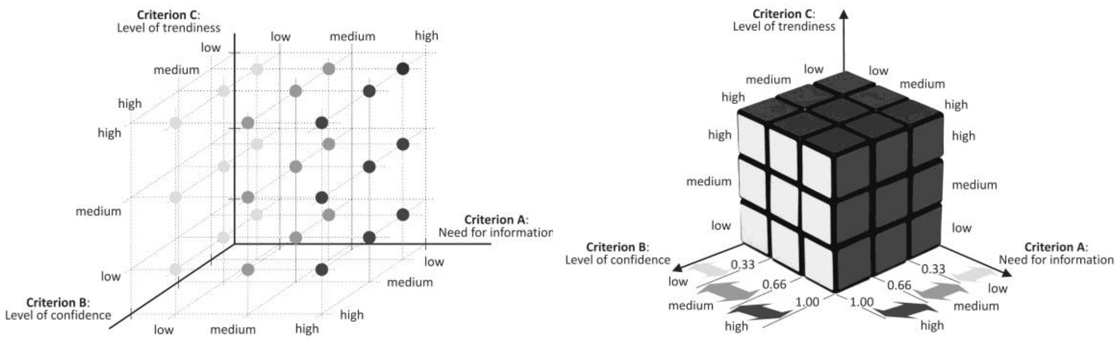
Figure 7. Graphical representation of the classification of e-Customers, based on two properties: the 'need for information' and the 'level of confidence', each with two possible outcomes



(a) Discrete case: four possible outcomes

(b) Continuous case: four possible outcomes

Figure 8. Graphical representation of the classification of e-Customers, based on three properties: the 'level of curiosity', the 'level of determination', and the 'level of trendiness', each with three possible outcomes



(a) Discrete case: 27 possible outcomes

(b) Continuous case: 27 possible outcomes

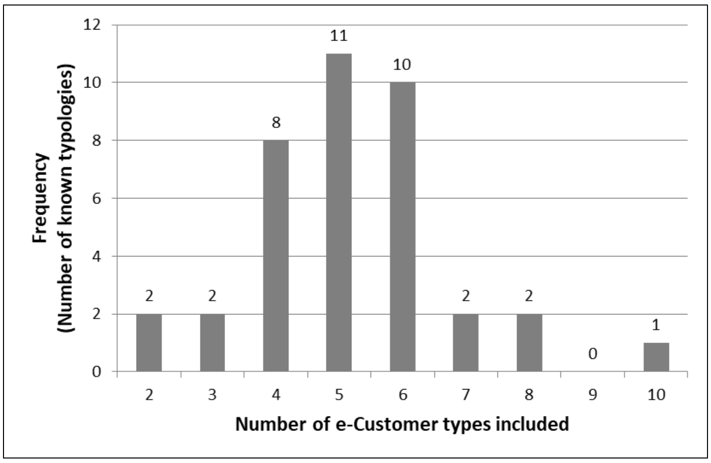
The inclusion of a fourth, fifth etc. criterion, which cannot be portrayed graphically due to obvious reasons, would certainly enlarge the set of possible outcomes. However, in practice, this is not the way things work. The main reason is the human's inability to cope successfully with such enormous outcomes, i.e. e-Customer classes. As a result, all known e-Customer taxonomies and typologies are partially complete, thus incorrectly defined. This finding is elaborated in more detail in the next section.

6. QUALITATIVE ANALYSIS OF SOME EXISTING TYPOLOGIES OF E-CUSTOMERS

We already pointed out that e-Marketers and e-Retailers are especially interested in the categorization of e-Customers because they are trying to convert the visitors to their e-Commerce websites into loyal buyers by understanding the characteristics of the possible types of e-Customers and the ways of how each of them typically engages online. A recent research made by the authors of this paper has confirmed the existence of at least 38 typologies of e-Customers, described by the following statistics (Figure 9):

- There are eleven typologies that include five e-Customer types;
- Six e-Customer types are recognized by ten typologies;
- Four e-Customer types are representing the basis of eight typologies;
- Two, three, seven, and eight e-Customer types have been taken into account by two typologies each;
- There is only one typology that is based on the inclusion of ten e-Customer types;
- There are no typologies that include nine e-Customer types.

Figure 9. An overview of the number of existing e-Customer typologies vis-à-vis the number of e-Customer types included



In the subsequent sections, we provide a short description of a small subset of the existing e-Customer typologies that include two, three, and four e-Customer types (a total of 12 typologies), with a single aim to analyze the underlying criteria that have led to such categorizations. In addition, we tag each identified criterion either as an endogenous (internal) or as an exogenous (external). Exogenous criteria are related to e-Customer's behavior outside the virtual store; these include all kinds of demographic, socio-economic, and psychographic factors that could possibly foster the e-Customer to decide to shop online. Endogenous criteria, on the other hand, are related to e-Customer's behavior during the online shopping process; as such, these include all factors that could possibly be mapped directly to one or more transitional probabilities found within the corresponding CBMG.

6.1 Two types of e-Customers

Rains (n.d.) and Menascé & Almeida (2000, p. 48) propose typologies of e-Customers based on the existence of just two types/classes of e-Customers. Rains distinguishes between 'Determined-to-Buy' customers and 'Just-Browsing' customers, whilst Menascé & Almeida make a clear distinction between two profiles of e-Customers: 'Occasional' buyers and 'Heavy' buyers (Table 1).

Table 1 – E-Customer types proposed by typologies including two classes

e-Customer type	Source	Description
'Determined-to-Buy' 'Heavy' buyers	Rains (n.d.) Menascé & Almeida (2000)	This type of e-Customers enters a store knowing exactly what they are looking for and what they are going to buy. Such e-Customers have a higher probability of buying via Web. (there is *e-Customers' determination to buy online; high probability of buying online*)
'Just-Browsing' 'Occasional' buyers	Rains (n.d.) Menascé & Almeida (2000)	This type of e-Customers is just browsing and has less intention of buying any products. Such e-Customers use virtual stores to find out information about existing products but are not likely to buy anything most of the time. (there is *no e-Customers' determination to buy online; low probability of buying online*)

Both typologies are based on a single criterion: the *e-Customer's determination (i.e. intention)* to buy a specific product online, in a way that both of them propose two distinctive e-Customer types, based on the two opposite values of the same criterion (exist – do not exist). The higher the level of determination, the higher is the probability of buying online, and vice-versa. Because *e-Customer's determination (i.e. intention)* and *e-Customer's non-determination* can be directly mapped to the probabilities of invoking e-Commerce functions like BUY_NOW and PAY/CHECKOUT within the CBMG, they both can be tagged as endogenous factors, since they are directly related to the behavior of e-Customers during online shopping sessions.

6.2 Three types of e-Customers

Quarters (n.d.) reports about three types of e-Customers, including 'Information Gatherers', 'Evaluators', and 'Committed Buyers', whilst Hernández-Ortega *et al*. (2008) consider it necessary to differentiate at least three types of e-Customers: 'Potential', 'New' and 'Experienced' ones (Table 2).

Table 2 – E-Customer types proposed by typologies including three classes

e-Customer type	Source	Description
'Information Gatherers'	Quarters (n.d.)	'Information gatherers' use the Internet to learn more about the product or service they are considering, still not being ready to buy. (*lower readiness to make an online purchase*)
'Evaluators'	Quarters (n.d.)	'Evaluators' know what they want and have already made the decision to buy a certain type of product, but they have not decided yet which model or brand is best, nor where to buy it from. (*moderate readiness to make an online purchase*)
'Committed Buyers'	Quarters (n.d.)	'Committed Buyers' have already made the decision to buy an exact product and are ready to make a purchase. (*higher readiness to make an online purchase*)
'Potential'	Hernández-Ortega *et al.* (2008)	'Potential' e-Customers are thinking about making their first purchase. (*no purchasing experience*)
'New'	Hernández-Ortega *et al.* (2008)	'New' e-Customers have made only a few purchases. (*some purchasing experience*)
'Experienced'	Hernández-Ortega *et al.* (2008)	'Experienced' ones have carried out a high number of purchases. (*big purchasing experience*)

The typology proposed by Quarters (n.d.) is being purely based on the *e-Customers' readiness* (low – moderate – high) to make an online purchase. This exogenous factor can be related to the *quantum/quality of information acquired* about a specific product, because it seems that the more information is available to the e-Customer or the higher is the quality of the information available to the e-Customer, the higher is their *readiness to make an online purchase* and, consequently, the higher is the probability that he/she is going to decide to make an online purchase, and vice-versa.

On the other hand, the typology proposed by Hernández-Ortega *et al*. (2008) is based on e-Customers' *purchasing experience* (no – some – big). The purchasing experience belongs to the group of exogenous factors since it is related to the number of sessions that ended with an online purchase, and thus gives no evidence about expected e-Customers' behavior during online shopping sessions.

6.3 Four types of e-Customers

Rohm & Swaminathan (2004) identify the existence of four types of e-Customers, including 'Convenience shoppers', 'Variety seekers', 'Balanced buyers', and 'Store-oriented shoppers', based on various *e-Customer's preferences* (Table 3). This is very unusual typology because the first three e-Customer types are introduced based on two sub-factors, including the *convenience* and the *variety*, i.e. {(the focus on the convenience), (the focus on variety), (the focus on both convenience and variety)}. The fourth e-Customer type is based on a totally different factor: e-Customer's preference of 'brick-and-mortar' physical stores over 'click-and-order' virtual stores. Because none of the aforementioned e-Customer types is based on their online shopping behavior, *various e-Customer preferences*, as a factor, belongs to the group of exogenous factors.

Delk (2012) introduces typology consisted of four distinctive e-Customers: 'The Seeker', 'The Researcher', 'The Bargain Hunter', and 'The Window Shopper'. 'The Seeker' e-Customer type is being defined on the basis of their high *readiness to make an online purchase*, which could easily result in a high probability of making an online purchase, but is not directly associated to any transitional probability within the CBMG. 'The Researcher' e-Customer type is based on the *browsing/searching intensity*, i.e. the higher probabilities of invoking BROWSE and/or SEARCH e-Commerce functions repetitively. 'The Bargain Hunter' is being introduced based on the *e-Customer's personality*, i.e. e-Customer's tendency towards *looking for lower prices of products*. 'The Window Shopper' is being identified based on the *e-Customer's browsing behavior*, i.e. the high probability of invoking the BROWSE e-Commerce function in conjunction with the extremely low *probability of buying*. Therefore, out of all these factors, the *e-Customer's readiness to make an online purchase* and the *e-Customer's personality*, i.e. his/her tendency towards *looking for lower prices of products* belongs to the group of exogenous factors, whilst the other three are endogenous factors.

According to De Datta (2012), the four different e-Commerce types are 'Window Shoppers', 'Hunters', 'Gardeners', and 'Gatherers'. 'Windows Shoppers' are based on the *e-Customer's browsing behavior*, whilst 'Hunters' are identified on a basis of their predominant *searching behavior*. 'Gardeners' are identified because of their ongoing *level of engagement* in cultivating tastes and brands. 'Gatherers' are identified on the basis of their *personality*, i.e. e-Customer's tendency towards *looking for lower prices of products*. Since both *e-Customer browsing* and *searching behavior* can be directly mapped into the CBMG, they belong to endogenous factors. The other two factors are exogenous.

Table 3 – E-Customer types proposed by typologies including four classes

e-Customer type	Source	Description
'Convenience Shoppers' 'Convenience Oriented'	Rohm & Swaminathan (2004) FuturePay.com (2015)	'Convenience Shoppers' are more motivated by convenience. (*type of motivation: convenience/variety*) 'Convenience Oriented Shoppers' prefer online shopping for its convenience; this customer type is focused on quick-payment systems, doesn't like filling out forms and prefer value fast checkouts; shopping needs to be quick, easy and convenient. (*level of convenience*)
'Variety Seekers'	Rohm & Swaminathan (2004)	The 'Variety Seekers' are substantially more motivated by variety seeking across retail alternatives and product types and brands than any other shopping type. (*type of motivation: convenience/variety*)
'Balanced Buyers'	Rohm & Swaminathan (2004)	'Balanced Buyers' are moderately motivated by convenience and variety seeking. (*type of motivation: convenience/variety*)
'Store-oriented shoppers'	Rohm & Swaminathan (2004)	The 'Store-oriented shoppers' are more motivated by physical store orientation (e.g., the desire for immediate possession of goods and social interaction). (*type of motivation: 'brick-and-mortar' oriented/'click-and-order' oriented*)
'The Seeker' 'Surgical Shoppers' 'Ready-to-Buys'	Delk (2012) Lee (2014) Davis (2015)	'The Seekers' are on a quest for one specific product; they know exactly what they want, and they're ready to make a purchase. 'Surgical Shoppers' know exactly what they want before logging online and only purchase that item. Typically they know the criteria on which they will base their decision, seek information to match against that criteria, and purchase when they are confident they have found

		exactly the right product. 'Ready-to-Buys' are e-Customers who are ready to buy. They have already added items to the shopping cart, or have once started the checkout process, but have suddenly quit it, with a high probability of buying. (*readiness to make an online purchase*)
'The Researcher' 'Researchers'	Delk (2012) Davis (2015)	'The Researchers' also have a specific goal in mind, but not a specific product; they are browsing/searching the website intensively. 'Researchers' usually browse within a single category, also without any intention to make a purchase. (*browsing/searching intensity*)
'The Bargain Hunter' 'Gatherers' 'Bargain Shoppers' 'Price Sensitives'	Delk (2012) De Datta (2012) Lee (2014) Davis (2015)	'The Bargain Hunters' are looking for bargains, deals, daily specials, coupon codes and discounts, holiday sales, seasonal promotions, limited time offers, or free shipping. 'Gatherers' are looking for time-sensitive deals or compelling special offers; they do not browse or search for products. 'Bargain Shoppers' use comparison shopping tools extensively; sporting no brand loyalty, these shoppers are just looking for the lowest price. 'Price Sensitives' usually visit sale categories, sorting the products by price from low to high; if the lowest price is within their expectations, they will possibly make a purchase. (*price of products*)
'The Window Shopper' 'Window Shoppers' 'Just-Browsers'	Delk (2012) De Datta (2012) Davis (2015)	'Window shoppers' or 'wanderers' don't have any specific product or even a goal in mind; they have no clear intention to buy online. 'Just-Browsers' make frequent visits to e-Commerce websites, and browse for multiple categories of products/services, especially the 'New products' category, without any intention to make a purchase. (*browsing behavior*)
'Hunters'	De Datta (2012)	'Hunters'' intent to buy a specific product is quite clear, but their patience is limited, so the search is their go-to shopping tool; they practice a 'caveman-style' during online shopping, i.e. they know what they need and they know it when they see it. (*searching behavior*)
'Gardeners'	De Datta (2012)	These e-Shoppers cultivate their tastes and the brands they favor with ongoing engagement. (*level of engagement*)
'Service Demanders'	Shah & Kumar (2012); Mallikarjunan (2013)	'Service Demanders' overuse customer service channels such as phone support or web support; the more products they buy, the greater is the load on e-Commerce website customer service channels; their customer service interactions are excessive or abusive. (*e-Customer value*)
'Revenue Reversers'	Shah & Kumar (2012); Mallikarjunan (2013)	'Revenue Reversers' frequently 'reverse' the revenue flow, usually in the form of returns on purchases. (*e-Customer value*)
'Promotion Maximizers'	Shah & Kumar (2012); Mallikarjunan (2013)	'Promotion Maximizers' may result from customers who visited an e-Commerce website and then used a search engine to find a coupon or promotion provider. (*e-Customer value*)
'Spending Limiters'	Shah & Kumar (2012); Mallikarjunan (2013)	'Spending Limiters' have small, fixed budgets for what they're going to spend with an e-Commerce company over a given time period. (*e-Customer value*)
'Enthusiast Shoppers'	Lee (2014)	'Enthusiast shoppers' use shopping as a form of recreation. They purchase frequently and are the most adventurous shoppers. (*frequency of online shopping*)

'Power Shoppers'	Lee (2014)	'Power shoppers' shop out of necessity, rather than as a form of recreation. They develop sophisticated shopping strategies to find what they want and do not want to waste time looking around. (*frequency of online shopping*)
'Security Oriented'	FuturePay.com (2015)	'Security Oriented Shoppers' prefer not to give out their credit card information online; security and safety are essential to these customers, who prefer to buy only from trusted e-Commerce websites. (*level of security*)
'Fiscally Responsible'	FuturePay.com (2015)	'Fiscally Responsible Shoppers' keep their finances simple, straightforward and organized; they are not impulsive shoppers; they can be enticed with promotions, best-priced options and value. (*level of responsibility*)
'Secret Shoppers'	FuturePay.com (2015)	Privacy and confidentiality is the key to getting 'Secret Shoppers' type to complete the purchase; their online shopping habits are secret and need measures in place to prevent others from discovering their purchase path; these customers want to protect their privacy by using payment options that don't require credit cards such as e-gift cards, "buy now, pay later" options or pre-paid credit cards. (*payment secrecy; level of privacy and confidentiality*)
'Potential Customers'	FATbit.com (n.d.)	'Potential Customers' have a high probability of bringing revenue and adding value to an online business; they are e-Customers who have not made any single purchase from a given Web store yet. (*frequency of buying = 0; high probability of buying*)
'New Customers'	FATbit.com (n.d.)	'New Customers' are mostly the ones who were converted from potential ones, i.e. they are 'Potential Customers' who just happened to use a given website for shopping once or twice. (*frequency of buying = several times*)
'Loyal Customers'	FATbit.com (n.d.)	'Loyal Customers' are the people who keep coming back to the same website to buy anything and everything they want. (*frequency of buying = many times*)
'Lost Customers'	FATbit.com (n.d.)	'Lost Customers' comprise the user group that e-Commerce businesses lost because either they couldn't convert, couldn't offer a good user experience consistently, or simply because some other e-Business gave them better deals and offers. (*frequency of buying = 0; low probability of buying*)

Shah & Kumar (2012) and consequently Mallikarjunan (2013) introduce 'Service Demanders', 'Revenue Reversers', 'Promotion Maximizers', and 'Spending Limiters'. All of these e-Customer types are based on *e-Businesses' perception of how much are they valuable over time*, a criterion that belongs to the group of exogenous factors.

Lee (2014) speaks about 'Bargain Shoppers', 'Surgical Shoppers', 'Enthusiast Shoppers', and 'Power Shoppers'. 'Bargain Shoppers' are identified on the basis of their *personality*, i.e. e-Customer's tendency towards *looking for lower prices of products*. 'Surgical Shoppers' are identified because of their *readiness to make an online purchase*. 'Enthusiast Shoppers' and 'Power Shoppers' are being introduced based on their high and low *frequency of online shopping*, respectively. All of these identified criteria belong to the group of exogenous factors.

According to Davis (2015), the four types of e-Customers are 'Just-Browsers', 'Researchers', 'Price Sensitives', and 'Ready-to-Buys'. This typology is an example of mixed approaches, too:

the first two categories are introduced based on *e-Customer's browsing behavior* and *browsing/searching intensity*, respectively. 'Price Sensitives' are based on their *personality*, i.e. e-Customer's *sensitiveness on product prices*. 'Ready-to-Buys' are being identified on a basis on their *readiness to make an online purchase*. Out of these, only the *sensitiveness on product prices* and *readiness to make an online purchase* can be considered exogenous factors, whilst the rest are all endogenous ones.

FuturePay.com (2015) introduces a typology based on the existence of four e-Customer types, including: 'Convenience Oriented Shoppers', 'Security Oriented Shoppers', 'Fiscally Responsible Shoppers', and 'Secret Shoppers'. 'Convenience Oriented Shoppers' are being identified based on the *level of convenience* offered by particular e-Commerce websites. 'Security Oriented Shoppers' are being identified on the basis of the *level of security* offered by particular e-Commerce websites. 'Fiscally Responsible Shoppers' are based on their own *level of responsibility* vis-à-vis their finances. 'Secret Shoppers' are introduced taking into account the *payment secrecy*, i.e. *the level of privacy and confidentiality* offered by the particular e-Commerce website. Because none of these factors can be mapped directly into corresponding probabilities within the CBMG, all of these belong to the group of exogenous factors.

FATbit.com (n.d.) also reports about four distinctive e-Customer types, including 'Potential Customers', 'New Customers', 'Loyal Customers', and 'Lost Customers'. This typology is built on the e-Customer's current status vis-à-vis the *frequency* how often have they visited and bought from a given e-Commerce website (e.g. 'Potential Customers' and 'Lost Customers' score for 0, 'New Customers' score for several times, and 'Loyal Customers' score for many times). Because the factor *frequency of buying online* has nothing to do with the e-Customer's actual online shopping behavior, it belongs to the group of exogenous factors.

7. CONCLUSION

Classifying e-Customers of a given B2C e-Commerce website into typologies (from a marketing point of view) and taxonomies (from an engineering point of view) becomes a crucial task nowadays. The first approach aims at identifying buyer personas in order to widen the population of current and prospective buyers, to increase the volume of online purchases and to make a profit. The second approach aims at building CBMGs for each identified e-Customer class based on their online shopping behavior in virtual stores. This significantly helps in building predictive models that can be used for capacity planning activities regarding the e-Commerce website hardware infrastructure, with a single aim to prevent bottlenecks and guarantee the preset QoS levels.

During the analysis of 12 existing e-Customer typologies, which included two, three, and four e-Customer types, we succeeded to identify 18 different factors/criteria that were used by their creators to specify various e-Customer types. Out of these, only 4 factors can be considered endogenous, since they can be directly mapped into corresponding transitional probabilities within the CBMG. These include e-Customer's determination/non-determination to buy online, e-Customer's browsing/searching intensity, e-Customer's browsing behavior, and e-Customer's searching behavior. The majority of factors (14 in total) belong to the group of exogenous factors since they reflect specific aspects of e-Customer's behavior outside the virtual store or even some aspects that are indirectly related to e-Customers. These are: the e-Customer's readiness to make an online purchase, e-Customer's purchasing experience, e-Customer's preferences regarding the convenience and variety of products offered online, e-Customer's preferences regarding the choice of the type of store to buy from ('brick-and-mortar' vs 'click-and-order'), e-Customer's personality vis-à-vis their tendency towards looking for lower prices, e-Customer's level of engagement with online shopping, e-Businesses' perception of e-Customer's value over time, e-Customer's frequency of online shopping, e-Customer's level of sensitiveness on product prices, e-Customer's frequency of buying online, the level of convenience offered by virtual stores, the level of security offered by virtual stores, the level of e-Customer's responsibility, and the level of privacy and confidentiality offered by virtual stores.

In general, the following findings have been drawn from the analysis of 12 existing e-Customer typologies, which included two, three, and four e-Customer types:

(1) Almost all analyzed e-Customer typologies are based on at least two factors/criteria of categorization;

(2) Multiple/different sources/authors refer to the same e-Customer types by using different naming;

(3) Certain distinctive e-Customer types that belong to the same typology are simply built on the two opposite poles, i.e. extreme values, of the same criterion/factor;

(4) Some e-Customer typologies are based on two or more distinct criteria/factors that do not only include any gradation levels (at least two) but also are not mutually matched via a Cartesian product, i.e. *N* different e-Customer types are based on *N* different criteria/factors;

(5) A relatively small number of the identified criteria (4 out of 18) can be mapped directly into the corresponding CBMG as particular values of some transient probabilities;

These findings suggest that the principles of the classical categorization, i.e. the requirements that categories should be clearly defined, mutually exclusive and collectively exhaustive, are not met. Instead, the vast majority of existing e-Customer typologies is based on the inclusion of two or more criteria and/or criteria that do not include any gradation levels. This way, such classifications leave enough space every e-Customer to be classified into several e-Customer types at the same time, which introduces ambiguity and fuzziness. Because e-Customers may belong to one or more classes simultaneously, in varying degrees of fitness/membership, contemporary e-Customer typologies can be seen as a form of some kind of *conceptual clustering*, which is a modern variation of the classical approach that derives itself from the attempts to explain how knowledge about particular e-Customer classes is represented. According to this approach, classes are generated by first formulating their conceptual descriptions and then classifying the entities according to the descriptions.

From the engineering point of view, the key challenge remains to be the answers to the following questions: (1) Can existing e-Customer typologies be mapped into corresponding taxonomies (CBMGs) in an efficient and consistent way? (2) If yes, are such mappings going to result in unique sets of CBMGs, specific to each identified e-Customer class within particular e-Customer taxonomies? These two questions are in line with another important consideration that has to be taken into account. Because the identified endogenous factors are related solely to particular transitional probabilities within the CBMG, whilst many, not just one e-Customer type, are based on a specific endogenous factor, it turns out that the same specific range of values for a given transitional probability will be used to define many different e-Customer online shopping behaviors. In order to map a specific e-Customer type behavior to a specific CBMG in a unique and consistent manner (1:1), it is of an utmost importance to find a way to map a specific e-Customer type behavior into whole sequences of invoked e-Customer functions within the CBMG, along with the corresponding probabilities of invoking such sequences. This, however, implies widening the descriptions of e-Customer types by including much more information about their specific behavior during the online shopping process.

Future work is going to be related to an identical analysis of e-Customer typologies that include five or more e-Customer classes, in order to identify additional endogenous and exogenous factors/criteria. Such analysis can contribute to the clarification, modeling, and specification of e-Customer taxonomies and corresponding operating profiles, which make the basis for building up predictive models suitable for evaluating performability measures.

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