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Leveraging Market Research Techniques in IS: A Review and Framework of Conjoint Analysis Studies in the IS Discipline

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Abstract:

With cloud and mobile computing, information systems (IS) have evolved towards mass-market services. While IS success requires user involvement, the IS discipline lacks methods that allow organizations to integrate the “voice of the customer” into mass-market services with individual and dispersed users. Conjoint analysis (CA), from marketing research, provides insights into user preferences and measures user trade-offs for multiple product features simultaneously. While CA has gained popularity in the IS domain, existing studies have mostly been one-time efforts, which has resulted in little knowledge accumulation about CA’s applications in IS. We argue that CA could have a significant impact on IS research (and practice) if this method was further developed and adopted for IS application areas. From reviewing 70 CA studies published between 1999 and 2019 in the IS discipline, we found that CA supports in initially conceptualizing, iteratively designing, and evaluating IS and their business models. We critically assess the methodological choices along the CA procedure to provide recommendations and guidance on “how” to leverage CA techniques in future IS research. We then synthesize our findings into a framework for conjoint analysis studies in IS that outlines “where” researchers and practitioners can apply CA along the IS lifecycle.

Keywords: Conjoint Analysis, Literature Review, Information Systems, IS Design, IS Evaluation.

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1 Introduction

With advances in technology, such as smartphones, the cloud, and the Internet of things (IoT), information systems (IS) have evolved to target a mass market of distributed and heterogeneous users. This evolution poses several challenges for organizations that want to integrate the "voice of the customer" into their products and services, the main criterion for ensuring customer acceptance (Jarke, Loucopoulos, Lyytinen, Mylopoulos, & Robinson, 2011; Tuunanen, Myers, & Cassab, 2010). IS studies have shown that IT products fail primarily because they do not meet users' expectations or are dysfunctional (Dwivedi et al., 2015). Therefore, understanding user requirements and involving users is considered "common wisdom" for IS success (Bano & Zowghi, 2014). Traditionally, user-oriented IS design relies on requirements-elicitation techniques that collect data from individual or group users via interviews, surveys, focus groups, or ethnographic techniques (Nuseibeh & Easterbrook, 2000). However, these techniques require close interactions with users or their representatives, which makes them difficult to apply in the mass-market IS context with individual and dispersed users. Moreover, these techniques depend critically on participant selection, which can bias the requirements that one elicits and prioritizes.

Market research techniques and specifically conjoint analysis (CA) represent promising approaches to address these issues and to support user-oriented IS design. As "a practical set of methods for predicting consumer preferences for multi-attribute options in a wide variety of product and service contexts" (Green & Srinivasan, 1978), CA adds quantitative measurement and allows one to analyze user trade-offs in selecting products and services. Accordingly, marketing research has argued that CA leads to more successful technical product designs (Green, Krieger, & Wind, 2001). In the IS domain, Bajaj (1999) first advocated the CA methodology for studying human behavior in assessing IS, specifically in IS purchase and adoption decisions. Following Bajaj's (1999) CA study procedure guide, IS researchers began applying CA to study users' adoption decisions and preference structures in various domains, such as e-commerce (Schaupp & Bélanger, 2005), enterprise resource planning (ERP) packages (Keil & Tiwana, 2006), and mobile applications (Bouwman, Haaker, & de Vos, 2008). CA offers an important advantage over other methods in that it uncovers how users make trade-offs between functional, non-functional and economic features. This advantage has motivated IS researchers to employ CA to study business model design for cloud services (Giessmann & Stanoevska, 2012) and privacy trade-offs in social networks (Krasnova, Hildebrand, & Guenther (2009), online data-sharing platforms (Schomakers, Lidynia, & Ziefle, 2019; Wessels, Gerlach, & Wagner, 2019) and IoT-based assistants (Mihale-Wilson, Zibuschka, & Hinz, 2017; Mikusz & Herter, 2016; Zibuschka, Nofer, Zimmermann, & Hinz, 2019). These studies illustrate how to empirically assess (existing or planned) IS in the form of a user preference model and how to use these data-driven insights to define design and pricing strategies that meet specific user profiles' or segments' needs.

Although the number of CA studies in the IS domain has risen over the past few years, the method remains a marketing research feature. Existing studies have demonstrated CA's value in the IS domain, but they have mostly been one-time efforts, and we have observed no cumulative research patterns to date. This observation raises three fundamental questions. First, existing studies have used CA for various applications and purposes (Bajaj, 2000; Schaupp & Bélanger, 2005; Krasnova et al., 2009) but they have not gone further and analyzed its relevance and role in IS. As a result, IS research and practice might miss opportunities to use the method as an aid in user-oriented design efforts due to the lack of knowledge about its applications. Second, researchers have largely conducted their studies independently and scarcely reused findings, which has resulted in little knowledge accumulation about CA's applications in IS. In fact, as a de-compositional method, CA views a system as a set of attributes and levels that correspond to relevant system features. Existing studies have not discussed the critical decisions in selecting attributes and levels, and we have not observed work that has reused previous research results in setting up CA or analyzing data. Third, IS researchers have not used CA to its full extent and potential. Most IS studies have applied the traditional techniques relative importance and willingness to pay. They have not embraced the more sophisticated techniques for simulation and variation analysis that the marketing discipline has developed and discussed. To summarize, we observe that the IS discipline has missed an opportunity to use CA to complement existing methods for designing and evaluating systems and lack general guidelines and recommendations for applying CA. Accordingly, we address the following research questions (RQs):

RQ1: What is the current state of CA in the IS discipline?

RQ2: What guidelines should future IS studies that apply conjoint analysis follow?

We argue that the CA method can have several positive outcomes if applied to IS research and practice as a data-driven approach for user-oriented IS design. With this paper, we lay the foundation for future research by analyzing the current state of CA applications in the IS domain and proposing a framework for future studies. Thus, we make three contributions. First, we comprehensively analyze 70 CA studies in the IS discipline published between 1999 and 2019. With this exhaustive descriptive review, we identify "interpretable patterns" or "trends" with respect to a pre-existing method (i.e., CA) in a body of empirical studies (Paré, Trudel, Jaana, & Kitsiou, 2015). Second, our study includes critical review elements (Paré et al., 2015) in that we assess CA applications in the IS discipline from a methodological and domain-specific perspective. By providing a critical account of this method from market research in the IS discipline, we identify recurring issues and develop recommendations as methodological support for IS-specific applications of CA. Third, based on our review, we develop a framework that supports IS researchers and practitioners in developing future CA studies. Since CA has multiple implementation scenarios, the framework identifies typical application areas (i.e., concrete situations where CA can be applied in different phases of the IS lifecycle). This framework highlights application areas where CA can complement existing IS methods by providing data-driven insights into user preferences that inform the initial conceptualization, iterative design, and evaluation of IS and their business models. Practitioners may also find our results relevant in that they can apply our recommendations in the defined IS lifecycle phases for designing high-utility systems and services.

This paper proceeds as follows: In Section 2, we review CA's foundations and evolution over time. In Section 3, we present the research approach we followed to conduct our literature review. In Section 4, we overview the 70 CA studies in the IS discipline. In Section 5, we summarize our findings along the analysis framework with a critical assessment and methodological recommendations. In Section 6, we present the reference framework for CA applications in IS. Finally, in Section 7, we summarize our findings, discuss the study's limitations and future research opportunities, and conclude the paper.

2 Conjoint Analysis

2.1 Foundations

Conjoint analysis has its foundations in Green and Rao's (1971) work in which they advocated for using conjoint measurement in consumer-oriented marketing research. As a concept from mathematical psychology that Luce and Tukey (1964) established, conjoint measurement measures "the joint effects of a set of independent variables on the ordering of a dependent variable" (Green & Rao, 1971). CA allows one to explore consumers' preferences by studying how people value product attributes and attribute levels while considered jointly (in combinations) during their evaluation. CA derives a utility function from how consumers evaluate product attributes and levels (Green & Srinivasan, 1978). One can translate this utility function into a preference structure, which provides information on the factors that most influence a consumer's decision or product choice. The preference structure not only provides importance measures but also depicts how differing levels in an attribute influence how an overall preference forms (utility value) (Hair, Black, & Babin, & Anderson, 2010). Accordingly, researchers have found CA to suit problems in marketing as an approach to quantify judgmental data related to product purchasing. Over time, CA has gained broad popularity in consumer research and spread to applied psychology, decision theory, and economics.

In general, one can summarize a CA study as containing three main phases (see Figure 1). In the first phase, one defines a product in terms of attributes and attribute levels to derive product profiles. In the second phase, consumers evaluate the different profiles in a survey setting. Based on the results, one can calculate a preference structure based on estimating utilities. Finally, in the third phase, one can use the utilities in applying different analysis techniques (Green & Rao, 1971; Johnson, 1974) to create data-driven insights on product design. Such techniques include:

1) **Relative importance** of attributes and levels used for various purposes such as vendor evaluation (to develop criteria to rate vendors), price-value relationship measurement (to analyze the trade-offs that consumers make between products' price and quality), and attitude measurement (to derive the importance of functional vs. symbolic characteristics such as brand image or to analyze utility for collections of items in order to package certain product types together).
2) **Cost-benefit analyses** to study customers' willingness to pay (WTP) for certain attributes.
3) **Clustering or segmenting customers** based on their utility functions.

4) **Market simulations,** which one can use to estimate the market shares of currently available or new products based on predicted consumer preferences.

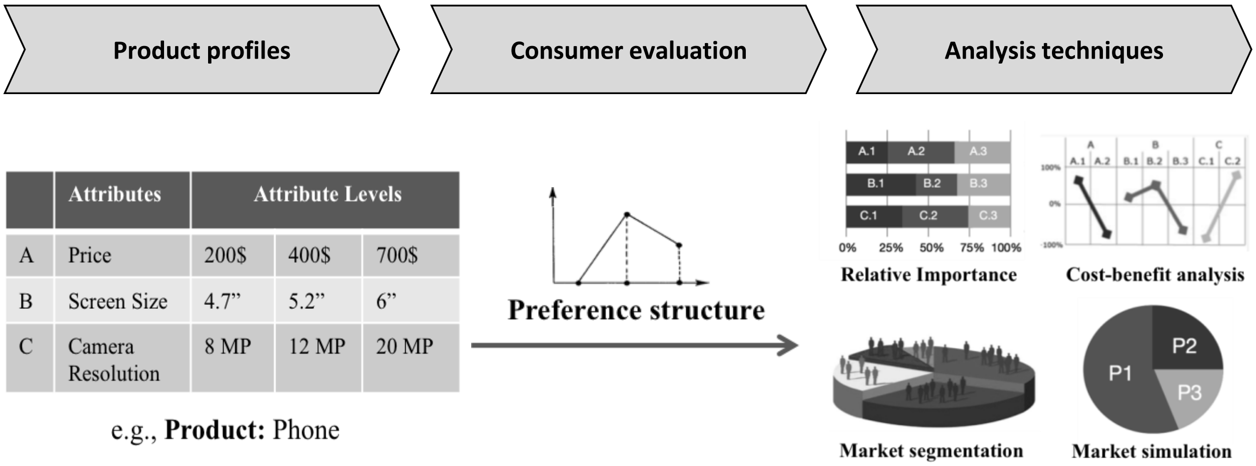

Figure 1. A CA Study's Three Phases

2.2 CA Methodology

One can find it challenging to apply the CA due to the many steps and methodological choices one needs to achieve the preference structure and the need to select from different alternatives. Green and Srinivasan (1978) highlight some differences between the alternatives for each step in a CA study (see Table 2).

The preference model that one selects determines the preference function based on the defined attributes' influence over the respondents' utility. It forms the basis for determining partial benefit values for the respective attributes. Green and Srinivasan (1978) suggest three main preference models: 1) vector, 2) ideal-point, and 3) part-worth models. With a set of T attributes and J stimuli in a study, y_{jp} denotes a respondent's preference level for the pth attribute of the jth stimulus. The vector model depicts the respondent's preference s_j for the jth stimulus as:

$$s_j = \sum_{p=1}^{T} w_p y_{jp} , \tag{1}$$

where w_p denotes the individual's importance weight for T attributes.

The ideal-point model depicts preference s_j as inversely related to the weighted squared distance d_j^2 of the location y_{jp} of the jth stimulus from the individual's ideal point x_p. The model defines d_j^2 as:

$$d_j^2 = \sum_{p=1}^{T} w_p \, (y_{jp} - x_p)^2 \tag{2}$$

The part-worth model depicts preference s_j as:

$$s_j = \sum_{p=1}^{T} f_p(y_{jp}), \tag{3}$$

where f_p is a function denoting the part-worth for the levels of y_{jp} of the pth attribute.

CA studies primarily use a part-worth function due to its flexibility in designing the attribute evaluation function. The part-worth function model works with differently shaped preference functions and allows for better estimation when evaluating categorical attributes. In addition, Green and Srinivasan (1978) suggest a mixed model that combines the three alternative models (vector model, ideal-point model, part-worth function model); it introduces a dummy variable and resembles a multiple regression approach.

Deciding on the **data collection method** determines the way consumers evaluate the attributes and impacts on response burden and cognitive load. Traditional approaches involve the full-profile or pairwise evaluation. The original approach in CA, also called concept evaluation or full profile, is based on rank orders of consumers' preferences regarding product profiles (also called stimuli), which comprise several attributes and levels associated with the product characteristics. As such, CA provides insights into user preferences for the different attributes based on a complete product evaluation. Besides concept evaluation, Johnson (1974) suggests an alternative approach called the trade-off matrix or pairwise approach. In this approach, respondents evaluate a pair of attributes that provide information about the trade-offs among all product features. Its strength lies in its ability to support a large number of attributes since it can provide predictions based on evaluating subsets of attribute pairs (Johnson, 1974). Researchers have most frequently applied the full-profile approach since it describes stimuli in a more realistic way. With the extensions of the adaptive and choice-based CA methods (see Section 2.3), researchers gain more choices for evaluating the full profiles.

Constructing the stimulus set involves decisions on the number of stimuli and attribute variation ranges. In the full-profile approach, a fractional factorial orthogonal design reduces the number of stimuli and facilitates the evaluation task for consumers. This method assumes no interaction effects between the selected attributes. For adaptive methods, researchers use partial profiles and self-explicated tasks to reduce the conjoint evaluation's complexity.

Several options exist to **present stimuli**, such as verbal description, paragraph description, or graphical representation. Stimulus presentation depends on the subject that one intends to study and can combine methods. Furthermore, when applying conjoint analysis to some product categories, one could use other stimulus types as prototypes or actual products.

The **measurement scale** depends on the study purpose and the data collection method. Both the full-profile and the pairwise approach can use ranking to capture the order of preferences or purchasing intentions. The full-profile approach can also use ratings, which requires respondents to grade (subjectively) the perceived benefit on a numbered scale. As an alternative, choice-based methods introduce another measurement scale that researchers can then treat a choice-probability model.

One selects the **estimation method** for the partial benefit based on the dependent variable type that results from the measurement scale. While MONANOVA works best for an ordinal-scaled variable, ordinary least squares (OLS) regression suits an interval-scaled variable. In addition, one could use LOGIT or PROBIT models for a choice-based data collection method. In that case, researchers should estimate individual-level utility function using Bayesian hierarchical modeling.

To illustrate CA, consider a smartphone as a simple example. In Table 1, we introduce attributes and attribute levels of the selected product class based on existing product specifications on the market. For the conjoint method, we selected a part-worth function model (first step) in a full-profile approach (step two). The stimulus set of three attributes with three levels would lead to 27 (= 3^3) product concepts. We could employ fractional factorial design (third step) to arrive at a reduced design; in this case, with nine stimuli. In our smartphone example, the stimulus presentation (fourth step) can benefit from a verbally description and pictorial representation in combination (or a de facto prototype if available) to help participants see the differences between screen sizes. For the measurement scale, we would ask the participants to rank (fifth step) the stimuli according to their preferences. We could employ multiple regression analysis to estimate the part-worth utilities (sixth step). We could then calculate the utilities by adding individuals' part-worth utilities (Equation 3 above). Finally, we would standardize the part-worth utilities in order to ensure the same unit of scale.

Table 1. Example for Attributes and Attribute Levels of a Conjoint Analysis

Product	Attributes	Attributes' levels		
Mobile phone	Price	\$200	\$400	\$700
	Screen size	4.7 inches	5.2 inches	6 inches
	Camera resolution	8 MP	12 MP	20 MP

2.3 CA Development and Extensions

Due to the traditional CA's prevalence, researchers have further developed and improved the CA method to address limitations in terms of attribute formulation and product evaluation (Green & Srinivasan, 1990). Sawtooth Software, as specialized software vendor, developed an adaptive conjoint analysis (ACA) to solve the traditional full-profile CA's issue with number of attributes (Johnson, Huber, & Bacon, 2003). The ACA relies on a hybrid technique that combines self-explicated tasks with an evaluation of partial-profile descriptions (Green, 1984; Johnson, 1987). The self-explicated task allows respondents to rate the attributes individually and exclude unacceptable attribute levels from the evaluation task in order to reduce its burden (Johnson, 1987).

We can consider choice-based conjoint analysis (CBCA) a replacement for ranking-based or rating-based conjoint methods. It simulates the process of purchasing a product and asks participants to make hypothetical choices in a scenario similar to a competitive marketplace (Johnson et al., 2003). The main concern with this approach is that participants need to evaluate a large number of purchase scenarios; however, it can deal with the complexity of choosing among competitive profiles, which makes it a mixed blessing (Green et al., 2001). Adaptive choice-based conjoint analysis (ACBCA) extends these two approaches to estimate part-worth utilities from a small sample size with fewer than 100 participants (Johnson et al., 2003). ACBCA asks participants to choose among a set of stimuli; thus, it simulates a purchase behavior similar to the CBCA after they perform a self-explicated task (as in ACA) to select the most relevant attributes and levels beforehand.

Several researchers have discussed further ways to develop the presented CA method (Rao, 2008; Netzer et al., 2008). In doing so, they have mainly targeted technique and application issues (see Table 2). Orme (2009) discusses the selection criteria for the CA method, which depend on product- and study-related factors, comprehensively by demonstrating the advantages and limitations of each CA type and then building a recommendation guide to select the appropriate method. He proposes the following main selection criteria: number of attributes, mode of interviewing, sample size, interview time, and whether a study includes pricing research. His recommendations suggest using adaptive methods for a large number of attributes or with small sample sizes and using choice-based methods for pricing studies.

Table 2. CA Steps and Extensions

Steps	**Traditional conjoint analysis** (Green & Srinivasan, 1978)	**Developments and extensions** (Johnson, 1987; Johnson et al., 2003; Rao, 2008; Netzer et al., 2008)	
		Adaptive conjoint analysis (ACA)	**Choice-based conjoint analysis (CBCA)**
1) Select a preference model	Vector model, ideal-point model, part-worth function model, mixed	-	
2) Decide on a data collection method	Two factor at a time (trade-off analysis), full profile (concept evaluation)	Adaptive choice-based CA (CBCA)	
3) Construct a stimulus set	Fractional factorial design, random sampling from multi-method variate distribution	Partial profiles, self-explicated method	-
4) Present stimulus	Verbal description (multiple cue, stimulus card), paragraph description, pictorial or three-dimensional model representation	Actual products, prototypes	
5) Select measurement scale	Paired comparisons, rank order, rating scales, constant-sum paired comparisons, category assignment	-	Choice
6) Select estimation method	MONANOVA, PREFMAP, LINMAP, Johnson's non-metric trade-off algorithm, multiple regression, LOGIT, PROBIT	-	Bayesian hierarchical modeling

3 Research Approach

3.1 Research Objectives and Method

IS researchers started using CA to study users' adoption decisions and preference structures that govern IS design based on Bajaj's (1999) CA study procedure guide. Although the number of studies that have used CA in the IS domain has risen over the past decades, they remain one-time efforts. As a result, we have observed little knowledge accumulation about CA applications in the IS discipline. To address this issue, we analyze how IS researchers have applied conjoint analysis to generalize application areas and provide recommendations for using CA in the IS discipline.

Given our research goals, we opted to exhaustively review existing CA studies in IS, which we can characterize as a combined descriptive and critical literature review (Paré et al., 2015). As a descriptive review, we analyze the current state of CA applications in the IS discipline by highlighting the main patterns and trends. As a critical review, we critically assess the main methodological choices that researchers have made in applying CA and suggest recommendations for methodological improvements.

3.2 Literature Selection

To attain completeness and quality in our review, we followed recommendations from vom Brocke et al. (2015) on conducting effective literature searches and searched for peer-reviewed publications from the first IS publication on CA by Bajaj (1999) until the end of 2019. We followed a sequential process to identify and select relevant CA studies from multiple sources (comprising publications from IS journals and conference proceedings). To cover a whole range of empirical studies using CA, we first performed an electronic search in the following databases: the AIS Electronic Library (AISe), EBSCOHost, ScienceDirect, SpringerLink, and Wiley. Next, we searched Google Scholar to identify literature we may have missed. To ensure that we captured all relevant studies, we based our search criteria on the following keywords: "*conjoint analysis*" AND (("*consumer"* OR *"customer"* OR *"user")* AND *"preferences*"). In an advanced search, we restricted the research area to information technology and business management whenever the search resulted in many irrelevant papers. Subsequently, we complemented our research process by searching for publications among the top 40 rated IS journals (Lowry et al., 2013), which included the IS Senior Scholar's basket of journals: *European Journal of Information Systems*, *Information Systems Journal*, *Information Systems* Research, Journal of AIS, *Journal of Information Technology*, *Journal of MIS*, *Journal of Strategic Information Systems*, and *MIS Quarterly*. With this step, we could capture any additional empirical studies that used CA in the IS discipline that we missed in earlier steps.

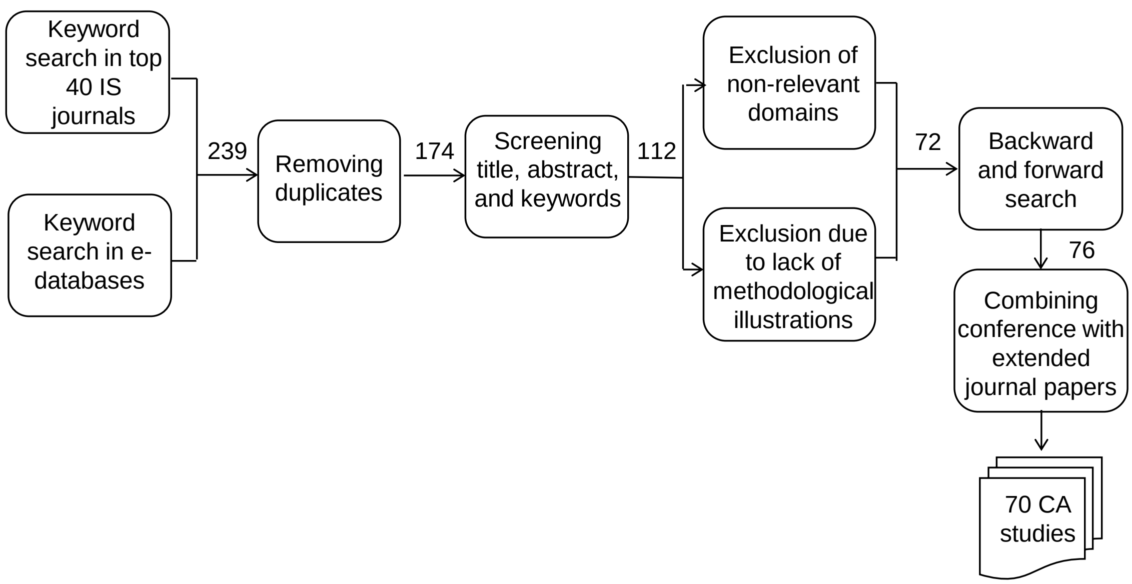

Figure 2. Literature Search and Selection Process

The literature search phase (see Figure 2 above) resulted in 239 publications. After we removed duplicates and screened the publications' title, abstract, and keywords, 112 publications remained. We carefully scanned these publications to judge their relevance before eliminating 40 that did not methodologically illustrate the CA procedure or that fell outside relevant IS domains, which left 72 remaining publications. For instance, we did not include decision-making studies in an IT related context that did not study system characteristics in our publication list (e.g., Schuth, Brosi, & Welpe, 2018). We restricted our search to purely IS-related outlets; thus, we removed studies outside core IS domains (e.g., health or medicine). In addition, we performed backward and forward citation searches to identify both prior and relevant publications that we may have missed with our search criteria. The procedure resulted in 76 publications. Bouwman et al. (2008) conducted two CA studies in the same publication, while certain authors published their CA study first in conference proceedings and then in a journal paper. Thus, the final sample comprised 70 unique studies since we combined six studies in conferences with their extended versions in journals.

3.3 Literature Analysis and Coding

To analyze the literature, we followed Webster and Watson (2002) in using a concept matrix and earlier advice by Salipante, Notz, and Bigelow (1982). The concept matrix divides the topic-related concepts into different units of analysis that we used to arrange, discuss, and synthesize the CA studies. In our case, the matrix builds on a CA procedure that combines the most relevant aspects of Green and Srinivasan (1978) and Bajaj's (1999) CA study procedure guide. The resulting coding scheme comprises the codes and subcodes below.

For the **attributes and level selection**, we identified the system class that researchers examined; the methods they used to select attributes, their number and levels; and the types relevant to each study purpose. The coding involved the **IS domain** (enterprise systems, mobile applications and communication, Online services, Cloud services, Internet of things), **attributes selection** (literature review, focus groups, user interviews, questionnaires, expert interviews, or existing products), **number of attributes**, and **attribute levels type** (binary, multi-leveled, or multi-criterion).

As **data collection method type**, we coded whether IS researchers mainly followed traditional (T) approaches (based on rankings and ratings of full profile), adaptive (ACA), or choice-based (CBCA and ACBCA) and for what purposes.

For **stimulus set construction and presentation**, we examined how the researchers designed their stimuli based on the CA type and how they presented the stimuli to gain the most valuable insights from the study participants. The coding included **stimuli design** and **stimuli type** (verbal description, paragraph description, pictorial representation, mixed representation, and actual prototype).

In terms of **study administration**, we examined how researchers decided on the sample size and user base on which they performed the CA study. Thus, the coding included **study sample size** and **subjects' background**. We also analyzed the **study setup**, which included whether researchers used face-to-face interviews, experiments, questionnaires, online surveys, and specific software to perform the study. We refer to this code as **software used** and can help to provide suggestions to researchers in designing future studies.

For **data analysis**, we examined the estimation method that researchers used to analyze data and other data-analysis techniques in CA that they frequently performed whenever they conducted a CA in IS (see Section 2.1). The items involved in this step included **estimation method** (part-worth utilities estimation, since it is the dominant preference model in conjoint analysis studies) and other **analysis techniques**, such as market segmentation (it also involves the clustering method), willingness to pay based on a defined price attribute, and market simulation to provide a competitive analysis.

With this coding scheme, we could obtain insights into the existing approaches and alternatives for each CA step of the study procedure. In addition, in the coding scheme, we included the **publication type** and the **study purpose** that we deducted based on the authors' objectives, study context, and sample's background.

The two authors conducted the coding process and validated the codes; the first author coded the literature before the second author validated the codes. In case we disagreed, we discussed the codes until we reached mutual consensus. For instance, we needed to come to a common consensus on derived items such as the IS domains and purposes to complete the coding scheme. We grouped the results for each unit in the concept matrix to highlight commonly used items and provide methodological reflections.

4 Overview of CA Studies in IS

We found 70 unique CA studies (36 journal papers and 34 conference proceedings) that have appeared since 1999 to 2019. We synthesize how we coded these studies with regard to their domain, study purpose, CA method type, attribute selection, and analysis techniques in Table 3. We provide detailed bibliographic and meta-information on each study in Table A1 in the Appendix.

Table 3. Overview of CA Studies in IS

Table 3. Overview of CA Studies in IS

Coding item	Coding options	Number of studies	Percentage (%)
IS domain	Enterprise systems	10	14.29
	Mobile applications and communication	23	32.86
	Online services	24	34.29
	Cloud services	7	10.00
	Internet of things	6	8.57
Study purpose*	Decision making	8	11.43
	Adoption	21	30.00
	Design	34	48.57
	Pricing	15	21.43
Attribute selection*	Literature review	56	80.00
	Existing products	24	34.29
	Expert interviews	16	22.86
	Questionnaires	9	12.86
	User interviews	10	14.29
	Focus groups	7	10.00
Method type	TCA	35	50.00
	ACA	6	8.57
	CBCA	26	37.14
	ACBCA	3	4.29
Analysis techniques* (in addition to relative importance)	Willingness to pay	21	30.00
	Segmentation	30	42.86
	Simulations	7	10.00
Note: * multiple coding possible			

We identified more than 20 IS applications and services that researchers investigated using CA. Based on the systems' type and nature, we grouped these predominantly innovative technologies into five parsimonious and inclusive domains:

1) **Enterprise systems (ES):** studies in this domain examined typical systems that organizations use, such as office applications, and ERP systems or their computing architecture.
2) **Mobile applications and communications (MC):** studies in this domain mainly examined innovative mobile platforms, mobile applications, and mobile communication (VoIP telephony)
3) **Online (O) services:** studies in this domain examined online shopping (e-commerce), online social networks, online banking, and online information privacy.
4) **Cloud (C) services:** studies in this domain examined the different services provided through the cloud such as data storage or infrastructure as a service (IaaS), software as a service (SaaS), and platform as a service (PaaS).
5) **Internet of things (IoT):** studies in this domain examined connected and smart devices.

From each study's objective, context, and results, we derived four typical reasons for why researchers have applied CA in the IS discipline (which we refer to as the study purposes). We mapped these purposes to applications in marketing research (see Section 2.1) and found that researchers often used one or more CA analysis techniques (i.e., relative importance, WTP, segmentation, and simulation) when pursuing particular purposes:

- **Decision making (DM):** studies in this category focused on examining managers' decisions about whether to adopt IS in an organizational context. Thus, these studies identified relevant decision criteria for systems evaluation based on the studied attributes' relative importance. These studies resembled vendor evaluations in marketing research.
- **Adoption (A):** studies in this category focused on understanding users' preferences or behavior in adopting new technologies. While they resembled the decision-making studies, they target the individual users' intention to use rather than the organizational rationale in selecting or evaluating a system. To obtain the users' adoption intentions, adoption studies predict users' preferences based on the utilities that they estimated from having users evaluate product characteristics. In addition, some studies employ segmentation to analyze different group preferences. Compared with marketing research, this study purpose is part of attitude measurement.
- **Design (D):** studies in this category focused on eliciting user preferences for designing an IS product, application, or service. To guide the design process of a particular product class, design studies measured user preferences and trade-offs among attributes and levels related to system characteristics to obtain the relative importance of each attribute and levels from the estimated part-worth utilities. These studies used the willingness-to-pay and user-segmentation analysis techniques and also examined user trade-offs for certain product attributes. Some also extended the set of attributes beyond functional and non-functional characteristics to embrace business model or information privacy attributes.
- **Pricing (P):** studies in this category focused on understanding consumers' willingness to pay for product or service features. These studies mainly involve cost-benefit analyses. They analyzed the effect of price attribute variations on the resulting user preferences and related predictions.

5 Methodological Choices along the CA Procedure

5.1 Attributes and Levels Selection

Selecting attributes constitutes the most demanding step in designing a good CA as attributes should represent a study object's most relevant characteristics and correspond to customers' most important needs. Most CA studies relied on a literature review (80%) to select domain-specific attributes or evaluate existing product features (34.29%). More than 50 percent followed a multi-stage selection process. Studies that combined methods most commonly performed a literature review and either evaluated existing products or interviewed experts to obtain insights into relevant features. In some cases, studies used a three-stage selection process to obtain user insights through questionnaires, interviews (Choi, Shin, & Lee, 2013), or focus groups (Brodt & Heitmann, 2004; Giessmann & Stanoevska, 2012; Nikou, Bouwman, & de Reuver, 2014).

The number of attributes ranged between two and 13 and extended beyond functional and non-functional attributes to cover pricing or channel selection. Thus, we can conclude that CA is interesting to use in IS whenever one explores user preferences about business model design of new or emerging IS. In fact, the number of attributes correlated with the conjoint method that authors selected. Most studies followed the pattern that Orme (2002) suggests to select attributes in that traditional full-profile studies considered up to six attributes and adaptive studies included more. However, we found exceptions in that some full-profile CA contained more than six attributes. These cases occurred in combination with two study purposes: 1) decision-making studies that limited attribute levels to binary (low or high) (e.g., Benlian & Hess, 2011; Keil & Tiwana, 2006) or multi-level (low, medium, or high) (e.g., Mahindra & Whitworth, 2005) or 2) service design studies that bundled options with binary attributes that corresponded to services (included or not included) (e.g., Daas, Keijzer, & Bouwman, 2014).

5.2 Data Collection Method

Interestingly, studies in the IS domain relied mostly on traditional full-profile CA (35). Thus, despite the criticisms that the traditional CA approach has attracted, most CA studies in IS did not consider the developments that researchers have made to method that we outline in Section 2.3. Furthermore, 26 studies used choice-based CA (especially between 2017 and 2019) as a preference measurement tool under relatively realistic purchasing situations. Even though studies with a large number of attributes (according to CA guidelines) should better rely on adaptive methods, only three studies applied ACBCA: Giessmann and Stanoevska (2012) to examine platform cloud services, Fölting, Daurer, and Spann

(2017) to examine information search mobile applications, and Naous and Legner (2019) to examine privacy design of cloud storage services.

The full-profile CA's dominance implies that CA studies in the IS discipline rely on hypothetical system representations rather than realistic choices and have more constraints with regard to the number of attributes. We also note that the studies did not strictly apply the CA method type that best suits the stated study purpose. For instance, researchers applied CBCA in pricing, adoption, decision-making, and service design studies although Orme (2009) have suggested that it mainly supports pricing decisions.

5.3 Stimulus Set Construction and Presentation

Constructing a stimulus set depends on the data collection method. Traditional or choice-based CA studies in our sample employed fractional factorial design to reduce the number of stimuli for a large number of attributes or levels. When researchers use adaptive methods, the self-explicated method helps them to reduce the attributes set to facilitate the study procedure. Most studies employed verbal description in the form of profile cards and paragraph description as vignettes and scenarios. Interestingly, few studies used visual representation to evaluate website features for online services (Mahindra & Whitworth, 2005; Hann, Hui, Lee, & Png, 2007) and e-commerce (Tamimi & Sebastianelli, 2015). In adoption studies that examine existing products in IS, an actual product would have great significance to study participants. In certain cases, researchers may not be able to present study participants with an actual product due to product complexity and insufficient resources (e.g., for enterprise systems). However, it would have major importance and be more feasible for domains such as online services, cloud services, e-commerce, and mobile applications.

5.4 Study Administration

Marketing research deploys commercial panels to identify target samples; however, IS research still lacks established panels for this type of methodology. So far, few studies have used existing online panels; examples include Fritz, Schlereth, and Figge's (2011) and Mihale-Wilson et al.'s (2017) work. In addition, Pu and Grossklags (2015) first used a crowdsourcing platform, Amazon Mechanical Turk, to hire participants and obtain a fast response rate, which we can consider a potential solution for future CA studies on mass-market systems. Although the sample in most CA studies exclusively comprises consumers, the sample background in the IS literature depends on the study purpose. Managers or employees would be a suitable sample for CA studies that examine organizational decision making regarding IS purchase or adoption. However, existing studies have often used student populations due to the relative ease with which they can access students. For example, students performed a decision-making study in which they took roles as managers in a situation that involved evaluating corporate browsers (Mahindra & Whitworth, 2005). Moreover, some researchers have applied CA in student-dedicated studies to examine, for example, mobile adoption (Head & Ziolkowski, 2010) and cloud service adoption (Burda & Teuteberg, 2015).

Market research and especially the studies that adopt a traditional CA approach use samples with a median size of 300, while studies that adopt adaptive methods can use sample sizes smaller than 100 and still retain their statistical significance. In IS research, we identified no specific patterns. The studies in our review used samples with a median size of 170. However, the sample size in the studies varied highly: some studies had more than 1,000 respondents (mainly corresponding to a sample from service subscribers) while others had fewer than 30 respondents (e.g., Brinton Anderson, Bajaj, & Gorr, 2002).

We note the data collection influences the sample size. Controlled studies that used interviews or experiments mostly have small sample sizes. The CA studies in our sample used online surveys more than any other data collection option due to their adaptability to a large sample size and the high availability of online resources and survey software. Ideally, researchers could perform a CA with statistical tools such as R and SPSS with a CA package integrated into them or with specialized commercial software such as Sawtooth Software (e.g., Berger, Matt, Steininger, & Hess, 2015; Giessmann & Stanoevska, 2012; Hu, Moore, & Hu, 2012), the market leader, or Globalpark Software (Mann, Ahrens, Benlian, & Hess, 2008). Studies that used commercial software typically administered an online survey and applied adaptive methods.

5.5 Data Analysis

In line with the CA literature, the method the studies used to estimate product attributes' part-worth utilities varied depending on the measurement scale. For ranking and rating, studies primarily used OLS as the main estimation method. Choice-based studies used both the LOGIT model to estimate utilities based on probabilistic assumptions from users' choices and Bayesian hierarchical modeling to obtain participants' individual utilities.

Besides attributes' relative importance based on the part-worth utilities, CA studies in the IS discipline have not frequently leveraged other data-analysis techniques. Only 30 studies (i.e., less than 50%)—predominantly those studies that involved end user samples to identify unique segments with defined characteristics for IS design and adoption—applied **market segmentation**. These studies develop market segments based on groupings generated from sample demographics or specific clustering-analysis techniques corresponding to the conjoint method type (studies most commonly used k-means clustering for full-profile or ACA and hierarchical agglomerative clustering analysis for CBCA). Predominantly the pricing, privacy trade-off, and decision-making studies that included a price attribute used the **willingness-to-pay** approach. In their study, Baek, Song, and Seo (2004) applied this technique in a different way. Specifically, they used price as the dependent variable, which their study participants determined for different online game options. Finally, seven design studies employed **market simulations** for competitive market analysis (Abramova, Krasnova, & Tan, 2017; Choi et al., 2013; Daas et al., 2014; Fritz et al., 2011; Keen, Wetzels, De Ruyter, & Feinberg, 2004; Song, Jang, & Sohn, 2009; Weinreich & Schön, 2013) to predict the market shares of new products or modified existing products based on the preference models and to evaluate the contribution margin. In addition, one CA study on the preference structure for PaaS (Giessmann & Stanoevska, 2012) used the market-simulation technique in designing cloud business models.

5.6 Critical Assessment and Methodological Recommendations

While the CA studies that we examined mostly used the basic techniques, many more options exist to use CA in specific situations. In Table 4, we derive recommendations to broaden the narrow focus and enhance methodological support on "how" to apply CA in IS studies. These recommendations can help IS researchers and practitioners in setting up their future CA studies and can simplify the decision-making process along the different CA steps for optimal conditions. We also found that domain-specific adaptations could make the procedure more efficient when it comes to selecting attributes and levels and analyzing data.

Table 4. Critical Assessment of CA in IS and Recommendations

CA procedure	Current state and limitations	Recommendations	Sample studies
1) Attributes and levels selection	Most studies used mixed methods in a multi-stage process to select attributes	Conduct a three-stage selection process in which they start with literature review and integrate users' and market perspectives	Giessmann & Stanoevska (2012), Naous & Legner (2019
		Create domain-specific user preference models to help them select attributes for typical categories of IS and study purposes	Not yet covered / area for future research
2) Data collection method	Studies predominantly used traditional CA, which constrained the number of attributes	Use adaptive and choice-based methods (ACA, CBCA and ACBCA) to deal with high numbers of attributes	Doerr et al. (2010), Choi et al. (2013), Giessmann & Stanoevska (2012
3) Stimulus set construction and presentation	Studies mostly used verbal and paragraph descriptions; only a handful of studies relied on pictorial representations for websites	Develop prototypes and actual products (or mock-ups) to simulate realistic choices, specifically in IS concept definition and IS design iterations	Baek et al. (2004), Mahindra & Whitworth (2005)
4) Study administration	Studies mostly employed online surveys and conducted subsequent analyses based on	Explore software and packages to combine online data collection and analysis	Hu et al. (2012), Berger et al. (2015)

Table 4. Critical Assessment of CA in IS and Recommendations

	statistical packages or commercial software. Sample depended on the study purpose (e.g., students or managers); the sample size largely varied but was often too small	Use online panels and crowdsourcing platforms (e.g., MTurk) for a larger user reach	Pu & Grossklags (2015), Naous & Legner (2019)
		Establish IS-specific panels to increase sample sizes	Not yet covered / area for future research
5) Data analysis	Studies did not exploit the full set of CA techniques; they mostly analyzed the relative importance of estimated utilities	Apply the recommended data-analysis techniques for the different suggested scenarios in a system lifecycle (IS concept definition, IS design iterations, and IS evaluation)	See framework for CA in IS (Section 6)

5.6.1 Attributes and Levels Selection

For a CA to succeed, one needs to choose the most relevant attributes that describe the study object. However, previous studies have provided little guidance in how to select them other than to use qualitative research methods such as interviews or focus groups (Bradlow, 2005). A mixed-methods approach to select attributes is common practice. In general, CA studies rely on literature reviews to capture the most relevant attributes for the product class. In addition, IS studies should also integrate users' and market perspectives to fully cover all product features and possible implementations. While questionnaires, interviews, and focus groups can suitably capture the users' perspective, expert interviews with software vendors and assessing existing products and features allow one to get market insights for feasibility checks. Thus, we recommend a three-stage selection process to obtain both users' and market perspectives (e.g., Giessmann & Stanoevska, 2012; Naous & Legner, 2019).

As domain-specific adaptations to the CA method, there is a need for supporting future studies in IS by creating user preference models for different categories of IS applications and study purposes. These preference models should describe the relevant system properties in terms of their functional and non-functional characteristics but also include business model elements. In addition to modeling the system itself, which can help in IS concept definition and IS design iterations, researchers can include other contextual and social aspects in the user preference model to support IS evaluation.

5.6.2 Data Collection Method

The dominant use of traditional full-profile CA in the IS discipline represents a major shortcoming. In line with the methodological development (see Section 2.3), we argue that future CA studies in the IS discipline should opt for adaptive and choice-based methods for two reasons: number of attributes and response burden. In fact, adaptive and choice-based methods allow one to set up CA studies with a larger number of attributes (Johnson et al., 2003) and, thereby, remove the constraints that one would typically face in evaluating complex systems with multiple features and design aspects (e.g., Doerr, Benlian, Vetter, & Hess, 2010; Giessmann & Stanoevska, 2012; Choi et al., 2013). Moreover, these methods simplify surveys for users by decreasing the response burden. When using adaptive methods, one can ensure that respondents focus on relevant features and that they do not consider unwanted or must-have features in a CA survey. Also, choice-based methods require respondents to select a product, which reduces the cognitive load of ratings or rankings that traditional CA requires.

5.6.3 Stimulus Set Construction and Presentation

The studies in our sample relied mainly on verbally describing attributes and levels. However, we see a potential for prototypes (and mock-ups) in this area to simulate realistic choices by displaying actual product features. In IS concept definition and IS design iteration scenarios, prototypes would allow researchers to add innovative features or remove existing ones and, thereby, better compare design variants. They would help specifically in designing online services (e.g., Baek et al., 2004; Mahindra & Whitworth, 2005) and mobile applications (e.g., Brodt & Heitmann, 2004).

5.6.4 Study Administration

Using specialized software packages that combine online data collection and data analysis facilitates CA studies. These packages (e.g., Sawtooth Software) allow one to construct a stimulus set and suit adaptive and choice-based CA procedures. As for respondents, the CA studies in our discipline have used restricted samples and relatively low sample sizes in comparison to market research studies. We recommend using crowdsourcing platforms such as MTurk or Prolific in order to obtain data from a large set of users (Pu & Grossklags, 2015; Naous & Legner, 2019). Moreover, by establishing IS-specific online panels, IS researchers and practitioners could better access larger samples with specific interests and reduce the challenges that they face in obtaining biased or convenient samples that might not represent the user population. These panels would help apply CA for IS design iterations that require continuous feedback or user evaluations for release planning.

5.6.5 Data Analysis

In the final step, we recommend IS studies leverage CA beyond relative importance measures or trade-off analyses and explore the other data-analysis techniques. While relative importance and trade-off analyses help select design features and propose weights in a decision-making context for IS evaluation, market segmentation can help understand varied preferences on different levels, and market simulations can have a great impact for studying alternative designs and simulations. We argue that willingness to pay and variation analyses represent two promising techniques that can help design purposeful systems that users find affordable and that correspond to their preferences. To apply analysis techniques, we suggest that IS researchers and practitioners follow recommendations for IS concept definition, IS design iterations, and IS evaluation as we outline in our framework in the Section 6 (see Table 5).

Table 5. CA Role and Applications in the IS Lifecycle

Phase	CA's role	CA applications (A)	CA supporting techniques (see Section 3.1)	Sample studies
IS concept definition	Validation of new IS concepts and business models	A1.1: Business model definition	Define business model and value proposition • Relative importance/ Trade-off analysis	Derikx et al. (2015), Giessmann & Stanoevska (2012)
		A1.2: Market segmentation	Define target segments • Market segmentation	Giessmann & Stanoevska (2012), Krasnova et al. (2009)
		A1.3: Pricing	Define revenue model and pricing • Cost-benefit analysis / Willingness to pay • Market simulation	Koehler et al. (2010)
IS design iteration	Complement existing requirements engineering techniques	A2.1: Release planning	Prioritize & select features • Relative importance/ Trade-off analysis • Market segmentation	Bouwman et al. (2008), Naous & Legner (2019)
		A2.2: Design variation	Evaluate alternative designs • Market segmentation • Market simulations • Variation analysis	Giessmann & Legner (2013)
IS evaluation	Extend IS success and adoption models	A3.1: Willingness to accept	Monitor acceptance and adoption by users and decision makers • Relative importance • Market segmentation	Benlian & Hess (2011), Chen et al. (2010)

6 A Framework for CA Studies in IS

Based on our review, we derive a framework for applying CA in the IS discipline (see Figure 3). The framework outlines opportunities for applying CA to complement existing techniques and methods in an IS lifecycle's different phases from ex-ante in IS conceptualization and IS design to ex-post in the evaluation of existing IS artifacts (see Table 5). We provide the framework to support both IS researchers and practitioners in identifying relevant CA techniques for typical study purposes. In this section, we elaborate on the framework and provide recommendations for future research on "where" to apply CA in the IS discipline in order to promote user involvement and data-driven approaches in user-oriented design.

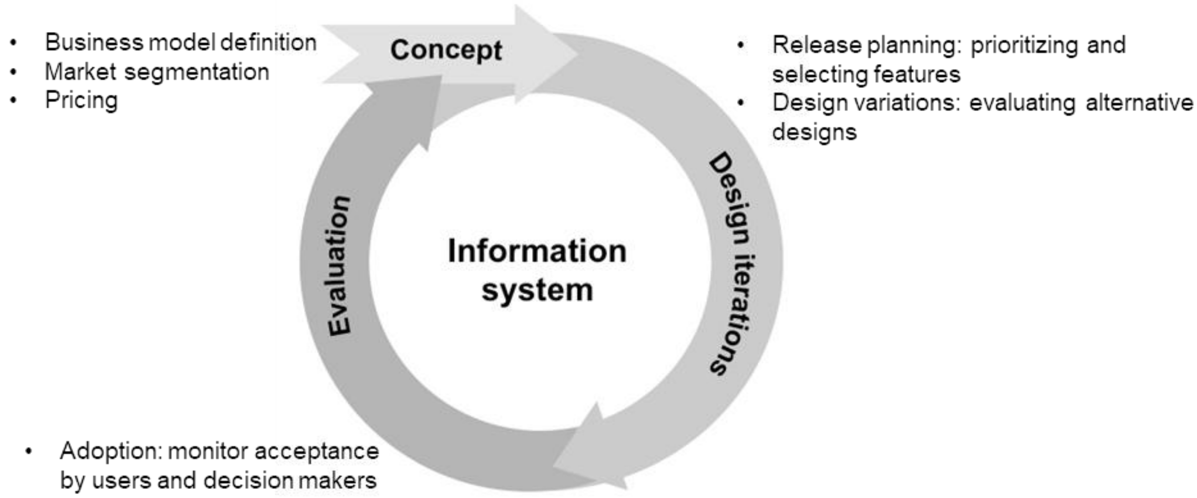

Figure 3. Framework for CA Studies in IS

6.1 CA for Defining IS Concepts

CA constitutes a good methodology for eliciting preferences. By offering a utility function as a quantitative measure, CA can complement and validate qualitative feedback that one gains through direct interactions with target customers and users. It can support IS design in its initial phase by allowing one to evaluate IS concepts ex ante (e.g., see Zubey, Wagner, and Otto's (2002) study on VoIP features and Giessmann and Stanoevska's (2012) study on cloud platforms). Unlike traditional requirements engineering methods that tend to evaluate individual product features, CA allows one to evaluate complete product configurations and obtain user insights about a product's initial concept, which can also include business model aspects. One can also use it to compare mock-ups or prototypes and, thus, potentially save time and financial resources when one plans and designs IS. CA also allows one to obtain design feedback from a large number of users, a particular concern in mass-market IS (Jarke et al., 2011; Todoran, Seyff, & Glinz, 2013; Tuunanen et al., 2010).

6.1.1 Application 1.1: Business Model Definition

CA studies extend beyond core system design to involve aspects of business model design. One can apply CA to study upfront commercial decision making and user trade-offs with respect to different business model elements and, specifically, value propositions that play a central role in business model design of IS (Mikusz & Herter, 2016). The CA method allows one to evaluate the highly perceived value propositions of specific business models as Derikx, de Reuver, Kroesen, and Bowman (2015) did for IoT systems' value propositions. Moreover, channel selection could also benefit from this type of analysis. For example, in the e-commerce context, Berger et al. (2015) used CA to investigate consumers' decisions on their preferred information-delivery format. In addition, one can apply CA to measure preferences for partnership-related characteristics, such as how Giessman and Stanoevska (2012) did to measure PaaS providers' preferences for migration. CA's application to design business model elements can go as far as using CA as a method for scenario planning when designing business models as Tesch (2016) has suggested for IoT business models.

6.1.2 Application 1.2: Market Segmentation

CA not only enables one to capture individual and group preferences through relative importance of features but also helps one to identify customer or user segments through applying user-clustering techniques. This clustering based on user preferences for certain business model elements can serve as a reference for market segmentation that one applies when designing business models (Osterwalder & Pigneur, 2010).

6.1.3 Application 1.3: Pricing

As a particularly relevant aspect in these early phases, one can apply CA to inform pricing decisions by analyzing customers' willingness to pay (e.g., Koehler, Anandasivam, Dan, & Weinhardt, 2010; Mann et al., 2008). In such scenarios, CA serves as an estimation method for consumer utilities for different price levels, which then enables one to determine attractive prices or bundle prices with respect to certain design alternatives. Moreover, one can use CA to simulate markets and evaluate market shares given a particular price strategy.

6.2 CA for IS Design Iterations

CA can inform subsequent IS design iterations at different levels (e.g., Bouwman et al., 2008; Kim, 2005). By capturing individual and group preferences, CA supports requirements management for customer-oriented IS (Kabbedijk, Brinkkemper, Jansen, & van der Veldt, 2009). So far, to elicit market-driven requirements, one interacts with market segment representatives or developers who come up with new system design invent them (Dahlstedt, Karlsson, Persson, NattochDag, & Regnell, 2003). In later stages, one collects new requirements from user feedback that serve as an input to plan further incremental releases and decide on additional features. CA can help one understand user preferences and trade-offs for product attributes when assessed simultaneously as an input for different design iterations. For example, CA helps to assess design variations in general system features or to focus on certain functional or non-functional requirements (e.g., as Naous & Legner (2019) did in designing secure cloud storage services).

6.2.1 Application 2.1: Release Planning

Prioritization constitutes a central activity that supports decisions regarding product releases. Prioritization allows one to implement stakeholders' preferential requirements. To prioritize requirements, users and designers have to compare requirements to determine their relative importance in implementing a software product (Achimugu, Selamat, Ibrahim, & Mahrin, 2014; Karlsson & Ryan, 1997). Traditional techniques for prioritizing requirements build on sorting and pair-wise comparisons (such as the analytic hierarchy process (AHP) and the cost-value approach) (Karlsson & Ryan, 1997; Karlsson, Wohlin, & Regnell, 1998) allow users to assess features individually to derive their relative importance. However, with an increasing number of requirements and stakeholders, this process becomes more and more complex. Moreover, handling a large set of requirements would create a burden and might be tedious for the customers and engineers performing it. In contemporary agile software development approaches, CA can be a fundamental method for release planning and selecting relevant features based on user choices. CA combines human intuition with a systematic approach that quantifies preferences for feature selection. Thus, in such approaches, CA could become a fundamental method for planning releases and selecting relevant features based on user choices. For example, product managers can use CA to present existing products or service combinations to users in order to evaluate and enhance their designs. The CA method allows users to assess a complete product offering and rate it based on their stated preference. By measuring preferences for attributes and varied levels, this method provides quantifiable input for prioritizing and selecting features for future releases. During these iterations, one can also use CA to determine target segments with group preferences for optimal bundling.

6.2.2 Application 2.2: Design Variations

One can also use CA to test design variations and, thus, enhance initial designs through market simulations' predictions based on estimated preferences. As an extension to a previous CA study on PaaS (Giessmann & Stanoevska, 2012), Giessmann and Legner (2013) illustrate how one can use market-simulation techniques to evaluate alternative designs through attribute variation analysis. By quantifying the effects that varying attributes have on market shares, one can identify which attribute one could refine or should change for better outcomes. Thus, software vendors can get data-driven insights on the business model elements and system features that have significant impact on users' choices. Market simulations based on CA also allow one to obtain benchmarks for competitive analysis. One can use these benchmarks to compare product combinations and their overarching business models and to generate virtual market shares for multiple vendors that reflect user preferences. Individual and group utilities derived from CA studies can also help one create product or service bundles in situations with contrasting preferences.

6.3 CA for IS Evaluation

Besides the concept and design aspects, one can use CA to allow users or organizations to evaluate systems ex post. Thus, CA can extend established judgment models for IS success and technology acceptance and use, such as the diffusion of innovation (DOI) theory (Rogers, 1995) and the technology acceptance model (TAM) / unified theory of acceptance and use of technology (UTAUT) (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003). These models rely mostly on traditional, questionnaire-based survey methods to examine a set of user beliefs or perceived values. CA could bring into the picture more detailed product attributes and external factors that surround them (such as vendor-related aspects). As such, CA can provide insights into the relationship between tasks, technologies, and context (Schaupp & Bélanger, 2005).

6.3.1 Application 3.1: Willingness to Accept

CA can help one understand how users and organizations adopt systems, such as in understanding the decision-making process that organizations follow to strategically purchase commercial IS (Benlian & Hess, 2011, 2010; Keil & Tiwana, 2006) and why individual users adopt mass-market IS. Thus, IS researchers and practitioners can use CA to study typical criteria that organizations use to evaluate packaged systems (such as functionality, cost, ease of use, implementation, customization, and integration) and to study domain-specific and vendor-related selection criteria. From a user perspective, CA allows one to measure adoption and predict consumers' intention to use IS products (e.g., Chen, Hsu, & Lin, 2010; Chen, Tsao, Lin, & Hsu, 2008) based on attributes' relative importance. It provides a valid and more realistic model of consumer judgments based on estimating their preferences and can identify user groups based on these estimations.

7 Conclusion

7.1 Summary and Contributions

Market research techniques are popular for new product development but have not been fully embraced in IS research and practice. Following Bajaj's (1999) call, IS researchers have used CA to study user preferences from multiple perspectives. However, we found inconsistencies in how IS researchers have applied CA and no cumulative research on its applications. Given CA's increasing popularity in the IS discipline, we need to more fundamentally discuss how CA complements existing methods and techniques in the IS discipline. By comprehensively reviewing 70 CA studies that have appeared from 1999 to 2019 in IS journals and conference proceedings, we synthesize and accumulate knowledge about CA's applications in IS. In our review, we identify patterns and trends to guide future research that applies this method. We illustrate that CA constitutes a data-driven approach to understand user preferences and that one can adapt it to several application areas in IS to cover an IS lifecycle's different phases.

In the design phase, CA can help one define IS concepts and construct early system features for further prototyping. Using CA to define concepts allows users to assess a complete product offering and rate it based on their stated preferences, which can lead a design process with initial product preferences. It can also help one design business models through scenario planning by incorporating contextual and economic elements that they need to consider in designing commercialized systems. In further stages, CA can support IS design iterations in release planning by providing quantitative insights into the most valued features. As such, CA combines human intuition with a data-driven approach that quantifies preferences (via a relative importance measure) and allows one to select future features from a defined set of attributes and attribute levels. In addition, market-simulation techniques advance a new proposition that can help one refine existing systems.

For IS evaluation scenarios, we show that CA allows one to derive decision models for user-selection and -adoption patterns. CA, unlike a simple survey tool, estimates a preference model and, thereby, explains the main system characteristics and external factors that drive user's intentions to use and acceptance in detail. Through this preference model, CA complements and extends IS theories and models on user adoption in that it allows one to study acceptance variables other than perceptions and attitudes. Thus, CA identifies the main factors that drive user adoption in a nuanced way and also provides input into IS design.

Our findings pertain to both IS theory and practice. For academics, we make two primary contributions. First, in our review, we critically assess the methodological setup or method variants from previous CA studies in the IS discipline. We show that CA studies in the IS discipline have not fully leveraged CA developments and techniques and outline recommendations for improving the study setup. Second, we provide guidance for future studies by proposing a framework for applications of CA in the IS discipline. Our framework suggests scenarios for applying CA along the system lifecycle in IS concept definition, IS design iterations, and IS evaluation starting from the core system and involving business model elements. In addition, we suggest domain-specific adaptations as a future research avenue to advance IS research that applies CA. More specifically, we see empirically validated user preference models as a prerequisite for leveraging CA in designing and evaluating mass-market IS. For practitioners, we show how they can employ CA in specific scenarios to help them design IS in a user-oriented manner. We show that CA complements and enhances existing requirements management techniques and has particular relevance for software providers (mainly in requirements elicitation and prioritization for developing new systems, applications, and service offerings).

7.2 Limitations and Implications for Future Research

While we comprehensively analyze CA studies in IS in this paper, we acknowledge certain limitations. Authors' subjectivity constitutes a main limitation when conducting literature reviews. We could have used different search keywords and could have categorized the domains and study purposes differently. To ensure our analysis's quality and validity, we followed a systematic process to select and code studies, and we crossed-checked our results. Another limitation that constraints our analysis concerns the fact that we set the scope of our literature search to CA studies in primary IS outlets and, thus, did not cover CA's use in neighboring domains such as health IS. Finally, in analyzing the literature, we focused on methodological and procedural aspects in applying CA but did not further analyze the nature of attributes and levels and their reusability. This area could be an interesting one for future research, and our suggestions for domain-specific adaptations can guide future research in this specific area.

In general, with this paper, we overview CA studies in IS and highlight application areas for guiding future IS research. Since CA studies in IS have mostly been one-time efforts, we outline interesting research opportunities for methodological contributions and domain-specific CA adaptations. More specifically, our findings open up a new research area that integrates CA into IS design and evaluation. We foresee a particular opportunity to integrate CA into software product management and agile development approaches (Naous, Giessmann, & Legner, 2020). Future research can also focus on domain-specific CA adaptations to complement existing models/theories on IS adoption and determine influential factors in human behavior and decision making.

Another interesting research opportunity concerns developing user preference models for typical IS solution categories as domain-specific CA adaptations. Choosing attributes often constitutes the most demanding phase in CA, and success depends on selecting the right attributes and levels. To address this issue for CA studies in IS, researchers could further refine the suggested user preference models in existing studies by proposing validated catalogs of attributes and attribute levels for the related domain-specific area and, thereby, increase the CA method's practicality. In doing so, they would allow other researchers and practitioners to construct CA studies rapidly and avoid the time-consuming task of constructing attributes and levels from scratch. Besides domain specificity, researchers could also categorize these user preference models based on the study purpose to reflect methodological CA applications. For instance, technology acceptance research on enterprise systems could benefit from previous TAM-based evaluation studies (e.g., Mahindra & Whitworth, 2005) to develop future reference models involving technology and vendor-related aspects.

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Appendix

Table A1. Overview of CA Studies in IS

Study	Study objectives (as each study stated)	Domain	Purpose	Type	Sample	Subjects
Bajaj (2000)	*Identify the factors that senior IS managers across mid- to large-size organizations would consider when making decisions regarding the adoption of a new architecture for their organization.*	ES	DM	TCA	23	Managers
Brinton Anderson et al. (2002)	*Study the relative values of these factors in the decision models of senior IS managers, when evaluating software for use by their organization.*	ES	DM	TCA	24	Managers
Zubey et al. (2002)	*Suggest those VoIP technology attributes that best meet users' needs.*	MC	D	TCA	254	Customers
Odekerken-Schröder & Wetzels (2003)	*Examine the trade-offs end-consumers are willing to make when making online purchases (1) in terms of choice-related attributes and (2) in terms of convenience-related attributes.*	O	D	TCA	(1) 323 (2) 282	Customers
Baek et al. (2004)	*Examining customers' WTP (willingness-to-pay) for online games.*	O	P	TCA	179	Customers
Brodt & Heitmann (2004)	*Drills down to the importance of service attributes (mobile multicasting).*	MC	D	ACA	103	Students
Keen et al. (2004)	*Investigate the structure for consumer preferences to make product purchases through three available retail formats—store, catalog, and the Internet.*	EC	D	TCA	290	Customers
Kim (2005)	*Build descriptions of hypothetical mobile service packages.*	MC	D	CBCA	1000	Customers
Mahindra & Whitworth (2005)	*A conjoint analysis of the contribution of these factors in a proposed corporate software purchase of browser.*	O	DM	TCA	28	Students
Mueller-Lankenau & Wehmeyer (2005)	*Gathering first insights into consumers' preferences for mobile couponing.*	MC	D	TCA	125	Students
Schaupp & Bélanger (2005)	*Examining the role of several technology, shopping, and product factors on online customer satisfaction.*	EC	A	TCA	188	Students
Haaker, Vos, & Bouwman (2006)	*Assess which combination of services and price is the most attractive for users.*	MC	P	TCA	156	Customers
Keil & Tiwana (2006)	*First empirical investigation of the relative importance that managers ascribe to various factors that are believed to be important in evaluating packaged software.*	ES	DM	TCA	126	Managers
Hann et al. (2007), Hann, Hui, Lee, & Png (2002)	*Estimate the individual's utility for the means to mitigate privacy concerns.*	O	D	TCA	268	Students

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Tiwana & Bush (2007)	*Examine the relative importance that IT managers ascribe to various factors from three complementary theories—transaction cost economics, agency theory, and knowledge-based theory—as they simultaneously consider them in their project outsourcing decisions.*	ES	DM	TCA	(1) 55 (2) 33	Managers
Mann et al. (2008)	*How consumer utility and willingness-to-pay within one specific channel may be correlated with time of availability.*	O	P	ACA	489	Customers
Bouwman & van de Wijngaert (2009), Bouwman et al. (2008)	*What are the relevant context-related, individual and technological characteristics that play a role in the use of mobile technologies by police officers, and where do they conflict with the requirements identified by police stakeholders?*	MC	D	TCA	23	Stakeholders
			A	TCA	106	Customers
Krasnova et al. (2009)	*First attempt to Assess the value of privacy in monetary terms (in the context of social networks).*	O	D	ACA	168	Students
Schwarz, Jayatilaka, Hirschheim, & Goles (2009)	*Provide theoretical rationalizations on the confluence of pertinent attributes when selecting an external source for an application service.*	ES	DM	TCA	84	Managers
Song et al. (2009)	*Estimate customer preferences and the relative importance of service factors*	MC	D	TCA	-	Students
van de Wijngaert & Bouwman (2009)	*Obtain insight into the factors that influence the use of wireless grid applications before a given technology is actually introduced on the market.*	MC	A	TCA	257	Students
Chen, Hsu, & Lin (2010), Chen, Tsao, Lin, & Hsu (2008)	*Understand what factors influence consumer purchase intention and the relative importance among these factors.*	EC	A	TCA	1567	Students
Doerr et al. (2010)	*Examines from a customer perspective, the importance of the different features of premium offers.*	C	P	ACA	132	Customers
Head & Ziolkowski (2010)	*Provides insights into how students value various mobile phone applications and tools.*	MC	A	ACA	188	Students
Ho, See-to, & Xu (2010)	*Find out the level of trade-offs between monetary rewards provided by the e-payment gateways and the buyers' protection excess imposed by the e-payment gateways.*	EC	D	TCA	1795	Customers
Koehler et al. (2010)	*Analyze the customer preferences for cloud services.*	C	P	CBCA	60	Customers
Lilienthal, Messerschmidt, & Skiera (2010)	*Compare the overall technology perceptions with particular attributes of product realizations with respect to their importance.*	C	A	CBCA	412	Customers

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Benlian & Hess (2010, 2011)	*The first empirical investigation to Compare the relative importance of evaluation criteria in proprietary and open-source EAS selection.*	ES	DM	ACA	358	Managers
Fagerstrøm & Ghinea (2011)	*Expand our understanding of approach / avoidance behavior by examining the motivating impact of price relative to online recommendation at the point of online purchase.*	EC	A	TCA	270	Customers
Fritz et al. (2011)	*Empirically estimate consumers' reaction to the offer of fair use flat rates.*	MC	P	CBCA	263	Students
Giessmann & Stanoevska (2012)	*Empirical investigation on the essential and necessary characteristics of PaaS from the perspective of third-party developers.*	C	D	ACBCA	103	Customers
Hu et al. (2012)	*Provide fuller conceptualization of technology design and advance our understanding of the impacts of essential design factors individually and jointly.*	MC	D	CBCA	105	Students
Nevo, Benbasat, & Wand (2012)	*Understand the relative importance of meta-memory in the transactive memory processes in order to fit the best technology support for each process.*	ES	D	TCA	180	Customers
Venkatesh, Chan, & Thong (2012)	*Examine key service attributes that affect citizens' pre-use intentions and subsequent use of transactional e-government services, as well as citizens' preferences across service attributes.*	O	A	TCA	2465	Customers
Choi et al. (2013)	*Assumes a consumer utility function for tablet pcs that reflects the variety of consumer preference.*	MC	D	CBCA	389	Customers
Luo, Warkentin, & Li (2013)	*Identify a hierarchy of importance with regard to the critical factors influencing the adoption of mobile office.*	MC	A	CBCA	101	Customers
Weinreich & Schön (2013)	*Analyze customer preferences for automation of service processes in the unified communications (UC) industry and derive managerial implications for optimal service design.*	ES	D	TCA	34	Customers
Constantinescu et al. (2014)	*Understand the user's perspective on tethering and motivations for sharing.*	MC	A	TCA	74	Customers
Daas et al. (2014)	*Determine the reservation prices of the services and to assess what price-bundle combinations are most attractive.*	C	P	TCA	47	Customers
Klein & Jakopin (2014)	*Examines users' perception of the utility of mobile service bundles.*	MC	D & P	TCA	116	Customers
Lee & Rhim (2014)	*Investigate user preferences for the information systems in order to achieve user satisfaction*	ES	A	TCA	55	Customers

Table A1. Overview of CA Studies in IS

Nikou et al. (2014) Nikou, Bowman, & de Reuver (2012)	*Determine the most important characteristics of the mobile platforms.*	MC	A	TCA	166	Customers
Rossnagel, Zibuschka, Hinz, & Muntermann (2014)	*Measure the impact of various aspects of the design of FIM solutions on users' WTP.*	O	D & P	CBCA	249	Customers
Berger et al. (2015)	*Explore differences in consumer preferences and WTP between offline and online formats.*	O	D & P	CBCA	506	Customers
Böhm, Adam, & Farrell (2015)	*Identify the relative importance of the mobile OS on the purchase decision.*	MC	A	CBCA	102	Customers
Burda & Teuteberg (2015, 2014)	*Uncovering the preference structure and trade-offs that users make in their choice of storage services when employed for the purpose of archiving.*	C	A	CBCA	340	Students
Derikx et al. (2015)	*Studies if and how privacy concerns for connected car services can be compensated financially.*	IoT	D	CBCA	55	Customers
Pu & Grossklags (2015)	*Quantify the monetary value people place on their friends' personal information in a social app adoption scenario.*	O	D	TCA	201	Customers
Siegfried, Koch, & Benlian (2015)	*Provides a nuanced analysis of platform and environment signals that drive app installation and also contributes towards a better understanding of the underlying decision process.*	MC	A	TCA	121	Customers
Tamimi & Sebastianelli (2015)	*Estimate the effects of selected e-tailer and product related attributes on a consumer's likelihood of making a particular online purchase.*	EC	A	TCA	122	Students
Yusuf Dauda & Lee (2015)	*Analyze the technology adoption pattern regarding consumers' preference for potential future online banking services in the Nigerian banking industry.*	O	A	CBCA	1291	Customers
Cwiakowski, Giergiczny, & Krawczyk (2016)	*Measure willingness-to-pay (WTP) for legal rather than illegal content as it compares to valuation of other features of the product.*	O	P	CBCA	228	Customers
Mikusz & Herter (2016)	*Investigate how consumers evaluate value propositions of connected car services with a high option and/or indirect value-in-context.*	IoT	D	TCA	70	Customers
See-To & Ho (2016)	*Investigate the impacts of six design attributes of an e-payment service.*	O	D	TCA	1795	Customers
Abramova et al. (2017)	*Differentiate among distinct influences produced by discrete trust-enhancing cues and derive a monetary value for each of these cues as evaluated by consumers.*	O	D & P	CBCA	450	Customers

Table A1. Overview of CA Studies in IS

Albani, Domigall, & Winter (2017)	*Understanding the customer value perceptions of smart meter services and the conditions under which customers are willing to change their behavior in order to increase the efficiency of the electricity use.*	IoT	A	CBCA	1594	Customers
Buck, Stadler, Suckau, & Eymann (2017)	*Targets users' preference structures when downloading apps.*	MC	A	CBCA	111	Students
Fölting et al. (2017)	*Measure consumers' preferences regarding product information search apps.*	MC	D	ACBCA	330	Students
Mazurova (2017)	*Consider the level of influence of three different factors, brand, color and the position of the product on the screen in the conditions of simultaneous perception by the customers.*	O	D	CBCA	60	Customers
Mihale-Wilson et al. (2017)	*Assessing the users' preferences and willingness to pay for a highly secure and privacy stringent UPA.*	IoT	D & P	CBCA	274	Customers
Rollin, Steinmann, Schramm-Klein, Neus, & Nimmermann (2017)	*Investigate which attributes of a mobile gaming app have an impact on users' choice decision.*	MC	A	CBCA	503	Customers
Mikusz (2018)	*Examine how customers concurrently consider several features of digitized, connected products in assessing usefulness and product intelligence.*	IoT	D	TCA	139	Customers
Penttinen, Halme, Lyytinen, & Myllynen (2018)	*Understanding which features companies value in selecting among platforms.*	ES	DM	CBCA	282	Decision makers
Baum, Meißner, Abramova, & Krasnova (2019)	*Explore the magnitude of user privacy concerns and preferences in the con-text of targeted political advertisement.*	O	D & P	CBCA	262	Customers
Naous & Legner (2019)	*Explore users' preferences and willingness-to-pay for privacy preserving features in personal cloud storage.*	C	D & P	ACBCA	144	Customers
Schomakers et al. (2019)	*Trade-offs between decisive attributes that shape the decision to share data are analyzed.*	O	D	CBCA	126	Customers
Wessels et al. (2019)	*Investigate the antecedents of users' willingness-to-sell information on data-selling platforms and their relative importance.*	O	D	CBCA	250	Customers
Zhou, Waltenrath, & Hinz (2019)	*We examine the role of refund policies for mobile app purchase decisions.*	MC	A	CBCA	52	Customers
Zibuschka et al. (2019)	*Explores users' privacy preferences for assistant systems on the Internet of things and ultimately quantifies the willingness to pay for various privacy functions of such assistance system.*	IoT	D & P	CBCA	293	Customers

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