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Research paper

Data and resource maximization in business-to-business marketing experiments: Methodological insights from data partitioning

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ABSTRACT

Data management is an integral part of knowledge engineering in business-to-business (B2B) marketing experiments. This article introduces the concept of data partitioning as a fresh and useful form of data management in the process of knowledge engineering in B2B marketing experiments; articulates the method for partitioning data in B2B marketing experiments; and discusses the implications of data partitioning in the form of data and resource maximization for B2B marketing experiments. It is the hope of the authors that this article will encourage greater visibility and contribute to the advancement of resource-efficient B2B marketing experiments.

1. Introduction

Experimental research is undertaken to engineer new knowledge[1] about cause-and-effect relationships. In the field of business-to-business (B2B) marketing, the experimental method of research allows B2B marketers to control and manipulate one or more independent marketing variables and measure the corresponding changes in dependent marketing variables in B2B settings.

Some B2B marketers qualitatively measure, through interviews, the outcomes of control and manipulation of B2B independent marketing variables (e.g. task manipulation; Laursen & Andersen, 2016; Van Bockhaven & Matthyssens, 2017). However, most B2B marketers, including the authors of this article, choose to do so quantitatively (e.g. Bonney, Plouffe, & Wolter, 2014; Ruiz & Kowalkowski, 2014). The results of statistical analyses used by quantitative experimenters to interpret cause-and-effect relationships are more narrowly defined. This makes them more reliable and valid than their qualitative counterparts. A narrow definition of the research and experimentation is encouraged as it allows other researchers to easily replicate the study and validate the results. This is becoming increasingly visible among elite business journals (Babin, Lopez, Herrmann, & Ortinau, 2018; Harzing, 2016), including *Industrial Marketing Management* (Laplaca, Lindgreen, & Vanhamme, 2018). Thus, the discussion of B2B marketing experiments will focus on quantitative experimental research.

In essence, B2B marketing experiments may be attributed with:

1. Categorical independent(s)–categorical dependent(s).
   The work of Ruiz and Kowalkowski (2014) is an example of a study with a single B2B marketing experiment. Its purpose is to test the causal effects of one categorical independent marketing variable (i.e. market representation) on one categorical dependent marketing variable (i.e. marketing strategy). In their study, Ruiz and Kowalkowski compared the influence of two types of market representation (i.e. ostensive vs performative representation) on two well-established strategies in industrial marketing (i.e. product vs service-focused). They found that the product-focused strategy is selected by B2B marketers when market representation is ostensive (e.g. when structures are emphasized in market representation). Service-focused strategy is selected by B2B marketers when market representation is performative (e.g. when market representation relies on agency in firms). Other experimental studies with categorical independent(s)–categorical dependent(s) in B2B settings include

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[1] Knowledge engineering is an empirical and scientific process that involves the acquisition and analysis of data using methods that generate accurate, reliable, valid, and useful information to help users of information, such as decision makers and problem solvers, improve understanding and decision making (Pierce, 2007).

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those carried out by Bendixen, Bukasa, and Abratt (2004), Corsaro, Ramos, Henneberg, and Naudé (2011), Erdogan and Baker (2002), Pulles and Hartman (2017), and Woodside (2015), among others.

Or

2. Categorical independent(s)–continuous dependent(s).
The work of Bonney et al. (2014) illustrates a study with three B2B marketing experiments. These experiments test the causal effects of three categorical independent marketing variables (i.e. competitive intensity, selling efficacy, and deal disclosure) on one continuous dependent marketing variable (i.e. commitment of salesperson to pursue business deals). The first study is of a sample of 71 sales representatives. In this study, Bonney and colleagues compared high versus low competitive intensity. They found that salespeople allocated significantly more selling time (as a measure of a salesperson's commitment to pursuing business deals) in the high competitive intensity condition compared to the low competitive intensity condition. The second study is of a sample of 109 sales representatives. Bonney and colleagues introduced and paired high and low selling efficacy with high and low competitive intensity. They found that salespeople allocated significantly more selling time when selling efficacy was perceived to be high rather than low in both high and low competitive intensity conditions. The third study is of a sample of 144 sales representatives. Bonney and colleagues encountered similar findings to the second study when they replaced high and low selling efficacy with instances in which sales representatives disclosed and did not disclose information about accounts of potential business deals to management. That is, salespeople allocated significantly more selling time when they disclosed, rather than keeping undisclosed, the information about accounts of potential business deals to management in both high and low competitive intensity conditions. Other marketing experimental studies with categorical independent(s)–continuous dependent(s) in B2B settings include those reported by Garrett and Gopalakrishna (2018), Geiger, Dost, Schönhoff, and Kleinaltenkamp (2015), Helm and Özergin (2015), Kalafatis, Riley, and Singh (2014), Keeling, Daryanto, de Ruyter, and Wetzels (2013), Kuijken, Gemser, and Wijnberg (2017), Liang, Kale, and Cherian (2014), Oh, Peters, and Johnston (2014), and Tangpong, Li, and Hung (2016), among others.

Despite the method's emerging popularity in B2B marketing (e.g. a total of 15 articles in *Industrial Marketing Management* as of January 1, 2018),[2] most B2B marketers face two major challenges when conducting B2B marketing experiments: limitations related to data and resources (Jahnke, Asher, Keralis, & Henry, 2012; Larson & Chow, 2003). Most experimental studies in B2B marketing conduct and report multiple B2B marketing experiments in a single B2B marketing investigation to generate a comprehensive pool of B2B marketing information to enable B2B marketers to make better-informed conclusions and recommendations for marketing theory and practice in B2B settings, and thus, in most instances, these studies often require a large pool of data and resources. For example, the study by Bonney and colleagues in 2014 consisted of three B2B marketing experiments, with a total sample size of 324 sales representatives. Yet, most studies in B2B marketing, including experimental studies, are carried out with limited budgets, particularly in terms of time, energy, and money, thus constraining the amount of data collected and subsequently made available for analysis (Jahnke et al., 2012; Larson & Chow, 2003). Moreover, the population of businesses that avails for B2B marketing research is significantly smaller and harder to access than the population of consumers that avails for business-to-consumer and consumer-to-consumer marketing research. This suggests that B2B marketers have less room for failed experiments. As such, B2B marketers must take greater care than their consumer-focused counterparts in approaching and utilizing their sample so as to avoid exhausting their pool of potential research participants.

To overcome the identified challenges, this article argues that the strategic planning and execution of data management practices[3] in B2B marketing experiments is of utmost importance, as they can contribute to data and resource maximization and thus help B2B marketers overcome data and budget constraints typically associated with B2B marketing experiments. In doing so, this article introduces the notion of data partitioning as a form of data management and discusses the method in which B2B marketing experimental data can be partitioned. This article will use equations (e.g. $T_1 = \boldsymbol{x_{1A}}$ x $\boldsymbol{x_{2A}}$ x $\boldsymbol{x_{3A}} = O_1$) and conceptual data (e.g. high and low competitive intensity, high and low sales efficacy, and high and low deal disclosure) in a mock B2B marketing experiment, which is a form of experiment that uses deduction (or deductive reasoning) to arrive at a conceptual or methodological conclusion without the use of actual data. This form of experiment is especially relevant herein given that the focus of this article is to illustrate the advantages of (or savings from) data partitioning rather than the magnitude or significance of causal effects, as in the case of experiments using actual data. Next, this article will identify the implications of engaging in data partitioning in the process of knowledge engineering in B2B marketing experiments. Although data partitioning is a common and useful method to obtain enhanced insights through post-hoc analysis in survey research, the method has rarely been used in experimental research. For example, none of the 15 articles on B2B marketing experiments published in *Industrial Marketing Management* from 2010 to 2017 mentioned data partitioning in their studies (see Appendix A). This article contends that data partitioning is a technique that can be used for both planned contrasts[4] and post-hoc tests.[5] Specifically, a thorough understanding of data partitioning should allow B2B marketers to be more thoughtful in the design of B2B marketing experiments, and in doing so, be better prepared for planned contrasts upfront (e.g. recruit a sample sufficient for high statistical power), as opposed to using data partitioning as part of exploratory post-hoc tests (e.g. low statistical power as a result of inadequate sample size). It is hoped that this research will encourage greater visibility of B2B marketing experiments in elite business journals such as *Industrial Marketing Management*.

2. Data partitioning

2.1. What is data partitioning?

Data partitioning is a form of data management that requires the data handler to plan and execute the partitioning (or division, segregation, separation) of variables and the data under those variables in a given data set.[6] This differs from existing alternatives that contribute to improving the knowledge engineering process, such as semantic-based segmentation (Ercan & Cicekli, 2016), due to differences in focus (e.g.

[2] A keyword search of “experiment” in the “Title, Abstract, and Keyword” field and “*Industrial Marketing Management*” in the “Source Title” field on ScienceDirect (i.e. the database for Elsevier journals, such as *Industrial Marketing Management*) for the period of 2010–2017 produced a list of 18 articles, of which 15 were related to experimental research (see Appendix A).

[3] Data management is a managerial process that involves the development, execution, and supervision of an established set of procedures and guidelines that control, protect, deliver, and enhance the value of data in knowledge engineering (Mosley, Brackett, Earley, & Henderson, 2010).

[4] Planned contrasts define in advance a set of independent comparisons between the levels of a given variable or a set of variables.

[5] Post-hoc tests consider all possible comparisons between specific levels of a given variable or a set of variables to see which ones differ after obtaining a significant effect for that variable or that set of variables.

[6] The data herein refer to quantitatively measured B2B marketing data.

quantitative nature of data in data partitioning vs qualitative nature of data in semantic-based segmentation), and thus they do not enjoy the same extent of flexibility as data partitioning to control and manipulate data in ways that can generate greater depths of empirical information.

2.2. Who is involved in data partitioning?

In the B2B marketing experiment setting, the data handler is often the *experimenter* (or the B2B marketer), who is required to expose *subjects* (e.g. marketing and procurement managers, salespeople) to a set of treatments (e.g. B2B scenarios) and subsequently measure and analyze their responses (e.g. attitude, intention, and behavior) toward those treatments (i.e. outcomes; Lim, 2015; Srinagesh, 2006).

2.3. What are the assumptions of data partitioning?

In the B2B marketing experiment setting, the condition for partitioning is dependent on the number of B2B marketing treatments (or B2B marketing interventions; i.e. T_i, where $_i$ refers to the number of B2B marketing treatments/interventions) and the B2B independent marketing variables (i.e. x_i [e.g. competitive intensity (high/low), sales efficacy (high/low), and deal disclosure (high/low)]) tested through those B2B marketing treatments in the B2B marketing experiment. More specifically, data partitioning in B2B marketing experiments is only *relevant* when more than one B2B marketing treatment is used (i.e. $T_{n>1}$) to measure two or more B2B independent marketing variables with *commonality* across those B2B marketing treatments (i.e. same set of $x_{n>1}$ in $T_{n>1}$), which allows the B2B marketer to measure the B2B marketing outcomes (i.e. O_i [e.g. salesperson commitment to pursue business deals]) from both the B2B marketing treatment (or collective B2B independent marketing variables [i.e. $T_{1,2\ldots n} = x_1 \text{ x } x_2 \text{ x } x_3 \text{ x } \ldots x_n$]) and individual B2B independent marketing variables (e.g. x_1; or a combination of B2B independent marketing variables that is less than the combination of collective B2B independent marketing variables [e.g. $x_1 \text{ x } x_2$]).

In other words, data partitioning is *irrelevant* when there is (i) only one B2B marketing treatment measuring one B2B independent marketing variable (i.e. $T_1 = x_1$), (ii) one B2B marketing treatment measuring two or more B2B independent marketing variables (i.e. $T_1 = x_1 \text{ x } x_2 \text{ x } \ldots x_n$), (iii) two or more B2B marketing treatments measuring one B2B independent marketing variable (i.e. $T_{1,2\ldots n} = x_1$), and (iv) two or more B2B marketing treatments measuring B2B independent marketing variables without any commonality (i.e. completely different B2B independent marketing variables [i.e. $T_1 = x_1$, $T_2 = x_2 \ldots T_n = x_n$]), as no significant partitioning can be carried out to generate any additional B2B marketing information beyond the direct effects between each B2B marketing treatment and measured B2B marketing outcome(s)—in these instances, data partitioning is not necessary. However, when the assumption for using data partitioning is met, engaging in data partitioning allows B2B marketers to exert greater control and make effective use of B2B marketing data in the knowledge engineering process in B2B marketing experiments.

2.4. How to perform data partitioning?

A $2 \times 2 \times 2$ factorial designed mock B2B marketing experiment is used to illustrate the data partitioning technique in the knowledge engineering process in B2B marketing experiments.[7] The mock B2B marketing experiment uses a conceptual data set that is modelled on the work of Bonney et al. (2014). This investigates the causal effects of three categorical independent marketing variables (i.e. competitive intensity, selling efficacy, and deal disclosure) on one continuous dependent marketing variable (i.e. the salesperson's commitment to pursue business deals). In particular, the mock B2B marketing experiment has eight marketing treatment combinations (i.e. T_1 to T_8; $2 \times 2 \times 2$) from three categorical independent marketing variables (i.e. $\boldsymbol{x_1}$ = competitive intensity, $\boldsymbol{x_2}$ = selling efficacy, and $\boldsymbol{x_3}$ = deal disclosure). Each of these take two levels (i.e. A and B; $\boldsymbol{x_{1A}}$ = low competitive intensity [LCI], $\boldsymbol{x_{1B}}$ = high competitive intensity [HCI], $\boldsymbol{x_{2A}}$ = low selling efficacy [LSE], $\boldsymbol{x_{2B}}$ = high selling efficacy [HSE], $\boldsymbol{x_{3A}}$ = low deal disclosure [LDD], and $\boldsymbol{x_{3B}}$ = high deal disclosure [HDD]), thus resulting in eight three-way interaction B2B marketing outcomes measuring the B2B marketing treatment effects (i.e. O_{1-8}; the salesperson's commitment to pursue business deals) (see Fig. 1).

Given that the assumption for data partitioning is met (i.e. same set of $x_{n>1}$ in $T_{n>1}$), the B2B independent marketing variables (i.e. $x_{1i\text{-}3i}$; LCI, HCI, LSE, HSE, LDD, and HDD) are partitioned to produce B2B marketing information pertaining to the individual effect of each B2B independent marketing variable on the B2B marketing outcomes (i.e. one-way B2B marketing outcomes) (see Fig. 2). For example, the B2B marketing outcomes of the first B2B independent marketing variable (i.e. x_1 = competition intensity) at the first and second level (i.e. x_{1A} = LCI, x_{1B} = HCI) are measured by O_9, which is the average (i.e. mean or μ) of O_1, O_3, O_5, and O_7, and by O_{12}, which is the average of O_2, O_4, O_6, and O_8, respectively. Note that the B2B marketing impacts produced by the individual B2B independent marketing variable (e.g. x_1) at two levels (e.g. x_{1A} and x_{1B}) are accentuated by controlling for the other B2B independent marketing variables (i.e. by having the same composition, e.g. x_2 [e.g. x_{2A} and x_{2B}] and x_3 [e.g. x_{3A} and x_{3B}]) in the B2B marketing experiment. Thus, six one-way B2B marketing outcomes (i.e. O_{9-14}) are produced to measure the individual effect of three B2B independent marketing variables (each taking two levels) through data partitioning.

Similarly, the same technique to data partitioning can be employed to obtain the effects of a combination of any two B2B independent marketing variables on the B2B marketing outcomes (i.e. two-way interaction B2B marketing outcomes) (see Fig. 3). For example, the B2B marketing outcomes of the combinations from the first and second B2B independent marketing variables (i.e. $\boldsymbol{x_1}$ = competitive intensity $\times$ $\boldsymbol{x_2}$ = selling efficacy) at the first and second level (i.e. $x_{1A} \times x_{2A}$ = LCI × LSE, $x_{1A} \times x_{2B}$ = LCI × HSE, $x_{1B} \times x_{2A}$ = HCI × LSE, and $x_{1B} \times x_{2B}$ = HCI × HSE) are measured by O_{15}, which is the average of O_1 and O_5, O_{16}, which is the average of O_3 and O_7, O_{17}, which is the average of O_2 and O_6, and O_{18}, which is the average of O_4 and O_8. Thus, 12 two-way interaction B2B marketing outcomes (i.e. O_{15-26}) are produced to measure the combinations of any two B2B independent marketing variables (each taking two levels), and together with the six one-way B2B marketing outcomes measuring the individual effect of three B2B independent marketing variables (each taking two levels) and the eight three-way interaction B2B marketing outcomes measuring the B2B marketing treatment effects, a total of 26 B2B marketing outcomes can be produced through data partitioning for a $2 \times 2 \times 2$ factorial design.[8]

[7] Note that the conceptual articulation proposed herein is an original contribution that is intended to offer B2B marketers a sound conceptual methodological foundation for conducting myriad tests (e.g. analysis of variance and *t*-test for continuous dependents, and chi-square test for categorical dependents) using the data partitioning technique on an actual data set in B2B marketing experiments.

[8] Bonferroni correction (i.e. computing a corrected threshold for significance [i.e. corrected *p*-value] by dividing the initial threshold for significance [e.g. *p*-value = .05] with the number of proposed hypotheses [e.g. corrected *p*-value = *p*-value/H_n = 0.05/26 = 0.002]) can be used to counteract the potential problem of multiple comparisons (i.e. the likelihood of incorrectly rejecting a null hypothesis due to an increase likelihood of a rare event as a result of increasing the number of hypotheses being tested; Dunn, 1959, 1961).

$$\boxed{T_1 = x_{1A} \times x_{2A} \times x_{3A} = \mathrm{LCI} \times \mathrm{LSE} \times \mathrm{LDD} = O_1}$$

$$\boxed{T_2 = x_{1B} \times x_{2A} \times x_{3A} = \mathrm{HCI} \times \mathrm{LSE} \times \mathrm{LDD} = O_2}$$

$$\boxed{T_3 = x_{1A} \times x_{2B} \times x_{3A} = \mathrm{LCI} \times \mathrm{HSE} \times \mathrm{LDD} = O_3}$$

$$\boxed{T_4 = x_{1B} \times x_{2B} \times x_{3A} = \mathrm{HCI} \times \mathrm{HSE} \times \mathrm{LDD} = O_4}$$

$$\boxed{T_5 = x_{1A} \times x_{2A} \times x_{3B} = \mathrm{LCI} \times \mathrm{LSE} \times \mathrm{HDD} = O_5}$$

$$\boxed{T_6 = x_{1B} \times x_{2A} \times x_{3B} = \mathrm{HCI} \times \mathrm{LSE} \times \mathrm{HDD} = O_6}$$

$$\boxed{T_7 = x_{1A} \times x_{2B} \times x_{3B} = \mathrm{LCI} \times \mathrm{HSE} \times \mathrm{HDD} = O_7}$$

$$\boxed{T_8 = x_{1B} \times x_{2B} \times x_{3B} = \mathrm{HCI} \times \mathrm{HSE} \times \mathrm{HDD} = O_8}$$

Fig. 1. Three-way interaction B2B marketing outcomes.

2.5. *What are the implications of data partitioning?*

The mock B2B marketing experiment offers conceptual articulation of how data partitioning can contribute to a larger pool of B2B marketing information. This pool is larger than B2B marketing information generated solely on the direct measurement of B2B marketing treatment effects. This was the case with the study of Bonney et al. (2014), which had three B2B marketing experiments. These experiments used a total sample size of 324 cases. However, the study produced information that only related to 10 B2B marketing outcomes. The gains from data partitioning can be understood by scrutinizing the B2B marketing outcomes and sample sizes of B2B marketing experiments with (i.e. mock experiment) and without data partitioning (i.e. Bonney et al., 2014) (see Table 1).

In particular, the mock B2B marketing experiment uses eight marketing treatment combinations from three categorical independent marketing variables. Each variable takes two levels to examine actual (i.e. eight three-way interaction marketing outcomes) and data partitioned (i.e. six one-way and 12 two-way interaction marketing outcomes) B2B marketing treatment effects (i.e. marketing outcomes in the form of the commitment of salespeople to pursue business deals). The mock experiment also takes a pragmatic approach to determine the sample size per actual, and data portioned, experimental group—that is, by taking the minimum sample size required to perform data analysis. Given that the experimental groups of Bonney et al. (2014) were analyzed using tests of difference (i.e. analysis of variance, *t*-test), a minimum of 15 cases per experimental group was assigned to each of the eight marketing treatments based on the recommended threshold of $n = 30$ for a robust comparison of variance between groups (Lim, 2015; McNabb, 2010; Verma, 2012). Thus, when data partitioning is used, the mock experiment produces (see Table 1):

1. Six one-way B2B marketing outcomes (i.e. O_9 to O_{14}) with a total data partitioned sample size of 360 cases. Each of the six data partitioned one-way B2B marketing experimental groups consist of 60 cases;
2. Twelve two-way interaction B2B marketing outcomes (i.e. O_{15} to O_{26}) with a total data partitioned sample size of 360 cases. Each of the 12 data partitioned two-way interaction B2B marketing experimental groups consist of 30 cases; and
3. Eight three-way interaction B2B marketing outcomes (i.e. O_1 to O_8) with a total actual sample size of 120 cases. Each of the eight three-way interaction B2B marketing experimental groups consist of 15 cases.

Compared with the B2B marketing experimental research by Bonney and colleagues, the mock experiment shows that data partitioning produces additional information in the form of 16 B2B marketing outcomes and savings of up to 516 cases. This suggests that data partitioning enables the B2B marketer to:

$$T_1 = \mathbf{x_{1A}} \times x_{2A} \times x_{3A} = \mathbf{LCI} \times \mathrm{LSE} \times \mathrm{LDD} = O_1$$
$$T_3 = \mathbf{x_{1A}} \times x_{2B} \times x_{3A} = \mathbf{LCI} \times \mathrm{HSE} \times \mathrm{LDD} = O_3$$
$$T_5 = \mathbf{x_{1A}} \times x_{2A} \times x_{3B} = \mathbf{LCI} \times \mathrm{LSE} \times \mathrm{HDD} = O_5$$
$$T_7 = \mathbf{x_{1A}} \times x_{2B} \times x_{3B} = \mathbf{LCI} \times \mathrm{HSE} \times \mathrm{HDD} = O_7$$
$$\boxed{\mathbf{x_{1A}} = \mathbf{LCI} = \mu(O_1 + O_3 + O_5 + O_7) = \boldsymbol{O_9}}$$

$$T_1 = x_{1A} \times \mathbf{x_{2A}} \times x_{3A} = \mathrm{LCI} \times \mathbf{LSE} \times \mathrm{LDD} = O_1$$
$$T_2 = x_{1B} \times \mathbf{x_{2A}} \times x_{3A} = \mathrm{HCI} \times \mathbf{LSE} \times \mathrm{LDD} = O_2$$
$$T_5 = x_{1A} \times \mathbf{x_{2A}} \times x_{3B} = \mathrm{LCI} \times \mathbf{LSE} \times \mathrm{HDD} = O_5$$
$$T_6 = x_{1B} \times \mathbf{x_{2A}} \times x_{3B} = \mathrm{HCI} \times \mathbf{LSE} \times \mathrm{HDD} = O_6$$
$$\boxed{\mathbf{x_{2A}} = \mathbf{LSE} = \mu(O_1 + O_2 + O_5 + O_6) = \boldsymbol{O_{10}}}$$

$$T_1 = x_{1A} \times x_{2A} \times \mathbf{x_{3A}} = \mathrm{LCI} \times \mathrm{LSE} \times \mathbf{LDD} = O_1$$
$$T_2 = x_{1B} \times x_{2A} \times \mathbf{x_{3A}} = \mathrm{HCI} \times \mathrm{LSE} \times \mathbf{LDD} = O_2$$
$$T_3 = x_{1A} \times x_{2B} \times \mathbf{x_{3A}} = \mathrm{LCI} \times \mathrm{HSE} \times \mathbf{LDD} = O_3$$
$$T_4 = x_{1B} \times x_{2B} \times \mathbf{x_{3A}} = \mathrm{HCI} \times \mathrm{HSE} \times \mathbf{LDD} = O_4$$
$$\boxed{\mathbf{x_{3A}} = \mathbf{LDD} = \mu(O_1 + O_2 + O_3 + O_4) = \boldsymbol{O_{11}}}$$

$$T_2 = \mathbf{x_{1B}} \times x_{2A} \times x_{3A} = \mathbf{HCI} \times \mathrm{LSE} \times \mathrm{LDD} = O_2$$
$$T_4 = \mathbf{x_{1B}} \times x_{2B} \times \mathbf{x_{3A}} = \mathbf{HCI} \times \mathrm{HSE} \times \mathrm{LDD} = O_4$$
$$T_6 = \mathbf{x_{1B}} \times x_{2A} \times x_{3B} = \mathbf{HCI} \times \mathrm{LSE} \times \mathrm{HDD} = O_6$$
$$T_8 = \mathbf{x_{1B}} \times x_{2B} \times x_{3B} = \mathbf{HCI} \times \mathrm{HSE} \times \mathrm{HDD} = O_8$$
$$\boxed{\mathbf{x_{1B}} = \mathbf{HCI} = \mu(O_2 + O_4 + O_6 + O_8) = \boldsymbol{O_{12}}}$$

$$T_3 = x_{1A} \times \mathbf{x_{2B}} \times x_{3A} = \mathrm{LCI} \times \mathbf{HSE} \times \mathrm{LDD} = O_3$$
$$T_4 = x_{1B} \times \mathbf{x_{2B}} \times x_{3A} = \mathrm{HCI} \times \mathbf{HSE} \times \mathrm{LDD} = O_4$$
$$T_7 = x_{1A} \times \mathbf{x_{2B}} \times x_{3B} = \mathrm{LCI} \times \mathbf{HSE} \times \mathrm{HDD} = O_7$$
$$T_8 = x_{1B} \times \mathbf{x_{2B}} \times x_{3B} = \mathrm{HCI} \times \mathbf{HSE} \times \mathrm{HDD} = O_8$$
$$\boxed{\mathbf{x_{2B}} = \mathbf{HSE} = \mu(O_3 + O_4 + O_7 + O_8) = \boldsymbol{O_{13}}}$$

$$T_5 = x_{1A} \times x_{2A} \times \mathbf{x_{3B}} = \mathrm{LCI} \times \mathrm{LSE} \times \mathbf{HDD} = O_5$$
$$T_6 = x_{1B} \times x_{2A} \times \mathbf{x_{3B}} = \mathrm{HCI} \times \mathrm{LSE} \times \mathbf{HDD} = O_6$$
$$T_7 = x_{1A} \times x_{2B} \times \mathbf{x_{3B}} = \mathrm{LCI} \times \mathrm{HSE} \times \mathbf{HDD} = O_7$$
$$T_8 = x_{1B} \times x_{2B} \times \mathbf{x_{3B}} = \mathrm{HCI} \times \mathrm{HSE} \times \mathbf{HDD} = O_8$$
$$\boxed{\mathbf{x_{3B}} = \mathbf{HDD} = \mu(O_5 + O_6 + O_7 + O_8) = \boldsymbol{O_{14}}}$$

Fig. 2. One-way B2B marketing outcomes.

$$T_1 = \boldsymbol{x_{1A}} \times \boldsymbol{x_{2A}} \times x_{3A} = \mathbf{LCI} \times \mathbf{LSE} \times \mathrm{LDD} = O_1$$
$$T_5 = \boldsymbol{x_{1A}} \times \boldsymbol{x_{2A}} \times x_{3B} = \mathbf{LCI} \times \mathbf{LSE} \times \mathrm{HDD} = O_5$$
$$\boxed{\boldsymbol{x_{1A}} \times \boldsymbol{x_{2A}} = \mathbf{LCI} \times \mathbf{LSE} = \mu(O_1 + O_5) = \boldsymbol{O_{15}}}$$

$$T_3 = \boldsymbol{x_{1A}} \times \boldsymbol{x_{2B}} \times x_{3A} = \mathbf{LCI} \times \mathbf{HSE} \times \mathrm{LDD} = O_3$$
$$T_7 = \boldsymbol{x_{1A}} \times \boldsymbol{x_{2B}} \times x_{3B} = \mathbf{LCI} \times \mathbf{HSE} \times \mathrm{HDD} = O_7$$
$$\boxed{\boldsymbol{x_{1A}} \times \boldsymbol{x_{2B}} = \mathbf{LCI} \times \mathbf{HSE} = \mu(O_3 + O_7) = \boldsymbol{O_{16}}}$$

$$T_2 = \boldsymbol{x_{1B}} \times \boldsymbol{x_{2A}} \times x_{3A} = \mathbf{HCI} \times \mathbf{LSE} \times \mathrm{LDD} = O_2$$
$$T_6 = \boldsymbol{x_{1B}} \times \boldsymbol{x_{2A}} \times x_{3B} = \mathbf{HCI} \times \mathbf{LSE} \times \mathrm{HDD} = O_6$$
$$\boxed{\boldsymbol{x_{1B}} \times \boldsymbol{x_{2A}} = \mathbf{HCI} \times \mathbf{LSE} = \mu(O_2 + O_6) = \boldsymbol{O_{17}}}$$

$$T_4 = \boldsymbol{x_{1B}} \times \boldsymbol{x_{2B}} \times x_{3A} = \mathbf{HCI} \times \mathbf{HSE} \times \mathrm{LDD} = O_4$$
$$T_8 = \boldsymbol{x_{1B}} \times \boldsymbol{x_{2B}} \times x_{3B} = \mathbf{HCI} \times \mathbf{HSE} \times \mathrm{HDD} = O_8$$
$$\boxed{\boldsymbol{x_{1B}} \times \boldsymbol{x_{2B}} = \mathbf{HCI} \times \mathbf{HSE} = \mu(O_4 + O_8) = \boldsymbol{O_{18}}}$$

$$T_1 = \boldsymbol{x_{1A}} \times x_{2A} \times \boldsymbol{x_{3A}} = \mathbf{LCI} \times \mathrm{LSE} \times \mathbf{LDD} = O_1$$
$$T_3 = \boldsymbol{x_{1A}} \times x_{2B} \times \boldsymbol{x_{3A}} = \mathbf{LCI} \times \mathrm{HSE} \times \mathbf{LDD} = O_3$$
$$\boxed{\boldsymbol{x_{1A}} \times \boldsymbol{x_{3A}} = \mathbf{LCI} \times \mathbf{LDD} = \mu(O_1 + O_3) = \boldsymbol{O_{19}}}$$

$$T_5 = \boldsymbol{x_{1A}} \times x_{2A} \times \boldsymbol{x_{3B}} = \mathbf{LCI} \times \mathrm{LSE} \times \mathbf{HDD} = O_5$$
$$T_7 = \boldsymbol{x_{1A}} \times x_{2B} \times \boldsymbol{x_{3B}} = \mathbf{LCI} \times \mathrm{HSE} \times \mathbf{HDD} = O_7$$
$$\boxed{\boldsymbol{x_{1A}} \times \boldsymbol{x_{3B}} = \mathbf{LCI} \times \mathbf{HDD} = \mu(O_5 + O_7) = \boldsymbol{O_{20}}}$$

$$T_2 = \boldsymbol{x_{1B}} \times x_{2A} \times \boldsymbol{x_{3A}} = \mathbf{HCI} \times \mathrm{LSE} \times \mathbf{LDD} = O_2$$
$$T_4 = \boldsymbol{x_{1B}} \times x_{2B} \times \boldsymbol{x_{3A}} = \mathbf{HCI} \times \mathrm{HSE} \times \mathbf{LDD} = O_4$$
$$\boxed{\boldsymbol{x_{1B}} \times \boldsymbol{x_{3A}} = \mathbf{HCI} \times \mathbf{LDD} = \mu(O_2 + O_4) = \boldsymbol{O_{21}}}$$

$$T_6 = \boldsymbol{x_{1B}} \times x_{2A} \times \boldsymbol{x_{3B}} = \mathbf{HCI} \times \mathrm{LSE} \times \mathbf{HDD} = O_6$$
$$T_8 = \boldsymbol{x_{1B}} \times x_{2B} \times \boldsymbol{x_{3B}} = \mathbf{HCI} \times \mathrm{HSE} \times \mathbf{HDD} = O_8$$
$$\boxed{\boldsymbol{x_{1B}} \times \boldsymbol{x_{3B}} = \mathbf{HCI} \times \mathbf{HDD} = \mu(O_6 + O_8) = \boldsymbol{O_{22}}}$$

$$T_1 = x_{1A} \times \boldsymbol{x_{2A}} \times \boldsymbol{x_{3A}} = \mathrm{LCI} \times \mathbf{LSE} \times \mathbf{LDD} = O_1$$
$$T_2 = x_{1B} \times \boldsymbol{x_{2A}} \times \boldsymbol{x_{3A}} = \mathrm{HCI} \times \mathbf{LSE} \times \mathbf{LDD} = O_2$$
$$\boxed{\boldsymbol{x_{2A}}\ \mathrm{x}\ \boldsymbol{x_{3A}} = \mathbf{LSE} \times \mathbf{LDD} = \mu(O_1 + O_2) = \boldsymbol{O_{23}}}$$

$$T_5 = x_{1A} \times \boldsymbol{x_{2A}} \times \boldsymbol{x_{3B}} = \mathrm{LCI} \times \mathbf{LSE} \times \mathbf{HDD} = O_5$$
$$T_6 = x_{1B} \times \boldsymbol{x_{2A}} \times \boldsymbol{x_{3B}} = \mathrm{HCI} \times \mathbf{LSE} \times \mathbf{HDD} = O_6$$
$$\boxed{\boldsymbol{x_{2A}}\ \mathrm{x}\ \boldsymbol{x_{3B}} = \mathbf{LSE} \times \mathbf{HDD} = \mu(O_5 + O_6) = \boldsymbol{O_{24}}}$$

$$T_3 = x_{1A} \times \boldsymbol{x_{2B}} \times \boldsymbol{x_{3A}} = \mathrm{LCI} \times \mathbf{HSE} \times \mathbf{LDD} = O_3$$
$$T_4 = x_{1B} \times \boldsymbol{x_{2B}} \times \boldsymbol{x_{3A}} = \mathrm{HCI} \times \mathbf{HSE} \times \mathbf{LDD} = O_4$$
$$\boxed{\boldsymbol{x_{2B}}\ \mathrm{x}\ \boldsymbol{x_{3A}} = \mathbf{HSE} \times \mathbf{LDD} = \mu(O_3 + O_4) = \boldsymbol{O_{25}}}$$

$$T_7 = x_{1A} \times \boldsymbol{x_{2B}} \times \boldsymbol{x_{3B}} = \mathrm{LCI} \times \mathbf{HSE} \times \mathbf{HDD} = O_7$$
$$T_8 = x_{1B} \times \boldsymbol{x_{2B}} \times \boldsymbol{x_{3B}} = \mathrm{HCI} \times \mathbf{HSE} \times \mathbf{HDD} = O_8$$
$$\boxed{\boldsymbol{x_{2B}}\ \mathrm{x}\ \boldsymbol{x_{3B}} = \mathbf{HSE} \times \mathbf{HDD} = \mu(O_7 + O_8) = \boldsymbol{O_{26}}}$$

Fig. 3. Two-way interaction B2B marketing outcomes.

1. Control and scrutinize the B2B marketing data set in various ways and from as many angles as possible through planned contrasts and post-hoc tests (e.g. the effects of B2B marketing treatments, individual B2B independent marketing variables, and combinations of common B2B independent marketing variables on measured B2B marketing outcomes);
2. Test for, or rule out, specific cases of causality with greater confidence in planned contrasts and post-hoc tests; and
3. Generate more specific B2B marketing information through planned contrasts and post-hoc tests in a resource-friendly way. This enables the market to gain a nuanced understanding of an investigated marketing phenomenon in B2B settings.

More important, the conceptual evidence from the mock B2B marketing experiment highlights the importance of strategic planning and execution of data management practices. This maximizes data and resource utilization to produce the greatest depth of B2B marketing information. This is possible even with the least amount of resources available from the knowledge engineering process in B2B marketing experiments. As such, this article encourages B2B marketers to creatively and innovatively develop B2B marketing experimental treatments. It hopes for others to strategically outline the avenues to partition the data from these treatments beforehand (i.e. planned) (Ruxton & Beauchamp, 2008), to produce more comprehensive solutions to the problems the B2B marketing study is attempting to solve in a resource-efficient manner (as compared to that without data partitioning; see Table 2).

3. Conclusion

In short, this article makes a case for engaging in data partitioning as part of data management in the knowledge engineering process in B2B marketing experiments. In doing so, it makes a new and useful contribution in the form of a sound conceptual methodological foundation for conducting myriad planned contrast and post-hoc tests (e.g. analysis of variance and *t*-test for continuous dependents, and chi-square test for categorical dependents) using the data partitioning technique in B2B marketing experiments (as well as counteracting

Table 1
Comparison of B2B marketing experiments with and without data partitioning.

Marketing outcomes	Data partitioning					
	With (mock experiment)		**Without** (Bonney et al., 2014)		Gains (with minus without)	
	Outcome	Sample size (actual and partitioned)	Outcome	Sample size (actual)	Outcome	Sample size (savings)
One-way						
LCI = O_9	✓	60	✓	Study 1: 35		+25
HCI = O_{10}	✓	60	✓	Study 1: 36		+24
LSE = O_{11}	✓	60			+✓	+60
HSE = O_{12}	✓	60			+✓	+60
LDD = O_{13}	✓	60			+✓	+60
HDD = O_{14}	✓	60			+✓	+60
Two-way						
LCI × LSE = O_{15}	✓	30	✓	Study 2: 27		+3
LCI × HSE = O_{16}	✓	30	✓	Study 2: 28		+2
HCI × LSE = O_{17}	✓	30	✓	Study 2: 27		+3
HCI × HSE = O_{18}	✓	30	✓	Study 2: 27		+3
LCI × LDD = O_{19}	✓	30	✓	Study 3: 36		−6
LCI × HDD = O_{20}	✓	30	✓	Study 3: 35		−5
HCI × LDD = O_{21}	✓	30	✓	Study 3: 37		−7
HCI × HDD = O_{22}	✓	30	✓	Study 3: 36		−6
LSE × LDD = O_{23}	✓	30			+✓	+30
LSE × HDD = O_{24}	✓	30			+✓	+30
HSE × LDD = O_{25}	✓	30			+✓	+30
HSE × HDD = O_{26}	✓	30			+✓	+30
Three-way						
LCI × LSE × LDD = O_1	✓	15			+✓	+15
HCI × LSE × LDD = O_2	✓	15			+✓	+15
LCI × HSE × LDD = O_3	✓	15			+✓	+15
HCI × HSE × LDD = O_4	✓	15			+✓	+15
LCI × LSE × HDD = O_5	✓	15			+✓	+15
HCI × LSE × HDD = O_6	✓	15			+✓	+15
LCI × HSE × HDD = O_7	✓	15			+✓	+15
HCI × HSE × HDD = O_8	✓	15			+✓	+15
Total	26	***840***: 120 + *720*	10	324	+16	+516

Notes:
1. Dependent variable = Marketing outcome = Salesperson's commitment to pursue business deals.
2. Independent variables = Competitive intensity (Low = LCI, High = HCI), selling efficacy (Low = LSE, High = HSE), and deal disclosure to management (Low = LDD, High = HDD).
3. ✓ = Availability of marketing outcome.
4. *Italic* value indicates data partitioned sample size.
5. Standard value indicates actual sample size.
6. **Bold** value indicates total.
7. With = Marketing outcomes and sample size of planned contrasts / post-hoc tests with data partitioning.
8. Without = Marketing outcomes and sample size of planned contrasts / post-hoc tests without data partitioning
9. Gains = Marketing outcomes and sample size savings gained from planned contrasts / post-hoc tests with and without data partitioning.

Table 2
Comparison of planned contrasts and post-hoc tests with and without data partitioning.

Characteristic	Data partitioning			
	Without		With	
	Planned contrast	Post-hoc	Planned contrast	Post-hoc
Conceptual limitation[a]	Yes	No	Yes	No
Type of comparison[b]	Hypotheses	Summaries	Hypotheses	Summaries
Marketing outcome[c]	Least	Little	Many	Most
Sample size required[d]	Large	Large	Small	Small
Type I and II errors[e]	Unlikely	Likely	Unlikely	Likely

[a] Conceptual limitation exists for theory-driven comparisons (i.e. yes) but not for data-drive comparisons (i.e. no).
[b] Type of comparison is reflective of the nature of comparison made (i.e. planned contrast = comparison of hypotheses; post-hoc = comparison of summaries).
[c] Marketing outcome is ranked based on the number of comparisons that can be made (i.e. starting from "least" for the lowest number of possible comparison, followed by "little," "many," and "most" for the third, second, and highest number of possible comparisons, respectively).
[d] Sample size is characterized based on the number of participants required for B2B marketing experiments with (i.e. small) and without (i.e. large) data partitioning.
[e] Type I (i.e. false positive) and II (i.e. false negative) errors are characterized based on experimenterwise errors associated with the nature of comparison made (i.e. planned contrast = unlikely; post-hoc = likely).

potential problems; e.g. Bonferroni correction for multiple comparisons). It is hoped that this article will inspire B2B marketers interested in knowledge engineering and experimental research to consider data partitioning as a creative and innovative method to overcome conventionally preconceived data and resource limitations by putting in place strategies for data and resource maximization in B2B marketing experiments, as well as to encourage greater visibility of conceptual and methodological papers that advances the conduct of experimental research in elite B2B marketing journals, such as *Industrial Marketing Management* (Midgley, Nicholson, & Brennan, 2017; Zaefarian, Kadile, Henneberg, & Leischnig, 2017). In addition, considering that the articulation and evidence provided herein is purely conceptual, the authors of this article encourage future B2B marketing experiments to employ empirical data from B2B settings to provide new evidence to support (or improve on) the conceptual articulation of data partitioning presented herein. Further investigation on the relationship between sample size adequacy and statistical power when using data partitioning is also encouraged to consolidate mixed findings and recommendations in the area and to avoid Type I (i.e. false positive) and Type II (i.e. false negative) errors (Lim, 2015; McNabb, 2010; Simmons, Nelson, & Simonsohn, 2011; Verma, 2012). Such dedication and efforts would contribute to the advancement of knowledge engineering in B2B marketing experiments.

Appendix A. Extracted results of a keyword search of "experiment" in the "Title, Abstract, and Keyword" field and "*Industrial Marketing Management*" in the "Source Title" field for the period 2010–2017 on ScienceDirect (as of January 1, 2018)

No	Source	Characteristic of research				Usage of data partitioning
		Quantitative experimental research		Qualitative	Non-experimental research	
		Categorical independent (s)–categorical dependent(s)	*Categorical independent (s)–continuous dependent(s)*			
1	Van Bockhaven and Matthyssens (2017)			✓		×
2	Pulles and Hartman (2017)	✓				×
3	Garrett and Gopalakrishna (2018)		✓			×
4	Laursen and Andersen (2016)			✓		×
5	Tangpong et al. (2016)		✓			×
6	Helm and Özergin (2015)		✓			×
7	Geiger et al. (2015)		✓			×
8	Woodside (2015)	✓				×
9	Oh et al. (2014)		✓			×
10	Ruiz and Kowalkowski (2014)	✓				×
11	Bonney et al. (2014)		✓			×
12	Rusko (2014)			✓		×
13	La Rocca and Snehota (2014)				✓	×
14	Kalafatis et al. (2014)		✓			×
15	Liang et al. (2014)		✓			×
16	Corsaro et al. (2011)	✓				×
17	Füller, Faullant, and Matzler (2010)				✓	×
18	Windahl and Lakemond (2010)				✓	×

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