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Abstract

The primary objective of the study was to quantitatively test the DART model, which despite being one of the most popular representations of co-creation concept was so far studied almost solely with qualitative methods. To this end, the researchers developed a multiple measurement scale and employed it in interviewing managers. The statistical evidence for adequacy of the model was obtained through CFA with AMOS software. The findings suggest that the DART model may not be an accurate representation of co-creation practices in companies. From the data analysis it was evident that the building blocks of DART had too much of conceptual overlap to be an effective framework for quantitative analysis. It was also implied that the phenomenon of co-creation is so rich and multifaceted that it may be more adequately captured by a measurement model where co-creation is conceived as a third-level factor with two layers of intermediate latent variables.

Keywords: DART, co-creation, measurement scale, survey, Polish companies
JEL: C1, C4

Introduction

In the knowledge intensive economy the capacity to serve individual customers is becoming a major source of competitive advantage. Therefore the operational instruments enabling the managers to understand and implement new business models enhancing the capacity of value co-creation are welcome. Despite its importance, research on co-creation with customers is still at an early stage. In particular, there is a dearth of quantitative evidence, obtained through research methods other than case studies and other qualitative approaches. The DART model is considered to be an important step forward and a valuable attempt to indicate the range of companies' capabilities necessary to effectively work with customers. It specifies the four main building blocks or groups of competencies that companies should develop to effectively engage in value co-creation with customers. Those blocks include Dialog, Access, Risk Assessment and Transparency, which taken together form the DART acronym. However, despite its theoretical appeal DART was not met with the adequate effort at quantitative validation. For this reasons, the present paper is focused on the task of developing a measurement system usable for survey approach and employing it to test the merits of the DART model.

The main body of the paper begins with an overview of the pertinent literature on value co-creation, followed by the presentation of the research method and sample structure. Discussion of survey findings comes next and the final section is dedicated to conclusions and limitations of the study.

Literature Review

The concept of co-creation emerged out of the core competences theory [Prahalad and Hamel, 1990] adding new elements to the resource based model [Barney, 1991]. The present paper is grounded in the literature demonstrating changing nature of competition and value creation process by C.K. Prahalad, V. Ramaswamy, M.S. Krishanan, [Prahalad, Ramaswamy, 2004; Prahalad, Krishanan, 2008]. Those authors suggested that digitization, connectivity and globalization impacts all the industries by radically changing the nature of value creation. They asserted that "value is based on unique, personalized experiences of consumers. Firms have to learn to focus on one consumer and his/her experience at a time, even if they serve 100 million consumers" [Prahalad, Krishanan, 2008, p. 11]. The recently emerged stream of publications concerning the concept of service dominant logic (SDL) proposed by Vargo and Lush [2004] was the source of another vital element of theoretical background to the current paper. SDL was designed in opposition to the goods dominant logic rooted in the pre-service era environment. According to the authors of the concept, the shift to the postindustrial knowledge economy required switching the focus to value creation. According to SDL, customers were value co-creators, as "value cannot be embedded in either the factory or the distribution process" [Vargo, Lush 2006, p. 49]. Other worth mentioning attempt at developing coherent conceptualizations of co-creation was that by von Hippel [2005].

The immediate theoretical foundation for the present paper was provided by the DART model, by Prahalad and Ramaswamy [2000, 2004a, 2004b, 2004c]. The DART model was not the only framework proposed to conceptualize co-creation processes. Another was developed by Payne for service organizations. It supported understanding customer behavioral and cognitive processes and goals. The third model by Grönroos distinguished value co-creation during customer and supplier interactions from value creation by customer alone. Grönroos suggested that firms should facilitate value creation by customers and make efforts to create opportunities to engage themselves with customer processes. [Mukhtar, Ismail, Yahya 2012; Grönroos, 2009]. All three aforementioned models employed the perspective of a supplier. There was also an attempt to look at the co-creation process from a customer perspective by developing a measurement scale for customer involvement in value co-creation. The scale comprised two dimensions: customer participation behavior and customer citizenship behavior [Yi and Gong, 2013].

In the recent marketing literature the DART model remains the most popular framework to conceptualize and guide implementation of customer value co-creation. The approach proposed by Prahalad and Ramaswamy was driven by recent advances in communications technology, that empowered customers to make more informed purchase choices and offered them the possibility to get involved in long-term relationships with suppliers. Prahalad and Ramaswamy suggested that technological advances in communication between suppliers and retail customers should be used by the firms to enhance customers' role in innovation processes and value creation. In particular they indicated the need to migrate from products and services to individual experience environments. As the experiences were the result of interactions, the interactions through different channels should be managed. In their view, implementing co-creation in practice called for a new business model.

The DART framework contains the following four constituent components (its building blocks) [Prahalad and Ramaswamy, 2004a]:

1. **Dialogue** represents interactivity between two equal problem solvers, eager to act and to learn.
2. **Access** implies facilitating co-creation by offering the right tools for communication between customers and suppliers; it also entails those marketing solutions that result in increased freedom of choice for customers.
3. **Risk assessment** is referring to the customers' right to be fully informed about the risks they face from accepting the value proposition.
4. **Transparency** represents resigning from information asymmetry between the customer and supplier and practicing the openness of information.

In terms of available empirical evidence the issues of co-creation and the DART framework are a clearly underdeveloped area. The only aspect of co-creation that is currently supported by a more substantive body of research is the involvement of customers in innovation creating processes (so called innovation co-creation or co-creation for others versus experience co-creation or co-creation for use [Gustafsson et al., 2012]. An extensive overview of literature presenting empirical findings on this topic can be found in Boger et al. [2010]. A few more recent examples of research on the role of users as innovators are presented by Gustafsson et al. [2012], Russo et al. [2012], Skibstedt and Bech Hansen [2011], Reay and Seddighi [2012].

In contrast, there are only a few studies that were centered on the co-creation for use, which is also the main focus of the DART model. The most likely reason for that are difficulties with operationalizing variables for quantitative, questionnaire-based approach. As a result most of the research projects on the topic were following case study methodology, quite often with only a single company being investigated, which might have benefits regarding internal validity but also seriously limits possibilities for generalizing the outcomes. One of such case studies concerned the Swiss Federal Railway operator (SBB), presenting the company's migration from value facilitation to value co-creation with customers [Gebauer et al., 2010].

Another example of research involving case study analysis and directly employing DART as a theoretical framework was a project investigating co-creation processes at five leading consumer product companies running the so called temporary shops in Milan, Italy [Russo Spena et al. 2012]. The authors found that the temporary shops offering customers direct multisensory interactions were an effective implementation of the DART concept resulting in intense involvement of customers in co-creating usage experience. Another study, not invoking directly DART but rather trying to operationalize the whole notion of service dominant logic, was performed in Singapore with the aim to compare two Internet-based travel planning system designs: one driven by service dominant logic and one informed by goods centered approach characteristic for traditional marketing. The authors operationalized service and goods dominant mindsets proposed by Lush and Vargo [2008] to arrive at a set of metrics which were used to collect data on user experiences from interacting with two different journey planning applications. The main finding was that the design guided by the service dominant mindset was superior in quality of customer experiences and customer satisfaction, in part due to its enabling intense co-creation.

There were only a few attempts to study any form of co-creation in Poland. Mazurek [2012] studied Internet impact on suppliers' and customers' roles. Relying on survey data he noticed that Internet was not only used for transmitting information to customers but also served as a tool for interacting with them in a dialog. Even though the study did not employ DART framework some of its aspects served as an inspiration in developing the present project.

The closest in scope and topic to the current paper was a study by Albinson et al. [2011] which sought to develop a questionnaire multi-item scale for measuring the application of the DART model by consumer product companies. The Likert type scale was developed through a series of depth and focus-group interviews and validated by a survey of university students. The 23-item scale was verified by confirmatory factor analysis to possess adequate levels of validity and reliability. The four constructs of DART were also found to be positively correlated with a sense of shared responsibility but with the exception of ACCESS they did not display any significant correlation with loyalty towards the provider of goods or services.

The original objective of the current study was to make use of the outlined literature sources to propose and test a comprehensive measurement system for survey research that would allow for effective evaluation of the firms' involvement in various aspects of co-creation represented by the DART framework. However – as it transpired during the analysis – the gathered empirical evidence pointed to possible intrinsic conceptual flaws in DART, which consequently became the main focus of the investigation.

Research Method and Sample Structure

The scale employed in the study was developed through a four-stage process. As an initial step we specified the domain of the scale following the suggestion by Churchil [1979]. Through a literature review, involving works exploring the DART model as well as titles pertaining to more general co-creation topics (referenced in the previous section of the current paper), we established broad operational definitions of each component of the framework and developed sets of Likert scale statements to encapsulate all relevant aspects of each component. Next, the items were examined and debated in a seminar with doctoral students in marketing who were not otherwise involved in the study. The refined list of statements was presented to a group of managers who discussed it in a manner akin to the focus group interview. Finally, the appropriateness of wording was verified in a pilot survey administered in the same way as the main survey through telephone interviews. The complete list of the 30 Likert-type scale items was given below.

TABLE 1 Statements used in the study for measuring firm's involvement in the four aspects of the DART model

DART component 1: DIALOG
Dialog 1: We maintain a multichannel dialog system engaging our customers in production and distribution processes
Dialog 2: We encourage customers to enter dialog leading to enhancing their experiences with our products/services
Dialog 3: We give our customers ample opportunities to share with us their ideas for increasing their satisfaction with product/service experience
Dialog 4: We substituted dialog with customers for one-way promotion
Dialog 5: We support a dialog with our customers to foster their preference for our products/services over products/services of competitors

Dialog 6: We enhance our credibility by holding a dialog with customers who are not satisfied with our products/services
Dialog 7: Our employees are actively involved in discussions on internet forums and in social media (e.g., on Facebook)
Dialog 8: We actively support user groups of our products/services
Dialog 9: We have open and sincere dialog with all our partners
DART component 2: ACCESS
Access 1: We provide our customers with technical capabilities to share with us their opinions and experiences
Access 2: We immediately respond to questions and comments from our customers
Access 3: We maintain an Internet forum where our customers can exchange opinions among themselves and with us
Access 4: We support dissemination of information about our company on third-party owned web sites
Access 5: In Internet media there is more information about our offerings than competitors'
Access 6: Our customers can communicate with us easily Access 7: Our customers are free to place their orders through a channel of their preference
Access 8: Our customers are free to choose their preferred delivery method of our products/services
Access 9: Our customers are free to choose their preferred time of receiving our products/services
Access 10: Our customers are free to choose their preferred location of receiving our products/services
DART component 3: RISK ASSESSMENT
Risk Assessment 1: We provide our customers with all relevant information about our products/services, so they could assess the benefits of our offerings on their own
Risk Assessment 2: We freely inform our customers of possible risk from using our products/services
Risk Assessment 3: We encourage our customers to learn about safety warnings and other kinds of risk from using our products/services
Risk Assessment 4: Our offerings are safe for everyone so informing of risk is unnecessary
Risk Assessment 5: We discourage from purchasing those customers who could be harmed by our products/services or dissatisfied with them
Risk Assessment 6: We advise our customers on how to use our products/services to avoid various kinds of risk
DART component 4: TRANSPARENCY
Transparency 1: We make available to customers all relevant information that facilitate their use of our products/services and/or inspire them with new ideas for consumption/application
Transparency 2: We put no constraints on our customers' access to information about prices of our products/services and costs that we have incurred
Transparency 3: Partner relationships with our customers encourage us to supply them with information that can augment their experience
Transparency 4: Information that we provide to our customers is up-to-date, which fosters the best possible experience with our products/services
Transparency 5: Our customers know about us as much as we do ourselves

Source: own elaboration.

As was already noted the main inspiration in devising the above indicators was co-creation literature, in particular the original presentation of the DART framework by Prahalad and Ramaswamy [2004a] and later works by these authors [2004b, 2004c, 2008] supplemented by several other papers with DART references. Here, we provide a more detailed rationale for using particular statements as measures of respective DART components.

Dialog Indicators

Explaining their understanding of Dialog, Prahalad and Ramaswamy [2004a] used such terms and phrases as: engagement, propensity to act, interactivity, shared learning, maintaining community of loyal customers and firms and customers being two equal problem solvers. Accordingly, the indicators developed to measure Dialog reflected those aspects and characteristics. In particular:

- Engagement was embedded in the Dialog 1 indicator,
- Increasing propensity to act in Dialog 2,
- Interactivity in Dialog 3,
- Relying on one-way communication instead of dialog in Dialog 4, to better control validity of other metrics,
- Shared learning in Dialog 7,
- Maintaining community of loyal customers in Dialog 8,
- Firms and customers taking on roles of equal problem solvers in Dialog 9.

In addition, Dialog 5 and 6 were aimed at identifying managers' perceptions of the changing nature of competition, shifting from the transactional model into value co-creation which strongly relies on dialog. Since DART is one approach to conceptualizing co-creation, this choice of statements seems to be justified.

Access Indicators

Not many guidelines are offered in the DART conceptual articles on how to define and operationalize Access; and what is offered there could be summarized by the phrase that "Access begins with information and tools" [Prahalad and Ramaswamy, 2004b].

Consequently, subsequent research by other authors did not employ a consistent outlook on this element of the framework. In one such paper, Russo Spena et al. [2012] stated that "Access covers how interaction empowers customer access to knowledge, tools, information and experience". Our view is similar in that we believe in defining Access by emphasizing availability of tools, procedures and routines that empower customers to gather information and enter into interactions, which result in enhanced experience. Accordingly, Access 1, 3 and 4 were designed to represent the use of various Access tools, while in items 2, 5 and 6 we tried to capture the functional aspects (or quality) of those tools, understood as reaction speed, amount of available information and the general ease of use, respectively.

The original DART concept do not extend the Access category beyond sharing information and knowledge. However, its authors stressed that "…co-creation experience occurs where individuals exercise choice, and where value is co-created." [Prahalad, Ramaswamy, 2004b]. In line with this suggestion, we decided to broaden Access scope to include elements of the distribution system beyond communication processes (Access 7 through 10). This idea was strongly influenced by the work of Albinson et al. [2011], who used similar approach in their DART survey scale.

Risk Assessment Indicators

Risk Assesment was originally defined as "the probability of harm to the consumer" [Prahalad and Ramaswamy, 2004b]. The main idea seems to be enabling customers to make informed choices. Hence, the consumer has the right to be aware of the risks involved in accepting the offer (items 2, 3, 5 and 6), as well as benefits it generates (item 1). The insights on harm probability allows the consumer to make an in-depth value proposal assessment. Item 4 was included to clearly identify those companies whose offerings (by perceptions of their managers) do not carry significant risks to consumers and thus informing on them may not be relevant.

Transparency Indicators

According to Prahalad and Ramaswamy [2004c] Risk Assessment and Transparency are two building blocks of trust. Thus their suggested motto for smart companies was "When in doubt, disclose". To their mind, Transparency was meant to promote the end of information asymmetry, so that customers had easy access to comprehensive, timely and accurate information resources on offered value propositions. The commitment of companies to removing information asymmetry was examined with items 1, 3 and 5, while item 4 was centered on the quality of offered information.

Using the above scales, the data were collected through a combination of CATI and CAWI interviews, in which company managers gave their answers by telephone while seeing the web based version of the questionnaire. This interviewing mode allowed for using more complex questions and scales due to enhanced communication between respondents and field workers as compared to the ordinary CATI. It total 440 managers participated in the survey in July and August 2013. The final response rate, defined as the ratio of completed to attempted interviews, amounted to 39%; a comparison of the sample and population distributions on known characteristics, such as profitability, size and ownership status, did not reveal significant differences, which suggests that obtained reply rate should not be problematic in generalizing results. The study sample encompassed in equal halves service and manufacturing companies directing their offers to mass retail markets. In particular the following industries were investigated: production of food (35.9% of the sample size) and beverage (7.8%), cosmetics manufacturing (6.8%), hotels and accommodation (20.7%), catering (20.5%) and other tourism services (8.9%). The sample included almost equal number of small (10–49 employees) and medium (50–250 employees) firms. Focusing the research on these types of companies lessened heterogeneity and thus offered a certain level of control over extraneous variables that could not be studied due to constraints on the length of the interview but could possibly have confounding effect on substantive covariance patterns. Overall, the random selection of firms for the study from a representative database of Polish companies allowed an adequate level of external validity, permitting generalizations to the pertinent industry groups in Poland.

Validation of the DART Measurement Model

The primary objective of the study – investigating relevance of the DART model for the Polish service and manufacturing companies – was approached with confirmatory factor analysis (CFA) as the main methodology. The CFA, implemented in AMOS 22 program, allows the evaluation of a whole measurement model with a single statistical test and also provides specific metrics for assessment of particular parameters of the model.

The first step in the analysis was running CFA for a solution including the whole array of 30 indicator items assigned to the four factors in accordance with the designations provided in Table 1. The graphical representation of the model together with estimated standardized regression weights, correlations and squared multiple correlations is shown in the Figure 1.

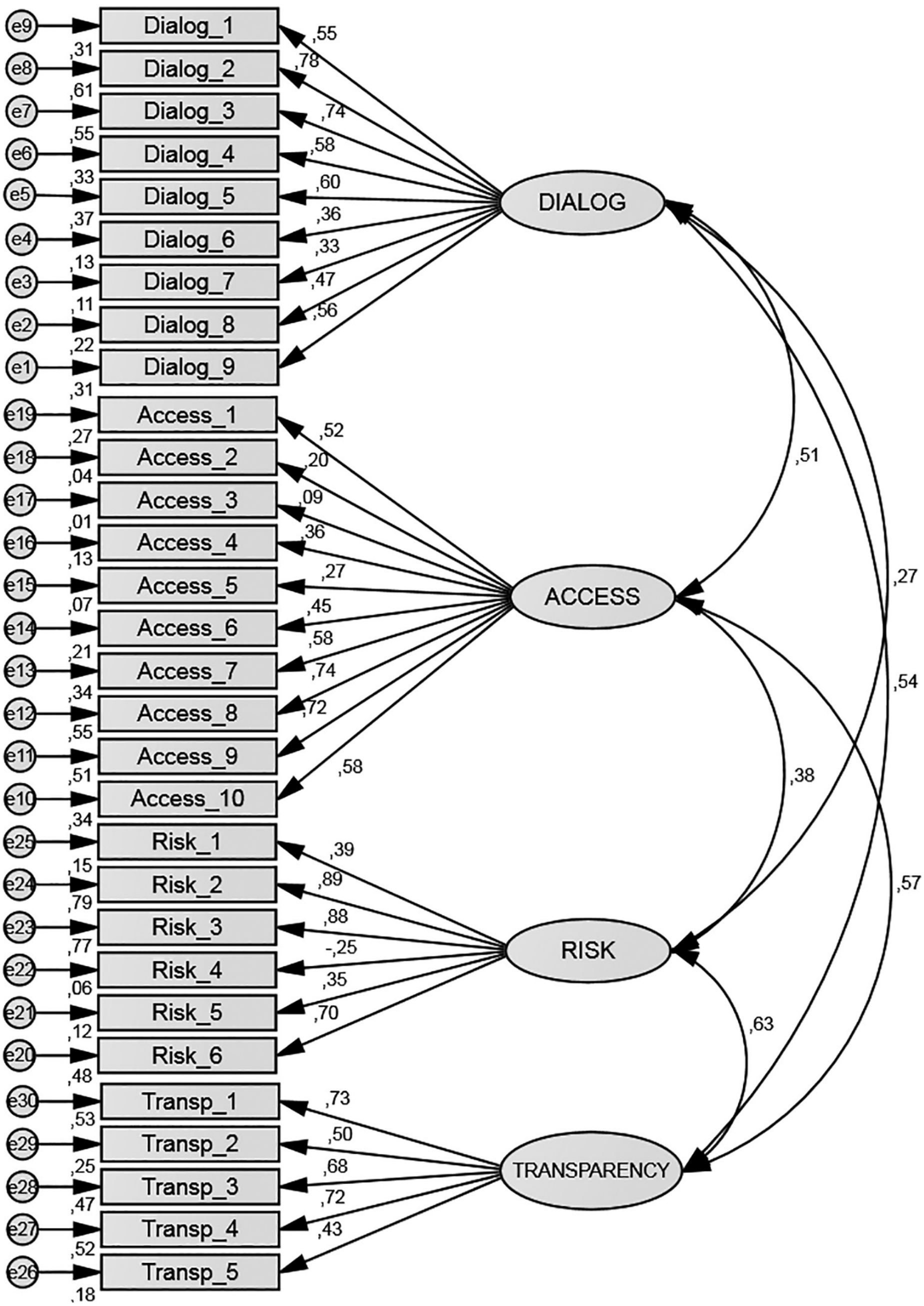
The graphical model uses standard symbols and shapes to depict elements of the CFA path diagram, in particular:

- Ellipses represent latent variables or constructs (in the present case the four building blocks of the DART model)
- Rectangles denote observed variables or indicators
- Circles stand for measurement error terms that in addition to actual measurement errors also represent all other factors (other than the model latent variables) that explain the variance of particular indicators not accounted for by the model
- One-headed arrows pointing from construct variables to indicator variables depict regression paths
- Two-headed arrows correspond to correlations between latent variables to account for the fact that the latent variables in the DART model, due to partially overlapping conceptualizations, may not be independent and show statistical associations.

In addition, the graph contains three kinds of statistics:

- Numbers attached to double-headed lines describe correlations between latent variables
- Numbers next to one-headed lines represent standardized regression weights that show how strongly latent variables affect particular indicators
- Numbers to the left of rectangles provide squared multiple correlations, which indicate what percentage of variance in an indicator is explained by the latent variables in the model

FIGURE 1. The CFA model of DART structure with all 30 indicators



Source: own elaboration.

Following the above explanations it is quite clear that the model is not a particularly good representation of the collected data. What is most striking is the considerable number of indicators which variance is explained only in a small fraction (e.g. Access_3 only 1% of variation, Access_2 4% and Access_5 7%). Those indicators, with small regression coefficients and negligible amounts of variance attributed to the model, do not contribute valuably and probably solution's parameters will be improved should they be removed.

Deeper insights into the model adequacy can be obtained from the overall goodness of fit measures of the model, which typically include chi-square statistic (χ^2=2246.229; df=399; p<0.0005), relative chi-square (χ^2/df=5.630), goodness-of-fit index (GFI=0.718), comparative fit index (CFI=0.631) and root mean square of approximation (RMSEA=0.103; LO 90=0.099; HI 90=0.107).

To aid in interpreting the goodness-of-fit metrics Garson (2012) gives the following guidelines for cutoff points to accept a CFA model:

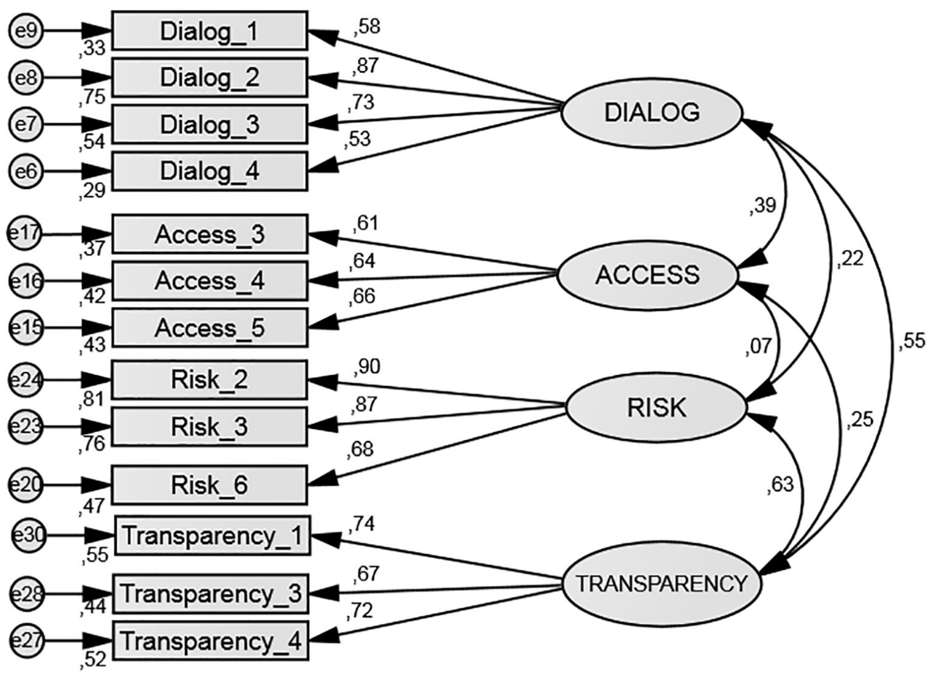
- Model chi-square should be statistically insignificant at 95% confidence level to consider the model consistent with empirical data
- Relative chi square: <2 for good fit, <3 for acceptable fit
- GFI: ≥0.9
- CFI: ≥0.9
- RMSEA: ≤0.05 for good model fit; ≤0.08 for adequate fit; in addition, the upper 90% confidence limit (HI 90) should be no more than 0.08 for a well-fitting model

Using the above criteria it was apparent that the CFA model is of too low quality to consider it a good approximation of the observed covariance structure (which serves as an input for CFA). First of all, chi-square test was statistically significant at a p level of 0.0005. Given that the null hypothesis for the test was that there were no significant differences between the observed covariance matrix and the one reproduced from the model, the p score of the test suggested poor model fit. However, the chi square test is thought to be unreliable, particularly for large sample sizes, often giving too large values signaling the need to reject otherwise adequately fitting models [Byrne 2010, pp. 76–77]. For that reason a number of additional indexes were developed for assessing the reliability and validity of a CFA solution relying on different features of model fit and using various assumptions about data. In fact, "although the chi-square value should always be reported it is widely considered acceptable to conclude that a model fits the data well, even when the value is statistically significant, if other preselected fit indices meet their established criteria for fit" [Bowen, Guo 2012, p. 142]. Following this set of recommendations on model verification it was clear that none of the four other measures of the solution quality was adequate, thus the hypothesized model should definitely be rejected.

The next steps in the analysis were focused on modifying the initial configuration of the model to try and achieve a solution with an acceptable fit with the sample data. As the starting point, the exploratory factor analysis (EFA) was performed four times: once for each group of indicators assumed to be correlated with each DART component. The

EFA was set up so that to extract only one factor from each group of indicators. It was consistent with the assumption that DART components are unidimensional constructs and accordingly their indicators are expected to have high factor loadings (i.e. correlation coefficients) only on one latent variable. As such, indicators that did not associate closely with an extracted factor were assumed to describe different construct and hence removed from further analysis. As the cutoff point for acceptable factor loadings served a value of 0.5 following suggestions in Hair at al. [2009, pp. 120–121]. Therefore, the EFA was used as a data reduction tool to retain only those observed variables that were highly associated with DART components and served as their reliable measures. To ensure that the EFA procedure was consistent with the CFA, the factors were extracted with the maximum likelihood method. In consequence, the total number of indicators was reduced from 30 to 13 so that DIALOG was represented by 4 variables, ACCESS by 3, RISK by 3 and TRANSPARENCY also by 3. With this configuration of observed variables the CFA was repeated to yield the following path diagram (Figure 2).

FIGURE 2. The CFA model of DART structure with 13 indicators

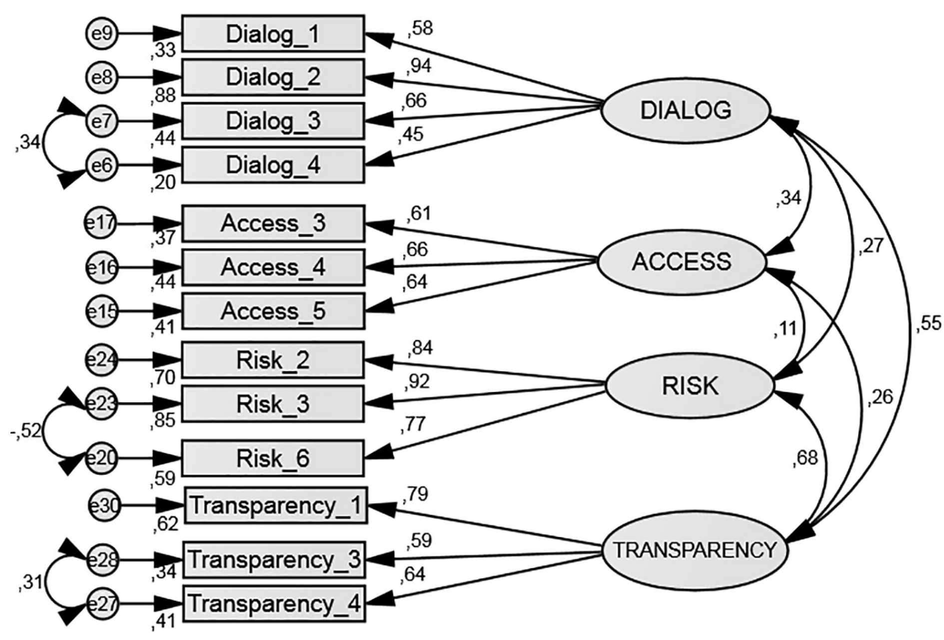


Source: own elaboration.

The adequacy measures for the new model were: (1) chi-square=280.48; df=59; p<0.0005; (2) relative chi-square=4.754; (3) GFI=0.912; (4) CFI=0.896; (5) RMSEA=0.092; LO 90=0.082; HI 90=0.103. The diagnostics indicated that the second model was a better representation of the sample data compared with the initial solution, however chi square test was still significant (though at a lower value) and fit indexes (apart from GFI) were outside the acceptance range. What was noticeable in relation to the starting model (Figure 2) was the lack of indicators with very low regression weights; here all indicators have factor loadings above 0.5 which suggests no further candidate variables for deletion.

To try to attain an even better data fit two avenues were available: to either modify the model by including correlations of error terms or reduce the sample to achieve a higher level of homogeneity of constituent companies. Given that introducing substantively and statistically justified correlations of error terms is thought to be less arbitrary than sample manipulation this is what was done in the next step. Using the modification indices provided in the AMOS output it was possible to identify the error terms that if correlated offered the most substantial gains in the model fit as measured by drops in the model chi-square value. In total three new covariance terms were brought in to arrive at a model (Figure 3.).

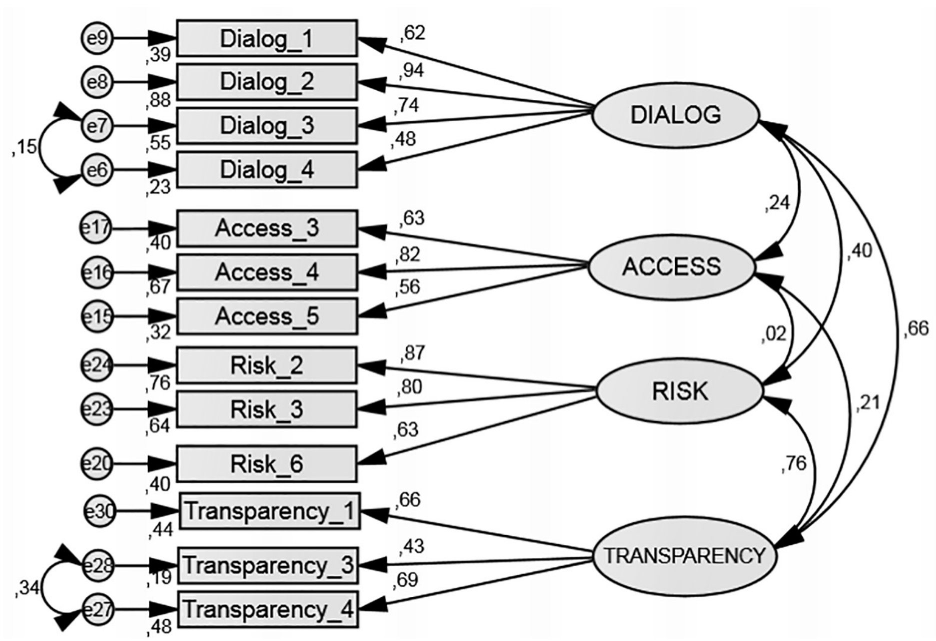
FIGURE 3. The CFA model of DART structure with 13 indicators and correlated intra-construct error terms



Source: own elaboration.

The third model yielded the following set of data fit metrics: (1) chi-square=204.297; df=56; p<0.0005; (2) relative chi-square=3.648; (3) GFI=0.935; (4) CFI=0.930; (5) RMSEA=0.078; LO 90=0.066; HI 90=0.089. The modified model showed an improved fit across all indices with GFI and CFI at an acceptable level and a borderline score on RMSEA. However, Chi square test still gave significant outcomes, suggesting poor fit.

FIGURE 4. **The CFA model of DART structure for 220 manufacturers with 13 indicators and correlated intra-construct error terms**



Source: own elaboration.

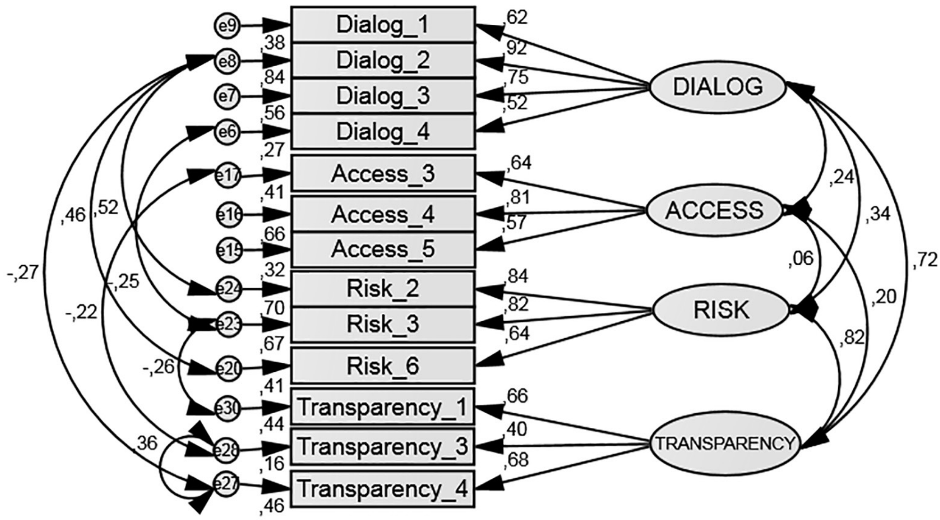
To further improve model parameters an attempt was made to exclude from the analysis certain groups of companies with a rationale that a more homogeneous dataset may yield more distinct correlation patterns, though at the cost of constraining external validity (i.e. after leaving out specified companies the generalizability will be only possible to a target population of firms that were left in the data set). Given the study sample composition the most natural choice was to run separate CFA for manufacturing and services companies on the assumption that their inherent similarities would result in better fitting models. It transpired that the service providers yielded a solution that was considerably worse on all of the diagnostic metrics than the earlier model. This suggests that the DART framework can be more effective at explaining aspects of co-creation in manufacturing firms, possibly because its development was apparently driven by data from case studies of manufacturing companies [Prahalad, Ramaswamy, 2004]. As a consequence, the next structural model was centered solely on the manufacturers subsample (Figure 4.).

The solution obtained for manufacturers was characterized by the following diagnostics: (1) chi-square=109.944; df=57; $p<0.0005$; (2) relative chi-square=1,929; (3) GFI=0.932; (4) CFI=0.945; (5) RMSEA=0.065; LO 90=0.047; HI 90=0.083.

As it stands, the model including only manufacturing companies and following the same specification as the previous structure (the only small exception being the lack of one error covariance which was deleted due to its insignificance in the new sample) provides acceptable data fit on 4 out of 5 criteria. Bearing in mind earlier remarks about unreliability of the chi-square test, the model can be accepted as providing adequate data fit.

When model generation strategy is guided by modification indices it is important to be able to substantively justify the addition of new parameters to the model. Furthermore, even though the indices may suggest introducing new parameters (or "freeing up parameters", as it is also termed in the literature) the researcher can decide against it in the interest of the rule of parsimony. The rule of parsimony in science is a principle that advises the simplest possible model design to avoid the risk of over-specification, which can result in a well-fitting model to the observed data but with no relevance for other data sets [see the discussion in Mulaik 2009, pp. 342–345]. Over-specification occurs because model components are developed by leveraging unique features of the studied data that may not repeat in other data files, i.e. through capitalizing on chance. Mulaik [2009, pp. 381] cautions against too liberally adding parameters to a model following the values of modification indices by noting that "if the lack of fit is not due merely to a missspecified parameter in a correctly specified model structure, this can be misleading. The problem could lie in a missspecified model structure, omission of important latents, and no amount of freeing up parameters in the current model could lead to a correct model, even though the resulting model might fit acceptably". **As the existent DART literature doesn't provide theoretical grounds to modify the model structure by introducing new latent variables or adding new regression paths, and heeding the rule of parsimony, the fourth model appears to be the best representation of the DART concept for the research data. However, to possibly reveal potential limitations of DART, further analysis was performed to attempt to achieve the maximum fit level even at the risk of overspecification**. The employed procedure involved sequentially adding and deleting covariances of error terms (not only within factors but also between indicators assigned to different factors) based on the changes in significance levels and effect sizes, although without altering the general structure of the solution. The outcome of this model building strategy was presented in Figure 5.

FIGURE 5. The CFA model of DART structure for manufacturers with 13 indicators and correlated inter- and intra-construct error terms



Source: own elaboration.

Every adequacy metric for the solution (chi-square=62.713; df=52; p=0.147; relative chi-square=1.206; GFI=0.958; CFI=0.989; RMSEA=0.031, LO 90=0.000, HI 90=0.005) is not only substantively better than for any previously considered alternative but also well within the range of acceptable values indicating a very close match with the data set of 220 manufacturing firms. However, the improvement in goodness-of-fit from the previous solutions was achieved due to the introduction of six covariances between errors of observed variables assigned to different constructs. The new covariance parameters rendered statistically insignificant the two error covariances between pairs of indicators within DIALOG and TRANSPARENCY factors, which were consequently removed from the model.

As was already explained, the error terms in regression analysis are taken to represent all variance in indicators that was not accounted for by latent variables. The variance could originate from random factors, measurement errors or – what is typical of missspecified models – other latent variables that were not included in the model [Hoyle 1995, pp.172–173]. Hence, **the presence of so many statistically significant correlations between indicators from different factors suggests that the observed variables are influenced by more than four factors, which in turn strongly implies that the DART model is incomplete and ought to include more than four latent variables.** The conclusion is corroborated by relatively low multiple correlation coefficients, that inform about percentage of variance in each indicator explained by the constructs present in the model. In fact, 8 out of 13 observed variables are explained in less than 50% by the DART components.

Another finding is that DART may not be a unidimensional structure as was assumed by the conceptual work of Prahalad and Ramaswamy [2000] and the survey by Albinsson et al. [2011]. As explained by Kline [2011, p. 115], unidimensional measurement is defined by (1) each indicator loading (correlating) on one factor and (2) independent error terms. Accordingly, a measurement model which contains indicators substantially correlated with two and more factors suggests multidimensionality. The same is indicated by the correlated error terms, reflecting the assumption that the pairs of corresponding indicators share something in common that is not explicitly represented in the model [Kline 2011, p. 115]. Thus, the source of multidimensionality is likely to be an unknown construct or constructs from outside the model. The present study enables to observe both causes of multidimensionality: (1) correlated error terms of indicators point to the existence of other explanatory latent variables, while (2) multiple factors loading on more than one indicator hint that the constructs are not independent since their substantive scopes markedly overlap. Table 2 provides more evidence to support this line of argument. It contains linear combinations of regression coefficients for all indicators in the model which could be used for estimating values of each of the DART components.

TABLE 2. Regression weights between factors and observed variables

	Transparency_1	Transparency_3	Transparency_4	Risk_2	Risk_3	Risk_6	Access_3	Access_4	Access_5	Dialog_1	Dialog_2	Dialog_3	Dialog_4
TRANSPARENCY	.09	.00	.11	.05	.10	.01	.00	.01	.00	.01	.08	.03	.03
RISK	.13	.02	.06	.29	.24	.12	.00	.00	.00	.03	-.16	.05	.06
ACCESS	.01	.07	-.01	-.02	.00	-.01	.20	.46	.20	.00	.05	.01	.00
DIALOG	.05	-.02	.14	-.10	.07	-.07	-.00	.00	.00	.04	.44	.07	.04

Source: own elaboration.

It can be seen that, with the exception of ACCESS, the factor scores were best predicted by a combination of indicators from within and without their respective domains (highlighted in grey). In fact, some indicators attributed in the model to a particular factor were less useful as predictors in comparison to indicators nominally assigned to other factors (a case in point being TRANSPARENCY, where Risk_3 and Dialog_2 had stronger impact on the construct score than Transparency_2; it was likewise for the constructs RISK and DIALOG). On the other hand, looking at the table column-wise, it is obvious that most indicators were associated with more than one factor, e.g. Transparency_1 and Transparency_2 loaded substantially on TRANSPARENCY, RISK and DIALOG, while dialog_2 was related in varying degrees to all factors. As it was already noted, **only**

ACCESS, which comprised three aspects of Internet applications in communication with customers, was truly independent of other constructs, and consequently its indicators did not load on other latent variables. The cross-loading of the indicators was symptomatic of questionable convergent validity of the DART model. On the other hand, high correlations coefficients (see Figure 5) between DIALOG and TRANSPARENCY and RISK and TRANSPARENCY, respectively 0.72 and 0.82, were an evidence of low discriminant validity (i.e. the same indicators measure two factors simultaneously).

Conclusions and Limitations

The findings of the study highlight possible shortcomings of the DART concept. First of all, it may imply that DART is too simplistic in that it assumes unidimensional structure with only four factors. The analysis necessitated exclusion of 17 indicators from the data set, that were coherent with various conceptualizations and exemplifications of DART found in extant literature sources, to be able to achieve an acceptable match to the actual observations with the remaining 13 variables. Regardless, the final CPM model seemed to display clear evidence of multidimensionality even in the reduced group of 13 observed variables. Apparently, to attain higher relevance of the model to the business practice it would be useful to overhaul the DART structure to arrive at a selection of constructs that do not overlap so markedly and possibly add new elements that are able to better address those aspect of co-creation that were captured by the discarded indicators. It is rather conceivable that the four DART constructs could actually be second level latent variables affecting indicators not directly but through the first level constructs serving as mediators.

In the extant literature there has not been a single widely accepted approach to measuring businesses' involvement in co-creation. The most common method assumed that value co-creation is a first level, one-dimensional construct with rather compact Likert-type measurement scales encompassing three [Auh et al., 2007], four [Grissemann, Stockburger-Sauer, 2012] or five [Zhang, Chen, 2008] component items. Consequently, the individual statements on the scales were phrased quite generally and seemingly did not include all designators of the concept of co-creation, which had very similar definitions across most pertinent papers. On the other hand, there was an attempt to employ a more complex measurement system [Yi, Gong, 2013], treating co-creation as a third-level construct directly affecting two second level-factors of customer participation and customer citizenship behavior, which in turn were reflecting on four first-level factors each. That operationalization when tested through a survey on a group of consumers was demonstrated to have acceptable reliability and validity. Although definitions of particular first and second level constructs as well as phrasing of individual Likert-scale items could be disputed, this outlook of having two intermediate layers of effects between co-creation and actual scale items is coherent with the perspective of the authors of the present study based on the conclusions from the analysis of the measurement model for DART. The positive validation of the quoted alternative conceptualization of value co-creation seems to lend credence to the authors' observation that the DART model, to closer mesh with actual practice, should be enhanced with an additional layer of hidden variables to form a three-level factor structure.

One has to admit though that the study has several limitations that could attenuate the appeal of its findings. Firstly, the final model was built entirely on data collected from a few consumer oriented manufacturing industries in a single Central-European country. As a result, any generalizations beyond the strictly defined target population of the study should be performed cautiously. Secondly, in addition to the limitations in external validity, it is possible to raise concerns about certain aspects of internal validity. Even though the authors did not have any particular reason to harbor doubts, it is not entirely certain if relying solely on managers' replies for data was not affected with measurement bias. Though in the data collection process as well as in further analysis nothing was indicative of existence of such a problem, it would be revealing to be able to tap into other sources of information about companies to achieve triangulation effect and thus enhance reliability and validity of findings.

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