EXPLORING DETERMINANTS OF THE MARKETING BUDGET ALLOCATION PROCESS ACROSS COUNTRIES USING NEURAL NETWORK CLASSIFICATION: JAPAN, GERMANY, UNITED STATES

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ABSTRACT

As firms continue looking for new ways to optimize expenditures, marketing managers have been forced to examine the transitory targets of efficient allocation levels and effective firm performance. Budget optimization has become the driving factor for marketing and sales expenditures given these optimal expectations. Although numerous studies exist addressing the relationship between marketing expenditures and sales performance, the impact of this knowledge has been slowly applied. Furthermore, very little previous research examines marketing budget allocation optimization in varying product categories or differing geographic regions. Moreover, there appears to be little consensus as to the identification of consistent input firm or customer level variables consistently associated with favorable outcomes and good practice. Therefore, this study will examine organizational, regional and performance determinants and their relationship to the marketing contribution performance in a cross-cultural context.

The proposition is a firm level examination of variables to confirm impact on marketing performance across cultural settings. Specifically, a sample of 770 retail trade firms from Japan, Germany and the United States are empirically investigated in an attempt to answer the following primary questions: (a) Does a common set of high-ranking determinants for Maximum Net Marketing Contribution exist among retail trade firms from the examined countries, combined? (b) Does a unique set of high-ranking determinants for Maximum Net Marketing Contribution exist within the retail trade firms from each country, individually? To confirm the classification capability, the variables examined employ both a non-linear probabilistic neural network (PNN) and a linear multiple discriminant analysis.

Keywords: Marketing Budget Allocation, Probabilistic Neural Network.

INTRODUCTION

The optimization of budget allocation has been examined by both academician and practitioner alike. Firms continually seek the sweet spot of allocation amounts to dollar returns. During the last 40 years there have been numerous studies searching for the *"rosetta stone"* of budgeting and budget allocation optimization. Fischer et al. (2011) note that although the managerial relevance and importance of marketing budget decisions are high, contributions to marketing budget allocation approaches by marketing scholars are rare. The problem is further exacerbated by a firm having multiple products being sold in multiple countries. Furthermore, Tull et al. (1985) suggested that profit improvement was more responsive to allocation across products and regions rather than the improvement of the overall budget.

Bigne (1995) reviewed 16 studies from the mid 1970's to the early 1990's. The three top determinations for marketing budget allocation were percentage of sales, objective and task, and affordability. These heuristic methods have not generally optimized marketing allocation outcomes resulting in performance inefficiencies. One of the contributing causes of this is the current trends addressing this problem. Solutions of late have been complex, incorporating decision calculus and non-linear modeling, making it difficult for many firms to understand, let alone incorporate these models into their decision making. Although these models have proven to be robust, they have had little impact on managerial decision making for budget optimization.

LITERATURE

The marketing budget allocation process and the myriad articles written over the last 40 years suggest that this topic and various constructs are mature. However, in examination of that work, many areas of discovery and application are still void. The core underpinning of the theory stems from several key works. Foremost, a mention of Cyert & March's (1963) Theory of the Firm should be addressed when examining managerial expectations of risk and return in the context of large corporations. This seminal work visibly analyzes management's motivation to make allocation decisions, such as budgetary practice and the relationship to expected outcomes providing a clear understanding of managerial motivations. Argote & Greve (2007) further substantiate the Theory of the Firm by examining how this traditional work has impacted organizational learning and decision making which include topics such as bounded rationality, organizational learning theory and firm level evolutionary economics.

In addition, the nature of managerial actions and decision making based on marketing theory exists in the Interactive-Economic School of Marketing focusing on the Managerial School (Sheth et al. 1988). This perspective suggests that marketing is a function of the firm's economic cost/benefit highlighted by approaches to efficiency in inputs and effectiveness in output.

While specifically examining the marketing budget allocation process, Gupta & Steenburgh, (2008) identify numerous implicit and explicit methods of budget allocation decision making through a review of previous literature. Some of the common approaches in construction of the marketing and sales budget identified were, percentage of sales, backward costing based on a desired marketing outcome, allocations needed for consumer stimulus and reach affects, or mere instinct or affordability. However, in the broadest sense, marketing and sales allocations can be categorized into a two dimensional matrix focused on demand estimation and economic impact. Within these two categories are various techniques to operationalize variables including price sensitivity, optimization, and scenario simulation.

An examination of the literature would not be complete without noting the work of Assmus et al. (1984) meta-analysis of how advertising affects sales. Using both short and long term advertising data, they uncover notable variables associated with sales performance but fall short of providing a core theoretical underpinning of the topic. While various elasticities of short term analysis clearly show carryover affects, no definitive conclusions were drawn. They concluded that advertising effectiveness was lacking an overall comprehensive model.

Several notable studies examined the marketing budget allocation process using a distinction of market and firm level characteristics. Sridhar et al. (2011) examine platform-firm markets, as opposed to one-sided firm markets. They were able to develop a platform-firm response model that accurately identified cross market effects with demand interdependence, suggesting the importance of a marketing manager's knowledge of cross market effect opportunities and carryover effects. In a similar work, Abedi (2017) examines multiple channel advertising allocations in multiple markets. Using a weighted non-linear optimization approach, several general findings were that optimization of multiple lines in multiple channels is achievable; however there were no constraints to the budgeted amount. As budget amounts may be preset prior to the performance outcome, no specific allocation amounts were included the study. Perdikaki et al. (2017) examine the retail environment with the purpose of examining ancillary marketing activities and the impact of budget decision making. Using store level budgets, an examination of store labor with advertising rates to retail store performance was performed. The study finds that an optimization of marketing spending allocations with store labor can produce the maximization of store performance concluding that budget allocations should not be done in isolation without consideration of store labor. The study included variables such as customer traffic patterns, variants of budget allocations, and variations in labor costs.

Another common approach to this paradigm is also found in the literature. Often referred to as the mathematical or calculus approach to marketing budget optimization, there have been several notable studies undertaken by (Basu & Batra, 1988; Tang, 2009; Koosha & Albadvi, 2015). Each of these studies incorporated a computer based, mathematical modeling technique to optimize promotional, advertising or marketing budget allocations. All three of the studies suggest that some level of optimization is possible given the constraints of the variable. Because of the number of possible variables, these approaches proved to be valuable in modifying the scenarios, seeking the most robust outcomes. While Basu & Batra (1988) use a traditional linear model, Koosha & Albadvi (2015) use a Calculus model, and Tang (2009) uses a non-linear probabilistic neural network, similar to the one used in this paper.

Recent trends in the literature over the last five years adding to the marketing allocation construct are emerging such as budget allocation models incorporating product level performance and the prioritization of allocation to performance (Nasution et al., 2019) and various portfolio approaches (Norouzi & Albadvi, 2016). Budget allocation using a variation of portfolio theory suggests that budgets can be examined based on some aggregate performance optimization incorporating both profitability and variability. Likewise, there continues to be an increased focus on metric based decision-making and accountable marketing (Pauwels, 2015). Metric based marketing budget allocation continues to be popular and is the basis for this study.

Lastly, Zhou et al. (2018) examined allocation optimization of the promotion budget. Using a proprietary web-based sales firm, they were able to track micro movements of promotions with traffic volume to the site, then eventual sales. They found that not all brands react the same therefore cannot be predicted based on budget allocations. In addition, they also found that website traffic volumes could be used to estimate actual sales.

Marketing and Sales Budget Performance Measures

In addition to understanding budgetary input drivers, a discussion of output performance measures is also warranted. There are many views on potential measures of expected firm performance in the literature. These variables would include profitability, sales volume, brand reach, brand development, market share and penetration, and various sales performance metrics.

Best (2013) highlights a metrics based approach, using hyper focused quantitative measures. He asserts that metric based analysis can be concluded on most expense inputs and performance outputs. This is particularly pertinent with marketing performance. Using several variables of analysis, he posits that the Net Marketing Contribution performance approach is a very articulate marketing performance and profitability metric, concentrating on the relationship between marketing efforts and firm profitability. Net Marketing Contribution is defined as sales revenue times percent gross profit minus marketing and sales expenses.

Cultural Dimensions

The justification for country selection is supported by Hall's (1977) contextual paradigm and Hofestede & Bond's (1988) cultural dimensions research. In order to provide a variety of cultural perspectives, the three countries used here represent diverse cultural perspectives. Using Hall's contextual continuum, Germany is considered a low context country, the United States medium, and Japan high. These contexts are based on numerous dimensions including, communication behavior, equality of members within the society, relationship development and action toward achievement. Anticipated results in this study, from the three selected countries, are expected to be diverse, supported by this previous cross-cultural research. Recently, (Peers et al., 2011) research suggested that a macro perspective of budget allocation should utilize and be based on business cycles of the targeted markets. This would include international markets suggesting that regions in different business cycles should receive different allocation considerations.

METHODOLOGY

The following four research objectives are targeted:

1. Offer support to substantiate that determinants of the marketing budget allocation process are impacted by cultural differences.
2. Determine if a common set of high-ranking organizational determinants for Maximum Net Marketing Contribution exists among retail firms from Japan, Germany and the United States. Specifically, (P1) a common set of high-ranking organizational determinants for Maximum Net Marketing Contribution exists among retail firms from Japan, Germany and the United States combined.
3. Determine if a unique set of high-ranking organizational determinants for Maximum Net Marketing Contribution exists within retail trade firms from Japan, Germany and the United States. Specifically, (P2) a unique set of high-ranking organizational determinants for Maximum Net Marketing Contribution exists within retail trade firms from Japan, Germany and the United States, individually.
4. Employ a proven non-linear statistical technique for accurately examining the classification patterns of the marketing budget allocation process, then comparing results to a linear discriminant analysis. Lastly, (P3) a probabilistic neural network classification approach is more accurate, by percentage, than the classification matrix of a multiple discriminant analysis.

Variables

There are 21 independent variables examined in the study. The variables are consistent with those found in earlier literature and are organizational in nature(managerial, regional, performance) (see Table 1). The three dependent variables for this study are related to the performance level of the firm's Net Marketing Contribution Percentage, a marketing profitability metric.

Net Marketing Contribution Percentage = ((sales revenue times percent gross profit) minus marketing and sales expenses) divided by sales revenue.

The performance levels are classified into one of three categories, Maximum Net Marketing Contribution – GT 30%, Moderate Marketing Contribution – 10% to 30%, and Minimal Net Marketing Contribution – LT 10%

Table 1 INDEPENDENT VARIABLES		
	Type	Label
MANAGERIAL		
Years In Business	Ratio	OYB
Marketing Budget To Sales	Ratio	OBS
Firm Asset Size	Ratio	OAS
Firm Revenue Size	Ratio	ORS
Change In Marketing Budget To Sales (1 Year)	Ratio	OB1
Change In Marketing Budget To Sales (3 Years)	Ratio	OB3
Change In Marketing Budget To Sales (5 Years)	Ratio	OB5
REGIONAL		
Product Price Position	Categorical	RPP
Regional Business Cycle	Categorical	RBC
Domestic Market Share	Ratio	RMS
Number Of Locations	Ratio	RNL
Retail Trade Product Class	Categorical	RPC
Number Of Direct Competitors	Ratio	RDC
Breadth Of Product Offering	Categorical	RPO
PERFORMANCE		
ROI	Ratio	PRI
ROA	Ratio	PRA
Sales To Inventories	Ratio	PSI
Inventory Turnover	Ratio	PIT
Current Ratio	Ratio	PCR
Firm Sales Growth Rate	Ratio	PGR
Average product margin	Ratio	PPM

Sampling

The specific respondent groups from each country are identified as retail trade firms (NAICS 44-45or equivalent) that have actively been in business for at least 5 years and are not subsidiaries or related to any other firms within the study, and have information available. The sampled firms are from Japan, Germany and the United States and are selected from a national business database with the inclusion of secondary data needed for analysis, accessed in 2017. The data yielded 770 usable responses in total (Japan 220-29%, Germany 258-33%, United States 292-38%). Within the usable responses, across countries, 218 firms had a Maximum Net Marketing Contribution, 302 firms had a Moderate Net Marketing Contribution, and 250 had a Minimal Net Marketing Contribution.

Probabilistic Neural Networks

Probabilistic neural networks (PNNs) continue to receive attention in solving complex, data driven problems in non-engineering areas. Specifically, neural network use in the social sciences has expanded both at the employee and organizational level. Firms are seeking to more objectively and proactively predict and classify employee performance metrics and organizational outcome drivers, such as revenues, earnings and rankings (Lopes et al., 2018).

The advantages of PNNs are: data compression, parallel computation, and ability to learn and generalize. The probabilistic neural network process consists of three key phases, learning, validation, and feature extraction (Bigus, 1996). The PNN is selected because of its ability to dependably and accurately recognize and predict category classification and for determining independent (input) variable impact strength (dominant=high weighted impact, limited=medium weighted impact, static=low weighted impact). When category membership is determined by the neural network, each input (independent variable) is ranked as to its importance in the classification model. Specifically, the optimization of a PNN is determined by modifying the weights of the connections during the learning phase (McClelland & Rumelhart, 1986) with the intent of establishing the specific architecture of the neural network (number of neurons and layers). Networks with too few (underfitting), or too many (overfitting) hidden processing elements will generalize poorly and result in poor variable classification and confidence concerns with the feature extraction

The formation of the probabilistic neural network is done using Parzen windows classifiers. The Parzen windows method is a non-parametric procedure that produces an approximation of the probability density function (pdf). The calculation of the pdf is done using algorithm one. The function fk(x) is an aggregate of small multivariate Gaussian probability distributions centered on each training example. Using probability distributions allows for generalization.

fk(x) = (1/(2p)d/2 sd) (1/N) Si=1Nk exp[- (x-xki)T (x-xki) / (2s2)] (1)

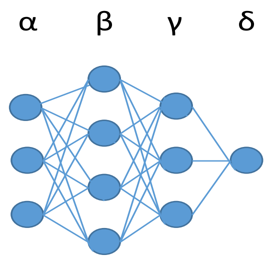
where: xki is the d-dimensional i-th example from class k

The number of training examples in the training set determine how well the estimated pdf reaches the true outcome. This occurs because increased examples generate increased Gaussians. The classification optimum occurs according to the inequalities which are established from previous calculated probabilities.

S i=1Nk exp[- (x-xki)T (x-xki) / (2s2)] > S i=1Nj exp[- (x-xji)T (x-xji) / (2s2)], (2)
for all j=/=k.

pk = Nk / N.
where: N is the number of all training examples
Nk is the number of examples in class k.

The probabilistic neural network is an extension of Bayes classifiers. The model initially learns to approximate the pdf using distribution maximization. The PNN has four layers: input (α), pattern (β), summation (γ), and output (δ). The pattern layer uses neurons, or nodes, which generate a weight vector and are then passed to the summation layer. The summation nodes receive the weight vector outputs, then calculate the optimal weights and are moved to the output function for the classification decision. These last two actions are often referred to as the activation function. Output nodes are binary seeking the specified optimal outcome category placement (see Figure 1).The data will be analyzed using Neuroshell Classifier for the purpose of predictive classification and determinant impact value. Neuroshell Classifier is a very popular neural network software package and has been used in numerous similar applications (Smith, 2006).



Input Layer α= Input Values

Pattern Layer β= exp[(xTwki-1) / s2]

Summation Layer γ= Si=1Nkexp[(xTwki-1) / s2]

Output Layer δ= Si=1Nkexp[(xTwki-1) / s2] > Si=1Njexp[(xTwkj-1) / s2]

FIGURE 1
STRUCTURE OF THE PROBABILISTIC NEURAL NETWORK WITH CORRESPONDING ACTIVATION EQUATIONS

Lastly, in order to gain a more robust understanding of the predictive fit among the variables, two analysis perspectives are offered, a combined inter-country analysis, and an individual intra-country analysis, for each country. Support for this bi-sectional analysis allows the data to incorporate differing impacts of exogenous variables impacting the sampled firms, such as cultural influence, decision-making criteria, resource constraints, and varying outcome objectives. Easley, Madden & Dunn (2000) suggest that although intra-studies tend to offer less information than inter-studies, the process is necessary to establish boundary conditions, create clarity in established construct support research and create confidence in hypotheses testing. Several other studies (Zhang et al., 2016; Beck, 2018) infer that using and intra-inter study approach provides better confirmatory results when examining ideas with many internal and external impacting variables. Lastly, Movahedi et al. (2016) note that by offering two perspectives of more developed theories, results generate more confidence in the myriad variables being examined.

RESULTS

The results of the data offer viable information and insight into the retail trade firms sampled from the three countries. The neural network displayed consistent learning and validation inferring confidence in the feature extraction results both in the individual countries and the countries combined.

Combined Inter-Country Analysis

Learning phase

The PNN consists of 21 input neurons (corresponding to the number of independent determinants), 1 hidden layers with 42 neurons, and 3 outputs (corresponding to performance category membership and scaled to 0.25 for *Minimal NMC*, and 0.50 for *Moderate NMC* and 0.75 for *Maximum NMC*). The learning rate was set at 0.7; the momentum rate was 0.9. The training set included 539 (70 percent) arbitrarily entered samples from across the countries. The number of epochs to complete the learning phase was 6,940. The normalized system error upon completion of the training was 0.0003.

The learning phase demonstrates that the neural network was able to sequence adequate category classification of the three performance groups in a combined country sample. The TRUE expected scores (0.25, 0.50, 0.75) are very close to the ACTUAL calculated ANN scores in each of the categories across countries (see Table 2). The closeness in results suggests that the neural network learned the optimal classification pattern with a high degree of accuracy providing confidence in the findings. The mean scores for each of the categories are provided, however each unique sample had its own ACTUAL score. It would have been awkward to display all 539 results here. For example, the predictive mean ACTUAL score for Japanese firms having a Maximum Net Marketing Contribution is 0.76034 compared to the expected TRUE score of 0.75000. The percentage of correctly classified cases in the combined sample is a robust 90.1 percent (see Table 2).

Table 2
COMBINED COUNTRY RESULTS – LEARNING PHASE MEAN SCORES

Respondent Category	Output	Minimal NMC Score	Moderate NMC Score	Maximum NMC Score
Japan Minimal NMC	ACTUAL	**0.23855**	0.00285	0.01022
	TRUE	**0.25000**	0.00000	0.00000
Japan Moderate NMC	ACTUAL	0.10858	**0.49118**	0.03981
	TRUE	0.00000	**0.50000**	0.00000
Japan Maximum NMC	ACTUAL	0.88548	0.00211	**0.76034**
	TRUE	0.00000	0.00000	**0.75000**
Germany Minimal NMC	ACTUAL	**0.25011**	0.00029	0.00084
	TRUE	**0.25000**	0.00000	0.00000
Germany Moderate NMC	ACTUAL	0.07112	**0.48848**	0.00464
	TRUE	0.00000	**0.50000**	0.00000
Germany Maximum NMC	ACTUAL	0.00038	0.00368	**0.77015**
	TRUE	0.00000	0.00000	**0.75000**
United States Minimal NMC	ACTUAL	**0.23998**	0.04716	0.00956
	TRUE	**0.25000**	0.00000	0.00000
United States Moderate NMC	ACTUAL	0.00274	**0.51222**	0.00085
	TRUE	0.00000	**0.50000**	0.00000
United States Maximum NMC	ACTUAL	0.00602	0.00844	**0.74047**
	TRUE	0.00000	0.00000	**0.75000**
Correctly Classified Cases: 90.1% n=539				

Validation/Hold-Out phase

The validation phase supports the soundness of the neural network established in the previous learning phase, by employing a holdout approach. Using the 231 (30 percent) randomly withheld samples from the learning phase, response data were entered and calculated using the same neural net function from the learning phase (see Table 3). The expected results are that the net marketing contribution category classification for the firms will be comparable. The resulting ACTUAL scores should be close to the TRUE scores. In keeping with the scenario above, the percentage of correctly classified cases is strong at 89.7 percent, within one percent of the learning phase results. This shows that the ANN places the holdout firms into their prospective membership categories with accuracy, confirming findings from the learning phase.

Table 3
COMBINED COUNTRY RESULTS – VALIDATION PHASE HOLDOUT SAMPLE CLASSIFICATION – MEAN SCORES

Respondent Category	Output	Minimal NMC Score	Moderate NMC Score	Maximum NMC Score
Minimal NMC				
Japan	ANN	0.23792		
Germany	ANN	0.24195		
United States	ANN	0.27007		
	TRUE	**0.25000**		
Moderate NMC				
Japan	ANN		0.49624	
Germany	ANN		0.49014	
United States	ANN		0.51999	
	TRUE		**0.50000**	
Maximum NMC				
Japan	ANN			0.72811
Germany	ANN			0.75677
United States	ANN			0.73927
	TRUE			**0.75000**
Correctly Classified Cases: 89.7% n=231				

Feature extraction phase

Feature Extraction provides the opportunity to identify the relative importance of the determinants based on their impact in developing the neural network model structure. Determinants with high importance in the model are those variables that are the strongest in predicting the dependent outcomes. Therefore, if a determinant has a high coefficient, it is more unique to the construct's predictive outcome. These higher determinants are also the variables most sensitive to smaller changes, while lower coefficients have little to no sensitivity to change. As noted above, when the neural network model has been built, the independent input variables (determinants) are grouped into one of three categories, based on their importance/sensitivity rank as indicted by their coefficient strength.

Examining the determinant impact strengths provides practical conclusions. These conclusions are based on the differences of impact strength as identified (see Table 4). The PNN model weights are the coefficient scores of strength for each determinant, based on importance to model construction, totaling 1.0 for all input variables combined. The PNN results find that five determinants are identified as dominant for the classification architecture across the three cultures. They are: Regional Business Cycle (RBC), Product Price Position (RPP), Firm Sales Growth, Rate (PGR), Current Ratio (PCR), and Change in Marketing Budget to Sales - 5 years (OB5).Results suggest that firms with the Maximum Net Marketing Contribution, regardless of culture, display these certain notable characteristics that most impact their predictive classification. This is important as small changes in these five variables generate large changes in Maximum Net Marketing Contribution outcomes. Therefore, with these findings, P1 is affirmed, with dominant predictive determinants coming from all three input categories (managerial, regional, and performance) across cultures.

Table 4 DOMINANT DETERMINANTS FOR MAXIMUM NET MARKETING CONTRIBUTION: ALL THREE COUNTRIES	
Determinant	**Coefficient**
Regional Business Cycle – RBC	0.148
Product Price Position – RPP	0.135
Firm Sales Growth Rate – PGR	0.109
Current Ratio – PCR	0.098
Change in Marketing Budget to Sales (5 years) – OB5	0.086

Individual Intra-Country Analysis

Learning and validation phase

Net Marketing Contribution within each country is also examined using the PNN technique. Even though new neural networks are produced for each of the three countries, the input parameters for the network are the same as the combined country analysis, principally because the variables remained the same and the network provided confident results. This approach ascertains the unique determinants that distinguish, in rank order, between firms with varying NMC. A PNN is run for each country, requiring individual learning and validation phases to be developed.

Here are the findings for the Japanese firms. Following the combined country method above, 70 percent (154) of the samples were randomly entered into the neural network during the learning phase and the other 30 percent (66) of samples were holdouts, used to confirm the network's consistency during the validation phase. After executing and confirming the PNN, excellent results became evident. The collective phases offered a 92.1 percent correct classification of Japanese cases (see Table 5).

<table>
<tr><th colspan="5">Table 5
INDIVIDUAL COUNTRY RESULTS – LEARNING AND VALIDATION PHASE: JAPAN</th></tr>
<tr><th>Respondent Category</th><th>Output</th><th>Mean Minimal NMC Score</th><th>Mean Moderate NMC Score</th><th>Mean Maximum NMC Score</th></tr>
<tr><td colspan="4">Learning Phase – 154 (70%) Cases</td><td></td></tr>
<tr><td rowspan="2">Japan Minimal NMC</td><td>ANN</td><td>0.24119</td><td>0.00655</td><td>0.00475</td></tr>
<tr><td>TRUE</td><td>0.25000</td><td>0.00000</td><td>0.00000</td></tr>
<tr><td rowspan="2">Japan Moderate NMC</td><td>ANN</td><td>0.00492</td><td>0.48088</td><td>0.00285</td></tr>
<tr><td>TRUE</td><td>0.00000</td><td>0.50000</td><td>0.00000</td></tr>
<tr><td rowspan="2">Japan Maximum NMC</td><td>ANN</td><td>0.00146</td><td>0.00809</td><td>0.76482</td></tr>
<tr><td>TRUE</td><td>0.00000</td><td>0.00000</td><td>0.75000</td></tr>
<tr><td colspan="4">Correctly Classified Cases: 90.8%</td><td></td></tr>
<tr><td colspan="4">Validation Phase – 66 (30%) Cases</td><td></td></tr>
<tr><td rowspan="2">Japan Minimal NMC</td><td>ANN</td><td>0.24004</td><td>0.00489</td><td>0.01000</td></tr>
<tr><td>TRUE</td><td>0.25000</td><td>0.00000</td><td>0.00000</td></tr>
<tr><td rowspan="2">Japan Moderate NMC</td><td>ANN</td><td>0.00098</td><td>0.48511</td><td>0.01315</td></tr>
<tr><td>TRUE</td><td>0.00000</td><td>0.50000</td><td>0.00000</td></tr>
<tr><td rowspan="2">Japan Maximum NMC</td><td>ANN</td><td>0.00206</td><td>0.00723</td><td>0.76941</td></tr>
<tr><td>TRUE</td><td>0.00000</td><td>0.00000</td><td>0.75000</td></tr>
<tr><td colspan="5">Correctly Classified Cases: 92.1%</td></tr>
</table>

Here are the findings for the German firms. This calculated PNN also provides dependable results. By means of 181 samples in the learning phase and 77 in the validation phase, correct classifications of the network comes in even higher than the Japanese results, at 93.7 percent combined (see Table 6). Healthy percentages remain consistent, offering confidence in the classification conclusion.

Table 6
INDIVIDUAL COUNTRY RESULTS – LEARNING AND VALIDATION PHASE: GERMANY

Respondent Category	Output	Mean Minimal NMC Score	Mean Moderate NMC Score	Mean Maximum NMC Score
Learning Phase – 181 (70%) Cases				
Germany Minimum NMC	ANN	**0.24913**	0.00455	0.00221
	TRUE	**0.25000**	0.00000	0.00000
Germany Moderate NMC	ANN	0.00142	**0.48551**	0.00678
	TRUE	0.00000	**0.50000**	0.00000
Germany Minimal NMC	ANN	0.00068	0.00512	**0.76285**
	TRUE	0.00000	0.00000	**0.75000**
Correctly Classified Cases: 94.7%				
Validation Phase – 77 (30%) Cases				
Germany Minimal NMC	ANN	**0.24002**	0.00584	0.00421
	TRUE	**0.25000**	0.00000	0.00000
Germany Moderate NMC	ANN	0.00128	**0.51198**	0.00268
	TRUE	0.00000	**0.50000**	0.00000
Germany Maximum NMC	ANN	0.00623	0.00396	**0.76800**
	TRUE	0.00000	0.00000	**0.75000**
Correctly Classified Cases: 93.7%				

Table 7
INDIVIDUAL COUNTRY RESULTS – LEARNING AND VALIDATION PHASE: UNITED STATES

Respondent Category	Output	Mean Minimal NMC Score	Mean Moderate NMC Score	Mean Maximum NMC Score
Learning Phase – 204 (70%) Cases				
United States Minimal NMC	ANN	**0.26810**	0.00985	0.00055
	TRUE	**0.25000**	0.00000	0.00000
United States Moderate NMC	ANN	0.00482	**0.51314**	0.00283
	TRUE	0.00000	**0.50000**	0.00000
United States Maximum NMC	ANN	0.00061	0.00026	**0.76432**
	TRUE	0.00000	0.00000	**0.75000**
Correctly Classified Cases: 92.2%				
Validation Phase – 88 (30%) Cases				
United States Minimal NMC	ANN	**0.23850**	0.00462	0.00332
	TRUE	**0.25000**	0.00000	0.00000
United States Moderate NMC	ANN	0.00313	**0.51656**	0.00284
	TRUE	0.00000	**0.50000**	0.00000
United States Maximum NMC	ANN	0.00182	0.00704	**0.76290**
	TRUE	0.00000	0.00000	**0.75000**
Correctly Classified Cases: 90.2%				

Lastly, here are the findings for the United States firms. Including 204 samples in the learning phase and 88 in the validation phase, results comparable to previous classifications are found, coming in at an aggregate percentage of 90.2 percent. This percentage is slightly lower than Japan and Germany, but well beyond statistical chance (see Table 7).

Feature extraction phase

Dominant determinants of the learned and validated ANNs for each country are also revealed. While several determinants are common among Maximum Net Marketing Contribution firms from each country, they are not included in this final feature extraction analysis. The intent is to identify those dominant determinants unique to each country individually, and are offered in Table 8.

Table 8
DOMINANT DETERMINANTS OF MAXIMUM NET MARKETING CONTRIBUTION, UNIQUE TO EACH COUNTRY

Country	Unique Dominant Determinants
Japan	Change In Marketing Budget To Sales (1 Year) – OB1
	Sales To Inventories - PSI
Germany	Firm Asset Size - OAS
	Domestic Market Share - RMS
	ROA – PRA
United States	Marketing Budget To Sales - OBS
	Change In Marketing Budget To Sales (3 Years) OB3
	Firm Sales Growth Rate - PGR

The PNN model identified unique dominant determinants for each country individually. The two from Japan are 1) change in marketing budget to sales after one year, and 2) sales to inventories. While the unique dominant determinants for Germany are 1) firm asset size, 2) domestic market share, and 3) return on assets. Lastly, the three unique dominant determinants identified for the United States are 1) marketing budget to sales, 2) change in marketing budget at 3 years, and 3) firm sales growth rate. While no causality can be inferred here, it is exceedingly important to know which variables are the most significant at driving firms with a Maximum Net Marketing Contribution. Therefore, given the unique subset of determinants for each country, P2 is affirmed.

PNN Comparison with a Discriminant Classification Matrix

Discriminant analysis and the use of a classification matrix are familiar tools for researchers when examining the question of group classification or prediction in a linear capacity (Klecka, 1980). When computing the discriminant function, a comparison of actual to predicted category membership is offered, generated by the significant independent variables of the function. To ensure the integrity of the PNNs classification results, four discriminant classification matrices are provided and presented as a comparison (see Tables 9 and 10).

Table 9
COMBINED COUNTRY CLASSIFICATION MATRIX FOR NET MARKETING CONTRIBUTION: JAPAN, GERMANY, UNITED STATES

Category	Maximum NMC		Moderate NMC		Minimal NMC		Total	
	n	%	n	%	n	%	N	%
Maximum NMC	**129**	**59.2**	49	22.5	40	18.3	218	28.3
Moderate NMC	34	11.2	**195**	**64.6**	73	24.2	302	39.2
Minimal NMC	55	22.0	58	23.2	**137**	**54.8**	250	32.5
Correctly Classified Cases: 59.8%Wilks' lambda: 0.447								

Table 10
INDIVIDUAL COUNTRY CLASSIFICATION MATRICES FOR NET MARKETING CONTRIBUTION

Category	Maximum NMC		Moderate NMC		Minimal NMC		Total	
	n	%	n	%	n	%	N	%
JAPAN								
Maximum NMC	**30**	**56.6**	13	24.5	10	18.9	53	24.0
Moderate NMC	14	15.6	**58**	**64.4**	18	20.0	90	41.0
Minimal NMC	16	20.8	20	26.0	**41**	**53.2**	77	35.0
Correctly Classified Cases: 58.6%Wilks' lambda: 0.462							220	100.00
GERMANY								
Maximum NMC	**40**	**54.8**	18	24.7	15	20.5	73	28.3
Moderate NMC	18	17.8	**63**	**62.4**	20	19.8	101	39.1
Minimal NMC	18	21.4	15	17.9	**51**	**60.7**	84	32.6
Correctly Classified Cases: 59.7%Wilks' lambda: 0.418							258	100.00
UNITED STATES								
Maximum NMC	**63**	**68.5**	15	16.3	14	15.2	92	31.5
Moderate NMC	15	13.6	**74**	**66.6**	22	19.8	111	38.0
Minimal NMC	12	13.5	15	16.7	**63**	**70.8**	89	30.5
Correctly Classified Cases: 68.5%Wilks' lambda: 0.409							292	100.00

The correct classification percentage for each matrix is on hand along with the Wilks' lambda score, signifying the statistical significance of the discriminant function not accounted for within the function and also indicating the relative relationship of the group centroids, the lower the measure, the better the function. The discriminant classification matrix was calculated using SPSS.A final table (11) is offered comparing the classification accuracy of both the probabilistic neural network and the discriminant classification matrix. It is evident that the PNN is more accurate in its classification accuracy for the various marketing contribution levels included in this study, and results are impressively clear. Therefore, P3 is affirmed in Table 11.

Table 11
COMPARATIVE CORRECT CLASSIFICATION PERCENTAGE

	Probabilistic Neural Network Correct Learning Classifications	**Discriminant Classification Matrix Correct Classifications**
All Countries	89.7%	59.8%
Japan	92.1%	58.6%
Germany	93.7%	59.7%
United States	90.2%	68.5%

DISCUSSION

The primary purpose of this study is to identify which organizational determinants impact the predictive classification of firms exhibiting Maximum Net Marketing Contribution both within and across three countries; Japan, Germany and the United States. The ability to accurately predict classification provides insight into those variables most impacting the predictive possibility and further provides marketing managers with an opportunity to focus on firm related activities that have proven to have the greatest impact on Maximum Net Marketing Contribution firms. The determinants of this study are both internal and external, and offer a broader view of the impact on the allocation to performance ratio. The effort is to uncover potential drivers of marketing budget allocation that were not seen or examined previously. The dominant determinants here suggest that variables within the known construct may be deficient and need a broader research approach. This leads to another opportunity for discussion. To date, the internalities of marketing budget allocation optimization have been examined, while significantly fewer studies have addressed the externalities such as the competitive environment, government policies, technological impacts or changes in buyer behavior. In order to more appropriately understand the construct, these types of future studies are warranted.

Probabilistic neural networks are selected as the statistical method because of the different perspective they provide for highly non-linear functions with numerous variables. As was the case in previous similar studies, the PNN provides impressive predictive modeling with clear identification of variables impacting predictive model development.

The study is useful because it: (1) fills a void in the research area for marketing managers in the retail sector seeking optimal marketing budget allocations while achieving Maximum Net Marketing Contribution; (2) identifies particular organizational determinants that associate with Maximum Net Marketing Contribution firms across diverse cultures; (3) employs a statistically sophisticated non-linear technique for classification, offering an alternative approach for analysis; and (4) assists in the development of a validated addition to the marketing budget allocation literature across cultural boundaries.

CONCLUSION

In summary, (P1), a common set of high-ranking organizational determinants for Maximum Net Marketing Contribution exists among retail firms from Japan, Germany and the United States combined is affirmed. They are: regional business cycle, product price position, firm sales growth rate, current ratio, change in marketing budget to sales at five years.

Furthermore, (P2) a unique set of high-ranking organizational determinants for Maximum Net Marketing Contribution exists within retail trade firms from Japan, Germany and the United States, individually is affirmed. The two from Japan are 1) change in marketing budget to sales after one year, and 2) sales to inventories. While the unique dominant determinants for Germany are 1) firm asset size, 2) domestic market share, and 3) return on assets. Lastly, the three unique dominant determinants identified for the United States are 1) marketing budget to sales, 2) change in marketing budget at 3 years, and 3) firm sales growth rate.

Finally, as expected (P3), the probabilistic neural network classification approach is more accurate, by percentage, than the classification matrix of a multiple discriminant analysis is affirmed. The non-linear PNN provides a substantially better classification predictive capability (21.7%) to that of the linear discriminant classification analysis.

IMPLICATIONS AND LIMITATIONS

The contribution and implications of this study can be seen both on a practitioner and researcher level. First, practitioners and researchers are offered insight into the organizational characteristics of firms exhibiting Maximum Net Marketing Contribution. This is regardless of cultural orientation. Second, the marketing manager is provided a framework for practical marketing budget allocation approaches and a hierarchical list of determinants known to have an excellent impact on allocation impact. Third, from a researcher perspective, this study provides quantitatively vibrant results using a statistical approach not often seen in social science research. An introduction to the use of probabilistic neural networks and an accuracy comparison of results to a multiple discriminant analysis are also presented, laying the groundwork for similar classification and prediction analysis to be undertaken in future work. Fourth, support is made for the belief that organizations across cultures, even within the same industry classification, behave quite differently and are strongly influenced by their cultural context, affirming previous cultural studies.

Numerous limitations of this study are also acknowledged. Only 21 firm level determinants are examined, however this is not inclusive of all possible impacting determinants. Many variables, some more tangent than others, have been offered in previous research and warrant understanding given this cross-cultural viewpoint. Statistically, no previous study in the area of Maximum Net Marketing Contribution optimization has incorporated a probabilistic neural network approach. This limitation does not allow for straightforward result comparisons, suggesting possible confidence concerns. Also, the process and techniques for determining PNN results can be complex at times, which may impact feedback or similar future research directions. Lastly, a greater understanding of the impact of external variables is warranted (competitive environment, government policies, technological impacts).

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