Systematic behavior research for understanding consumer decision making

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This study incorporates means–end chain (MEC) theory and dynamic programming for understanding the implications of consumer decision making. The conceptual framework of this study can help programmers design information systems for analyzing consumption behaviors. Such analyses will provide marketers with meaningful information for formulating marketing strategies. The main contributions of this article are as follows: (1) to enable researchers to obtain information for consumer cognitive hierarchies utilizing an information system, (2) to enhance the functions of traditional MEC methodology and provide an integrated method for analyzing consumption information, and (3) to construct an information system for analyzing consumer decision-making processes.

Business survival in dynamic and competitive environments depends on an ability to analyze consumption information and determine which products consumers want. Collecting consumption data, hence, becomes a primary activity for product and marketing strategy development. Businesses typically gather consumption data from consumers shopping in the retail market. Data for items purchased are transmitted through retail information systems to inventory controllers for product-ordering decisions. Although such decisions may reflect consumer behavior in the retail market, they cannot reflect consumer desires and wants. Since consumers can purchase only what retailers offer, consumer purchases represent consumer product choices only for limited offerings, rather than consumer needs and expectations. Thus, understanding consumer needs and wants, as well as online consumer behavior, is a significant issue for businesses wanting to provide customers with the best value (Stibel, 2005; Wisniewski, 2001).

The means–end chain (MEC) methodology is typically applied to arrive at consumer value satisfaction (Gutman, 1982). Reynolds and Gutman (1988) adopted the logic of MECs to develop a laddering technique for understanding consumer product cognition. When a cutoff value is determined, the salient attribute–consequence–value ($A-C-V$) linkages, by computing the frequency of consumer $A-C-V$ linkages for a given product, can be determined and displayed in a hierarchical value map (HVM). Marketers can use HVMs to generate product, advertising, and segmentation strategies. This study, which is based on that by Reynolds and Olson (2001), applies the MEC methodology to the analysis and understanding of consumer decision making and adopts dynamic programming (DP) analysis to enhance the computing procedure in the conventional laddering technique.

Figure 1 exhibits the conceptual framework of the DP approach. In laddering data collection, all data are input into a table for the summary implication matrix (SIM). The DP and systematic procedures can transform the laddering data into meaningful information for consumer product cognition. Such information can assist marketers in understanding consumer perceptions and in developing effective marketing strategies.

In the traditional MEC methodology, the cutoff value is predetermined subjectively by the researcher in order to establish an HVM. In the present study, DP analysis overcomes the controversy associated with subjective cutoff value decisions and is the basis for establishing the information system, which stores consumer preference perceptions of a particular product. The following is a list of study objectives.

1. To capitalize on the advantages of DP in analyzing MEC data sets, this study integrates DP and laddering procedures to gather consumer preference information.
2. This study uses an information flowchart to demonstrate the logic of DP, leading to an analysis of consumer decision making. Such an analysis will provide marketers with salient market intelligence for rapid response to market demands.
3. To enhance the advantages of MECs and utilization of a computer information system for storing and analyzing consumer product knowledge, this study integrates the system interface and human consumption behavior to obtain objective information for real consumption demands derived from the computer system.

Means–End Chain Theory

The MEC methodology is widely used in the marketing field. This method assumes that a reasonable aggregate $A-C-V$ chain for a given product can be constructed using

Figure 1. Conceptual framework of the dynamic programming (DP) approach.

consumer product perceptions. Restated, a product's attributes in line with a consumer's preference yield particular consumption consequences, creating a relationship between consumer value satisfaction and consumption consequences. In applying the laddering technique, the $A-C-V$ linkages in a consumption model represent consumer preference toward a particular product. Bourne and Jenkins (2005) indicated that the laddering technique derived from Hinkle's (1965) laddering method can be applied to generate consumer consumption hierarchies. The development of such elaborate hierarchies has progressed from using in-depth interviews (soft laddering) in the early years of MEC development to using structured questionnaires (hard laddering) to obtain information for consumption psychology from various quantitative analyses.

Conventional MECs have three key variables: attribute, consequence, and value. An attribute can consist of concrete and abstract attributes (Snelders & Schoormans, 2004). A consumption consequence can be positive or negative. Most researchers agree that positive feelings are the result of benefits from consuming a product; therefore, benefit can be considered a substitute for consequence in a conventional MEC linkage (Goldenberg, Klenosky, O'Leary, & Templin, 2000; Lin, 2003; Vriens & ter Hofstede, 2000; Woodside, 2004). Furthermore, value can be considered a product of satisfaction based on consumption behaviors or actions (Valette-Florence, 1998). Lages and Fernandes (2005) concluded that value classification systems include a general system, such as the Rokeach Value Scale (RVS; Rokeach, 1968) and list of Schwartz and Bilsky (1990), and a consumer perspective system, such as the MEC model (Vinson, Scott, & Lamont, 1977), list of values (LOV; Kahle, 1986), values and lifestyles (VALS) typology (Mitchell, 1983), and list of values (Durgee, 1996). Lin (2003) indicated that personal value and consumption perception are embodied in a consumer's cognitive structure and noted that the RVS, LOVs, and VALS are the most popular value classification systems.

Variables of attribute, consequence, and value. Snelders and Schoormans (2004) indicated that an abstract attribute can be communicated by several concrete attributes. Brand intensity of a digital camera, for example, is an abstract attribute preferred by some consumers, which consists of various concrete functions, such as high resolution, number of megapixels, and zoom lens, which provide consumers with a positive product image. Snelders and Schoormans revealed that when a "romantic" consumer perceives a product, he/she may focus on a product's abstract attributes via intuition and ignore concrete attributes.

As has been mentioned, consumption consequence can be positive or negative. Positive consumption feelings can be expressed as consumption benefits derived through

consumption, whereas negative feelings can be regarded as associated cost or perceived risks (Goldenberg et al., 2000). Benefits are related to consumer attribute preference and consumer-perceived product quality (Snelders & Schoormans, 2004). Lin (2003) determined that a product design based on information of $A-C-V$ linkages increases the degree of consumer satisfaction toward product quality. Hence, consumption feelings are used to assess product quality; the cost paid for a product should equal consumer quality expectations (Orsingher & Marzocchi, 2003).

Bourne and Jenkins (2005) used the laddering technique to analyze managerial values in order to understand their recognition of organizational activities. In fact, many value classification systems have been used in marketing research. The LOV inventory is the most popular value system used in MEC methodology (Lin, 2003); Lages and Fernandes (2005) agreed that the LOV is adequate for analyzing consumer behavior. In analyses of lifestyle, consumer behavior, and personal value, value variables affect consumer behavior through a lifestyle mediator (Brunsø, Scholderer, & Grunert, 2004; Scholderer, Brunsø, & Grunert, 2002). Generally, $A-C-V$ hierarchical linkages strengthen the logic of MECs, which can be used to analyze consumer cognition toward a particular product to develop segmentation, product, and advertising strategies (Bourne & Jenkins, 2005; Vriens & ter Hofstede, 2000).

Summary implication matrix. In MEC research, an HVM is employed to develop marketing strategies (Bourne & Jenkins, 2005; Goldenberg et al., 2000; Lin, 2003; Orsingher & Marzocchi, 2003; Woodside, 2004). When the laddering technique is used to construct an HVM, all interview data should be input into a summary implication matrix (SIM; Goldenberg et al., 2000; Langerak, Peelen, & Nijssen, 1999; Lin, 2003; Orsingher & Marzocchi, 2003). When each attribute variable (A_j) is linked once to a consequence variable, the researcher records one in the cell of A_jC_k in the SIM. When the frequency of the $A-C$ linkage is p times, p is entered into the tabulated SIM. The same procedure is used to inscribe $C-V$ linkage frequencies in the C_kV_l cells.

The concept of abstract ratio. Without the need to predetermine the hierarchical relationships of $A-C-V$ variables, the abstract ratio can be used to determine the $A-C-V$ hierarchies (Goldenberg et al., 2000; Langerak et al., 1999; Orsingher & Marzocchi, 2003). The abstract ratio is acquired by computing the connections between variables. In-degree is the sum of the frequencies of a particular variable linked with other variables; out-degree is the number of variables connected to a particular variable. Abstract ratio is the in-degree divided by the total of in-degree plus out-degree; therefore, the abstract ratio is 0–1.

As the abstract ratio of a particular variable increases, the rank of a variable in a hierarchy increases. Restated, the variable with the highest abstract ratio is placed highest in the hierarchy and is regarded as a value variable.

Pieters, Baumgartner, and Allen (1995), in referring to the study by Knoke and Burt (1983), clarified the concepts of abstractness, centrality, and prestige. The following definitions are cited from the study of Pieters et al.

1. Abstractness = (in-degree)/(in-degree + out-degree):

“The definition of Abstractness: the higher the abstractness index, the larger the proportion of a variable’s connections with other variables in which the variable’s is the destination rather than the source. Variables with a high abstractness score are predominantly ends, while variables with low abstractness scores are predominantly means.”

2. Centrality = (in-degree + out-degree)/(sum of all cell entries in SIM):

“The definition of Centrality: the higher the centrality index, the larger the proportion of connections in the variable structure that run through the particular variable.”

3. Prestige = (in-degree)/(sum of all cell entries in SIM):

“The definition of Prestige: the higher the prestige ratio, the more the particular variable is the destination of connections with other variables.”

Dynamic Programming: Method and Flowchart

In DP, a mathematical method can be employed to handle multistage strategic problems, and its problem-solving procedure can be forward or backward. In this study, the backward recursive relationship of DP analysis developed by Hillier and Lieberman (1995) was adopted to account for the product–consumer relationships in terms of $A-C-V$ linkages. The formula and its notations are identified as follows:

$$f_n^*(s_n) = f_n(s_n, V_{kn}^*) = \max_{V_{kn}} \{f_n(s_n, V_{kn})\},$$

where

$f_n(s_n, V_{kn})$ = contribution of stages $n, n + 1, \dots, N$ to objective function if system starts in state s_n at stage n , immediate decision is V_{kn} , and optimal decisions are made thereafter,

n = label for current stage ($n = 1, 2, \dots, N$),

N = number of stages,

$k = 1, 2, 3, \dots, n_1$; n_1 represents the number of value variables,

s_n = current state for stage n ,

V_{kn} = decision variable for stage n ,

V_{kn}^* = optimal value of V_{kn} (given s_n),

and

$f_n^*(s_n, V_{kn}^*)$ represents the highest linkage frequency that value variable k is linked with in a particular group of a product’s attributes.

On the basis of the concepts of MECs, linkages with higher frequencies are more salient than those with lower frequencies. Thus, solving MEC issues using DP should focus only on the maximum value of the final solution. The following are some characteristics of DP that should be amended in MECs.

1. Each variable belongs to a particular attribute, consequence, or value inventory.

2. Analyzing $A-C-V$ chains starts with value variables. When the researcher wants to determine which product attributes can achieve consumer value satisfaction, he/she should refer to the recurring relationships of DP analysis; consumer value satisfaction (V) becomes a variable in Stage N and product attribute (A) variables becomes a variable in Stage 1.

3. In MEC theory, consumer $A-C-V$ chains are the most important components of an HVM (Reynolds & Gutman, 1988). Theoretically, the linkages or connections among $A-C-V$ variables can be as simple as three-layer $A-C-V$ structures or as complex as multilayer structures such as the types of Reynolds and Olson (2001) (i.e., $A-C-C-V$ and $A-A-C-C-V-V$) and the types of Reynolds and Gutman (i.e., $A-A-C-C-C-V$, $A-C-C-V$, $A-C-C-C-C-V$, $A-A-C-C-V$, and $A-C-C-C-V$). Both linkage structures appear in an HVM. Thus, the solution procedure of DP starts at the end stage and moves backward, stage by stage.

4. Because consequences, intermediate variables, bridge variables A and V , and, normally, V variables exceed two, the $f_n^*(s_n)$ function should be changed to $f_n^*(s_n, V_{kn})$, $k = 1, 2, 3, \dots, n_1$, where n_1 is the number of value variables—namely, $f_n^*(s_n, V_{kn})$, which is the maximum number of $A-C-V_k$ linkages.

5. The number of linkages between two variables, such as $A-C$, $C-C$, and $C-V$, is summarized in the SIM. Practically, linkages or connections among $A-C-V$ variables using data from interviews may not follow $A-C-V$ linkage rules with three or more level structures. In some cases, linkages or connections between variables may not exist. Such linkages or connections in DP analysis are zero; however, these values are recorded as blanks on the analytical table of DP.

On the basis of amended DP, the systematic procedure (see Figure 2) is as follows.

1. Select a value variable V_k . If V_k is analyzed, check whether all value variables are examined and then stop; otherwise, choose another variable.

2. List all V_k connection variables, including A_i and C_j . If V_k is directly linked to A_i , the frequency of A_i-V_k linkages should be recorded in the database; otherwise, mark the maximum frequency of C_j-V_k linkages as a virtual variable w_ℓ .

3. Examine whether virtual W is related to attribute variables A_i . If it is, then record the frequency of $A_i-C_j-V_k$ linkages in the database; otherwise, continue the procedure and mark the $C_{j1}-C_{j2}-V_k$ linkages with the highest frequencies as virtual variable w_ℓ .

4. In this study, we assume consequences C_j are derived from consumer perceptions of a product’s attributes A_i after consumption. Thus, if C_j is not linked with A_i , con-

Figure 3. Hierarchical value map for wine coolers at a cutoff level of 10.

Reynolds and Gutman (1988) to collect raw data and construct the HVM. Mapping hierarchical A – C – V linkages has five steps. (1) Classify all responses into one of the three basic A , C , and V levels and differentiate them into individual summary codes (see Table 1). (2) Apply content analysis to summarize and recode each A , C , or V variable when the individual summary codes are overly broad or detailed. (3) Interview consumers to obtain the A – C – V variable linkages and summarize these linkages in an A , C , and V implication matrix (see Table 1). (4) Determine the cutoff value and map A , C , and V linkage relations with the SIM. (5) Construct the HVM (see Figure 3).

Traditional means–end chain methodology. Reynolds and Gutman (1988), who proposed the laddering technique, indicated that when 50–60 interviews are conducted, the cutoff value should be three to five linkage frequencies. When the laddering technique is used to construct the HVM, determination of the cutoff value should be based on two criteria: (1) Information in the HVM should be most informative in representing consumer product knowledge, and (2) the selected data set should be the most stable set of relations, regardless of the number of retests (Reynolds & Gutman, 1988). These criteria, however, do not have objective or critical measurement standards. Pieters et al. (1995) adopted the concepts of abstractness, centrality, and prestige proposed by Knoke and Burt (1983) to generate information about variable position in a variable structure. This study utilized the concepts of abstractness, centrality, and prestige to generate wine cooler information (see Table 2) about variable position in the HVM.

Table 3 lists the cutoff values of 2–10. When the cutoff value is 7, 67% of all connections between variables made by subjects (column 5) use only 13% of all the possible cells in the SIM (column 2), and only 35% of the cells contain a nonzero entry (column 3). Given the two criteria from the work by Reynolds and Gutman (1988) to determine the cutoff value, the lower the number of active cells as a proportion of all the cells and the number of active cells as a proportion of all the cells mentioned at least once, the more informative. Moreover, when the ratio of active linkages to all linkages is high, the information in the HVM can be considered informative. Thus, when the cutoff value is 7, the information in the HVM is informative. These analytical results are similar to those obtained by Pieters et al. (1995).

If the cutoff value is increased to 10, the ratio of active cells to all the cells is reduced, as is the ratio of active cells to all the cells mentioned at least once. Unfortunately, the ratio of active linkages to all linkages also decreases, meaning that increasing the cutoff value does not increase the informative value of the analytical results. Figure 3 shows the HVM of wine coolers, using a cutoff value of 10. When the cutoff value is 7, the number of active cells (column 1) is almost twice that when the cutoff value is 10. Consequently, the number of active cells and active linkages increases roughly two times when the cutoff value is reduced from 10 to 7. The number of active linkages affects the complexity of the HVM. Thus, to construct an HVM with a cutoff value of 7, the figure becomes significantly more complicated than that with a cutoff value of 10 (see Figure 3).

Table 2
Abstractness, Centrality, and Prestige of Wine Coolers

	In-Degree	Out-Degree	Abstractness	Centrality	Prestige
A_1 , Carbonation	0	45	.000	.065	.000
A_2 , Crisp	0	78	.000	.112	.000
A_3 , Expensive	0	83	.000	.119	.000
A_4 , Label	0	23	.000	.033	.000
A_5 , Bottle shape	0	102	.000	.147	.000
A_6 , Less alcohol	0	39	.000	.056	.000
A_7 , Smaller	0	46	.000	.066	.000
C_8 , Quality	80	41	.661	.174	.115
C_{10} , Refreshing	64	35	.646	.142	.092
C_{11} , Consume less	46	13	.780	.085	.066
C_{12} , Thirst-quenching	111	34	.766	.208	.159
C_{13} , More feminine	25	36	.410	.088	.036
C_{14} , Avoid negative	54	13	.806	.096	.078
C_{15} , Avoid waste	15	16	.484	.045	.022
C_{16} , Reward	51	24	.680	.108	.073
C_{17} , Sophisticated	34	24	.586	.083	.049
C_{18} , Impress	54	35	.607	.128	.078
C_{19} , Socialize	39	9	.813	.069	.056
V_{20} , Accomplishment	28	0	1.000	.040	.040
V_{21} , Family	19	0	1.000	.027	.027
V_{22} , Belonging	52	0	1.000	.075	.075
V_{23} , Self-esteem	24	0	1.000	.034	.034

Dynamic programming based on the flowchart procedure. To overcome shortcomings of traditional MEC methodology, DP does not need to predetermine the cutoff value, thus avoiding the controversy associated with researcher subjective judgment. Furthermore, by not constructing an HVM, DP can provide more accurate information than can traditional MECs. Thus, DP can be considered a substitute for the laddering technique.

To demonstrate the implementation of DP, this study adopted the logic of DP analysis (see Figure 2) to select a value variable as an initial stage for computing the frequencies of C - V or A - V linkages. For example, V_{23} was selected for a backward procedure in DP analysis. On the basis of the logic of DP analysis, the procedure is as follows.

1. List all variables that are linked to V_{23} .
2. The SIM (see Table 1) indicates that four variables, A_5 , C_{13} , C_{17} , and C_{18} , are related to V_{23} .
3. Apply the logic of the DP flowchart. Since V_{23} is linked with A_5 twice, 2 was recorded in the linkage fre-

quency column (see Table 4). This procedure is followed to record all frequencies of A_i - V_k linkages in the database.

4. Since C_{13} , C_{17} , and C_{18} did not belong to the attribute (A) inventory, a virtual variable W was utilized to mark the variable with maximum C - V linkage frequency. At Stage 5 ($n = 5$), determine whether W belongs to the A_i inventory and select the mediator variable C_j with the highest value. For example, A_4 can link to V_{23} through mediator variables C_{13} , C_{17} , and C_{18} . Because C_{18} had the highest linkage frequency of 15 times, C_{18} was selected as a mediator linking A_4 and V_{23} . In DP, all mediator variables of A_i/V_{23} and their linkage frequencies were input into the database.

5. At Stage 5, use C_{16} as an example; C_{16} is connected only with C_{17} and C_{18} . Compare the frequency of the C_{16} - C_{17} - V_{23} linkage with that of C_{16} - C_{18} - V_{23} ; the latter is 26, which is greater than that of the former (10). Thus, C_{18} was selected as the mediator of C_8 and V_{23} . Because C_{16} did not belong to the attribute (A) inventory, according to the DP flowchart, the computing procedure should go

Table 3
Statistics of Determining Cutoff Value Level

Cutoff Value	(1) Number of Active Cells	(2) Number of Active Cells As a Proportion of All Cells	(3) Number of Active Cells As a Proportion of All Cells Mentioned at Least Once	(4) Number of Active Linkages	(5) Number of Active Linkages As a Proportion of All Linkages
2	95	.37	1.00	696	1.00
3	76	.29	.80	658	.95
4	60	.23	.63	610	.88
5	56	.22	.59	594	.85
6	47	.18	.49	549	.79
7	33	.13	.35	465	.67
8	29	.11	.31	437	.63
9	22	.08	.23	381	.55
10	18	.07	.19	345	.50

Table 4
The Modified DP Analysis

W_ℓ	$f_6(s)$	V^*_{236}	End	LF	W_ℓ	C_8	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	$f_3^*(s)$	V^*_{233}	End	LF
$n = 6$	A_5	2	V_{23}	**	2												
	C_{13}	2	V_{23}														
	C_{17}	8	V_{23}														
	C_{18}	12	V_{23}														
$n = 5$	A_2																
	A_3																
	A_4																
	A_5																
	A_6																
	A_7																
	C_8																
	C_{11}																
	C_{13}																
	C_{14}																
	C_{15}																
	C_{16}																
	C_{17}																
$n = 4$	A_1	26															
	A_2	28															
	A_3	50															
	A_4	27															
	A_5	38															
	A_6																
	A_7	31															
	C_8																
	C_{10}																
	C_{11}																
	C_{12}																
	C_{13}																
	C_{14}																
	C_{15}																
	C_{16}																

W_ℓ	C_8	C_{11}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	$f_4^*(s)$	V^*_{234}	End	LF
$f^*_{5}(s)$	20	14	17	14	15	26	14				
A_1	26							26	C_8	**	26
A_2	28							29	C_8	**	29
A_3	50	50		20		29		17	C_8, C_{11}	**	50
A_4	27		23					16	C_8	**	27
A_5	38		25	18		32		20	C_8	**	38
A_6		16	23	23				16	C_{13}	**	23
A_7	31	22	22		23			16	C_8	**	31
C_8				21	17	41		31	C_{16}		
C_{10}				19		35		35	C_{16}		
C_{11}				22				22	C_{14}		
C_{12}				25		44		44	C_{16}		
C_{13}				18			23	23	C_{17}		
C_{14}							19	19	C_{17}		
C_{15}							17	17	C_{17}		
C_{16}							16	16	C_{17}		

W_ℓ	C_8	C_{10}	C_{11}	C_{12}	C_{13}	$f_2^*(s)$	V^*_{232}	End	LF
$f^*_{3}(s)$	47	65	27	34	23				
A_1	53	78		60		78	C_{10}	**	78
A_2	55	91		67		91	C_{10}	**	91
A_3	77		63			77	C_8	**	77
A_4	54				29	54	C_8	**	54
A_5	65	76		56	31	76	C_{10}	**	76
A_6		79	29	40	29	79	C_{10}	**	79
A_7	58		35		28	58	C_8	**	58
C_8				37		37	C_{12}		
C_{10}				55		55	C_{12}		

W_ℓ	C_8	C_{10}	$f_1^*(s)$	V^*_{231}	End	LF
$f^*_{2}(s)$	37	55				
A_1	43	68	68		**	68
A_2	45	81	81	C_{10}	**	81
A_3	67		67	C_8	**	67
A_4	44		44	C_8	**	44
A_5	55	66	66	C_{10}	**	66
A_6	69		69	C_{10}	**	69
A_7	48		48	C_8	**	48

Note—LF, linkage frequency.

back to select a mediator variable C_j with the highest value (see Table 4 at Stage 4).

6. Repeat this computing procedure until W belongs to attribute (A) inventory and record related variables and frequencies. The DP approach ends at this point. The DP approach was stopped when W was equivalent to A in Stage 1 (see Table 4).

Comparison of DP and traditional MECs. Six stages are required to link variable V_{23} to all variables (see Table 4). When computing is stopped at Stage 2, the $A_2-C_{10}-C_{12}-C_{16}-C_{18}-V_{23}$ linkage is obtained with a maximum linkage frequency of 91. Moreover, if computing is stopped at Stage 1; $A_2-C_{10}-C_{12}-C_{16}-C_{17}-C_{18}-V_{23}$ has a maximum linkage frequency of 81. Obviously, using the logic of systematic procedure in multistage DP, one can easily count the linkage frequency of each value variable as the ultimate level of MEC hierarchies. Simultaneously, marketers can determine the importance of $A-C-V$ chains on the basis of the linkage frequencies. Gutman and Reynolds (1986) developed the means-end conceptualization of components of advertising strategy (MECCAS) to generate advertising strategy contexts. They used seven to eight ladders to construct an HVM. When the ladders and $A-C-V$ variables increased, the HVM became very difficult to construct and too complex to read. That is, when the levels of MEC hierarchies increase, the difficulty in constructing an HVM using the traditional laddering technique increases accordingly. Thus, as the complexity of the HVM increases, difficulty in reading the HVM increases. Consequently, marketers cannot benefit from reading an HVM to obtain consumer cognitive information. Conversely, using the proposed computerized MECs, marketers can deploy DP to analyze consumer-related information efficiently.

Discussion, Conclusions, and Future Research

The development of information technology has been phenomenally rapid, providing businesses with software for analyzing consumption information, and assisting marketers in developing effective marketing strategies. In the marketing field, MEC methodology is commonly used to understand consumer product knowledge and decision making (Reynolds & Olson, 2001). In the present study, MEC methodology, combined with the DP and a programming flowchart, was used to generate MEC hierarchies and, thereby, overcome shortcomings associated with MECs. Once the DP flowchart of the MEC concept has been implemented to generate an information system, researchers can retrieve consumer product knowledge from the database and can provide marketers with valuable information for formulating marketing strategies.

Enhancing the traditional MEC approach. When determining the cutoff value, one should consider MEC hierarchies as the most informative and most stable set of $A-C-V$ relations (Reynolds & Gutman, 1988). Pieters et al. (1995), in referring to the network analysis by Knoke and Burt (1983), used centrality and prestige as indexes to assess the importance of variables. The ratio of active cells to all cells was used to determine cutoff values. As the cutoff value increases, the amount of information

$A-C-V$ linkages can reveal decreases; that is, some salient $A-C-V$ chains will not appear on the HVM when the cutoff value is determined subjectively by researchers. To use wine coolers as an example, when the cutoff was 10, only 50% of the $A-C-V$ linkages of respondent perceptions (see Table 3) emerged on the HVM (see Figure 3). In fact, the determination criteria of the cutoff value by Reynolds and Gutman (1988) have two defects that warrant further discussion. (1) In traditional MECs, the cutoff value subjectively determined by researchers eliminates some important information before the HVM is constructed; thus, the constructed HVM is not the most informative in representing consumer cognition of a particular product. (2) Reynolds and Gutman concluded that interviewing homogeneous respondents yields an HVM construction with the same $A-C-V$ linkage structures.

The present study integrated MEC methodology and DP to overcome defects in traditional MECs and provide the most informative consumption information with the most stable criteria. In using DP to explore consumer product knowledge, no dilemma exists in determining the cutoff value. Not only can important and meaningful information be retrieved, connections among variables can be examined. In this study, *self-esteem* (V_{23}) was used as an example to demonstrate how DP can be applied in MEC methodology. The analytical results indicate that the highest linkage frequency is 91, and the linkage content is *crisp-refreshing-thirst-quenching-reward-impress-self-esteem* ($A_2-C_{10}-C_{12}-C_{16}-C_{18}-V_{23}$). If marketers want to meet consumer *self-esteem* (V_{23}) value satisfaction, they can focus on the *crisp* (A_2) attribute to formulate product strategies for wine coolers. In addition, *refreshing* (C_{10}), *thirst-quenching* (C_{12}), *reward* (C_{16}), and *impress* (C_{18}) can be used to develop advertising content. Ultimately, by adopting the proposed integrated method to establish information systems, marketers can benefit from storage capability, analog, and analytical elasticity of information systems to achieve stable and informative measurements using traditional MEC methodology.

Enhanced analysis of consumption information.

Consumer lifestyle and personality are important factors when implementing information technology (Damodaran, 2001). The development of information technology must meet user demand satisfaction (Kujala, 2003; Mahmood, Burn, Gemoets, & Jacquez, 2000; Preece, 2001; Tanin et al., 2000) and provide functions for analyzing consumption data. Traditionally, consumption data are collected from retailer sales reports. These retailer sales reports, however, provide marketers with information regarding consumer preferences for limited product categories, rather than for what consumers really need and prefer. Thus, if a company designs products only on the basis of analytical results of retail panel data and ignores real consumer demands, establishing an information system will not help the company survive in today's dynamic and competitive environments. In this study, combining MECs and DP provided new insights for marketers implementing an MEC and an understanding of consumer-product relationships. Marketers can use the concepts in this study to rapidly respond to market demands by constructing an information system.

Businesses encountering competitive operational environments should gear product designs to real consumer demands to achieve consumer value satisfaction. However, how to identify real consumer demands is an important issue today. A consumer-oriented company will ask its marketers to analyze retail panel data and use a field study to identify actual consumer desires and expectations. The MEC approach provides a theoretically elaborate conceptualization of abstracted consumer product knowledge. Such an approach can identify real consumer needs and wants. Importantly, this study enhances the MEC method by adopting DP and provides researchers with potential directions for future refinements and theory construction.

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