Journal of Supply Chain Management Systems
12 (2) 2023, 14-25
http://publishingindia.com/jscms/

An Interpretive Structural Modelling for Studying the Effect of E-Consumer Behaviour on Company's Value Chain

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Abstract

An E-Consumer differs from a regular consumer in many aspects. There are many additional parameters involved in online transactions vis-a-vis offline ones. For example, the physical evidence, one of the Ps in the marketing mix, is very different for a brick-and-mortar consumer and an E-Consumer. An E-Consumer gets affected by the design and user-friendliness of the website, online customer service available, etc. A company's value chain needs to be flexible enough to respond to the needs of the online consumer by incorporating advancements in technology. This paper begins with the development of a conceptual framework that explores dimensions of marketing, artificial intelligence and value chain affecting the company. The model is further explored to enlist identified variables, and identify their contextual relationship using Nominal Group Technique. Interpretive Structural Modelling and Matrice d'impacts croisés multiplication appliquée á un classment analysis have been adopted to understand the complex interrelationships amongst identified variables and to create a simpler hierarchical structure to understand the effect of E-Consumer behaviour on a company's value chain.

Keywords: E-Commerce, Big Data, Marketing Intelligence, Interpretive Structural Modelling, MICMAC, Systems Approach, E-Consumer Behaviour

Glossary: Table A contains the keywords and their contextual definition as adopted in the paper.

Table A

Sr. No.	Term	Meaning
1.	Customer Online Tracking	Customers' whereabouts on the internet can be tracked by the companies to understand their digital habits and behaviour.
2.	E-Database	This is the searchable electronic collection of resources by a company to understand E-Consumer behaviour pattern.
3.	E-Logistics	Set of activities involved in the logistics of a company through internet-based technologies.
4.	Less Time-Consuming Solution Delivery	The solution provided to the consumer by the company with the help of artificial intelligence is much more rapid & accurate.
5.	New Pattern Recognition	Machine Learning of AI is a continuous process and hence, the new actions taken by the E-Consumer are recognised by the AI and in turn help the companies to gain new kinds of information about the E-Consumer behaviour.

Sr. No.	Term	Meaning
6.	Online Customer Service& Relationship Management	Various E-commerce websites assist their customers/potential customers in making cost effective and correct product/service decisions.
7.	Repetitive Searches	Machine learning occurs when a consumer repeatedly behaves in the same way on the internet. E-Consumer habits lead to machine learning by A.I.
8.	Search History	It includes the entire web browsing history of a web-user (consumer) that can be analysed by the company.
9.	Search Suggestions and Personalised Information Delivery	The company provides the search suggestions to the consumers according to the information extracted from various data sources. Artificial Intelligence can help the companies to provide personalised information to each E-Consumer on the basis of their perceptions & habits.
10.	Social Media Tracking	Information extraction from social media channels by the company to measure current trends in the industry and to evaluate consumers' actions regarding the products/services.
11.	Surveys & Feedbacks	A source of information that can be used by a company for understanding E-Consumer's expectations & preferences.

INTRODUCTION

An electronic/online transaction is quite different from an offline transaction. The E-Consumer uses the electronic medium to make purchasing decisions, purchase products/services and make post-purchase decisions, and is influenced by the website's design and user-friendliness, as well as online customer care. Consumers who conduct business online must be treated differently than those who conduct business in a traditional store. To respond to the needs of E-Consumers and generate a positive perception of its brand, a firm must adjust and modify its operations, marketing, human resources, research and development and technology.

The perspective that an E-Consumer has about all aspects of electronic transactions might be considered the E-Consumer perception. This perception can be about a product/service, the physical evidence (e.g., the website layout), delivery-related factors, post-purchase services and return/refund practices, among other things, all of which must be thoroughly examined to provide them with the best possible solution. Consumer habits can be analysed by an assessment of consumer's online transactions which includes online search trends, past online purchases, influence of social media on purchase decision and the person's actual purchase or non-purchase activity. The attitude of an E-Consumer is the consequence of a person's perceptions and habits, which are reinforced by factors mentioned above and firms, must ensure that forming and nurturing of these perceptions are continuously improved. As a result, understanding E-Consumer behaviour is critical for a firm to develop customer joy and go beyond the concept of ordinary customer happiness. Artificial Intelligence (AI), based on big data and machine learning as two crucial pillars of adoption, is the greatest way to understand E-Consumer perceptions, habits and behaviour. The impact of adopting AI to improve and modify company's effort to improvise the value chain will be moderated by accuracy of Marketing Intelligence. The word "Marketing Intelligence" refers to the practice of gathering data and information to penetrate a certain market. Marketing Intelligence ensures that the organisation has all of the essential and relevant information to enter a new market, maintain an existing market and make other decisions.

Fig. 1 below represents the conceptual framework, based on the notion of IPO (Input-Processing-Output) methodology, which provides the paradigm for adopting Soft Systems Approach, for analysing the impact of E-Consumer behaviour on company's value chain.

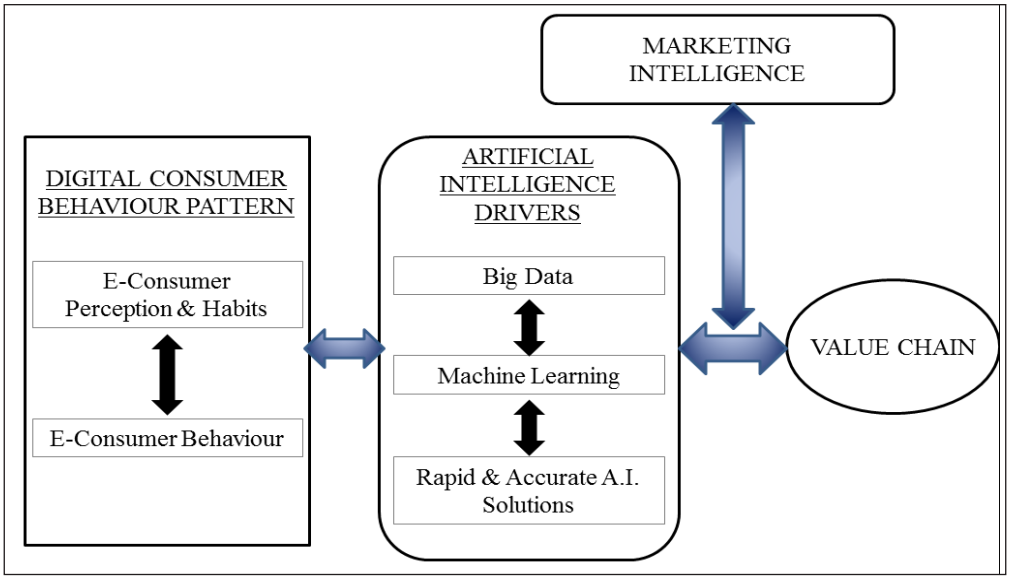

Fig. 1: Conceptual Framework with Marketing Intelligence in Play

The first component of the conceptual framework is the digital customer behaviour pattern. It includes all different sources of data and information gathering regarding E-Consumer perception and habits and behaviour. The various potential sources to gather such information are search history, social media, survey & feedback, customer online tracking and historical data and trends. The information from one source complements the information received from other sources, forming a reinforcing loop and thus, improves the reliability of and adds to the validity of the overall data and information pool. Social media is a digital platform where people freely express their views and connect across the world. Marketers can use this enormous amount of data and information flowing around on these websites, to understand the consumer and market trends, keeping in mind; respect, trustworthiness and honesty towards their customers.

Apart from the data gathered from the repository of the company itself, the data gathered by tracking consumers online, marketers can explore their customer journey analytics and understand how their customers treat their competitors' websites, products and services. Market surveys, a source of information that can validate the interpretation and comprehension of all available data, and can collect relevant information like characteristics, expectations and requirements of the target audience (Adi Bhat – Global VP - Sales and Marketing QuestionPro), serve as, reliable and valid source of information, as this is the only source of information directly provided by the E-Consumers. This source provides a control mechanism at every stage of information gathering and, is therefore a crucial aspect of understanding E-Consumer behaviour.

The second component of the conceptual framework is the AI drivers. It has three basic variables namely; big data, machine learning and rapid and accurate AI solutions. All these parameters get the necessary information collectively from the digital customer behaviour pattern. Big data can be defined as complex and large amount of data that contains invaluable information which, with the increasing exposure and improving technologies continues to grow at an unimaginable rate. Big data includes business transactions, e-mail messages, photos, surveillance videos, activity logs, unstructured text posted on the Web- such as blogs and social media (Source: pcmagencyclopedia). Machine learning refers to the ability of machines to learn from past experiences, just like human beings, hence, the word 'Intelligence' is an application of AI, which without being overtly programmed, provides systems the ability to automatically learn and improve from experience (Source: expert system). This huge amount of data is mined, by AI, using systematic segregation and evaluation, by way of algorithms, to extract information from the big data and ultimately provides quick and accurate solutions to the companies for better E-Consumer experience. Real-time and precise information is termed as rapid and accurate AI solutions.

The third component of the framework is of the marketing intelligence, which includes advertising optimisation, surgical segmentation, refined content delivery, sentiment analysis, smarter ads and trend analysis, rely on bots, continued learning and customer influence & usage analysis. Smart searches, the mechanism that provides keywords and results based on previous searches, to optimise the time and effort of the E-Consumer. Smart

searches, eventually lead to refined content delivery, which means providing "quality content" on website, in terms of usefulness and ensure optimised space and timely delivery and paves way for dynamic customer analysis through sentiment analysis. Sentiment analysis, which basically means to understand and extract the opinion involved in some text, is a type of data mining, also known as 'opinion mining', that measures the proclivity of people's opinions, sentiments and feelings through natural language processing, computational linguistics and text analysis, which are used to extract and analyse subjective information from the web - mostly from social media and similar sources. The data which is collected converts the qualitative input of people's sentiments and reactions towards a product/service and reveal the contextual polarity of the information (Source: techopedia, referred on 25th April, 2018). Relying on bots, for example, chatbots, spider bots, scraper bots, etc. and trend analysis, quantifiable study of past and current market behaviour and dominant patterns of the market and consumers, enable marketers to target and reach the right customer efficiently through, smarter ads and its impact on E-Consumers is optimised through advertising optimisation.

The last component of the framework is the value chain. Value chain encompasses the entire process, from the point of product inception, till the point, where the product is actually consumed by the end user. The process can be broadly classified as having three components namely product development, marketing and sales and inbound as well as outbound logistics. Variables like social media, search history, historical data and trends, customer online tracking and survey and feedbacks, which together constitute the sources of data, have a profound impact on marketing efforts like advertising optimisation, surgical segmentation, customer influence and usage analysis. As these variables impact each other in real time, this creates a reinforcing loop, which is moderated by marketing intelligence. Marketing intelligence analyses and limits the extent to which one variable impact another. In order to have an agile value chain, the company must adopt AI, which can provide quick and real time solutions, to effectively respond to the dynamics of E-Consumer behaviour.

Research Gap

As established through the conceptual framework, the impact of E-Consumer on company's value chain requires understanding of all these variables, making an agile value chain a complex system with multiple variables in play. Each variable plays a unique and vital role in the system and hence, needs to be defined and categorised effectively. Systems approach is a line of thought in the management field which stresses the interactive nature and interdependence of external and internal factors in an organisation depicting logical flow of information between variables (Source: business dictionary, referred on 25th April, 2018).

In order to establish and understand the inter-relationship between different variables, interpretive structural modelling has been deployed. *"ISM is a well-established methodology for identifying relationships among specific items, which define a problem or an issue" (Source: Attri, Dev & Sharma 2013).* A comprehensive systematic model comprising of a set of directly and indirectly related elements, is created using ISM. This conceptual model is then examined under given contextual relationship to establish the hierarchy of elements, which enables the user to understand poorly articulated, complex and ambiguous relationship of variable in more defined and logical manner.

Matrice d'impacts croisés multiplication appliqué e á un classment (MICMAC) analysis had been adopted, which was developed by Michel Godet and François Bourse. MICMAC a cross-impact matrix multiplication applied to classification is a structural prospective analysis used to study indirect relationships (Saxena et al., 1990); by developing a graph that classifies factors based on driving power and dependence power. This analysis complements the ISM approach by exploring constraints that usually refer to the ISM method: it explores the relationship "yes" or "no" and ignores the so-called grey area between 0 and 1 (Sushil, 2012).

Research Question

- To identify factors which establish the impact of E-Consumer on company's value chain?
- To establish hierarchical relationship amongst the identified variables which establish the impact of E-Consumer on company's value chain?
- To classify the identified factors as drivers, linkages, independent and autonomous variables of the system.

LITERATURE REVIEW

Previous studies have suggested using ISM identify relationships among specific items, which define a

problem or an issue (Attri et al., 2013). Mandal et al., 1994 adopted ISM to show the interrelationship of different criteria and their levels of importance in the vendor selection process. Kanan et al. (2012) used ISM to analyse third party reverse logistic and found that in multi-dimension and multi-criterion scenario, it is ideal to adopt ISM.

IM is an interactive learning tool in which a variety of closely linked parts are organised into a comprehensive models. It converts hazy, poorly articulated system models into easily visible, well-defined models that can be utilised for a variety of purposes (Warfield, 1974). As according Mandal and Deshmukh (1994), ISM is "a well-established technique for identifying and synthesising relationships between many specific items that define an issue or problem; it serves as a means by which a group can establish order on the sophistication of the items, and its sculpting identifies the significant associations and overall structure, and is portrayed in a digraph model". As a result, ISM is a procedure that aids in the development of a model of the intricate relationships among the various variables in a delicate subject. It's a good strategy for determining the impact of one aspect on the other. There are only a few of the many benefits of this methodology (Talib et al., 2011). It incorporates subjective expert judgments as well as their knowledge base in an orderly manner and allows for the improvement and revision of judgments. It is best used as a qualitative tool in real-life situations as well as for gaining quick managerial insights and combines subjective expert judgments and also their skill set in an orderly manner.

The basic procedure for understanding the development of ISM to show the interrelationship of different criteria and their levels of importance impact the structural modelling have been published in (Malone, 1975), (Attri et al., 2013) which includes identification of variables, that are relevant to the problem or issue, followed by identification of a contextual relationship. The Structural Self Interaction Matrix (SSIM) is then developed based on a pairwise comparison of the variables, which using binary symbols is converted to a reachability matrix. Then, the partitioning of the elements and an extraction of the structural model is performed. ISM methodology infuses expert opinions using brainstorming, nominal group technique (NGT), idea engineering, etc. in contextual variable relationship development. MICMAC analysis has been adopted in the scenario of selection of interdependent criteria and to classify them into four categories (Mandal et al., 1994). They further predicted that robotics, automation and AI will have an unprecedented disruptive impact on the future, probably even exceeding the influence of the Internet and mainstream information technologies. They have discussed the impact of AI on marketing, and stated that variables of AI adoption need to be discussed further. Bowen, 1991 has also discussed the potential areas for understanding the variables of AI and the ways they affect the variables of other aspects of marketing. Sahney et al., 2006 have discussed the impact of data management on E-marketing intelligence and three basic ways on how AI will impact marketing automation, connection and context and talks about exploring similar variables that will affect marketing.

The review of literature shows that ISM is an ideal tool to transforms unclear, poorly articulated mental models of systems into visible and well-defined models. Hence, ISM methodology has been adopted in this study, to create a hierarchical model, of the factors affecting E-Consumer behaviour and its impact on company's value chain.

RESEARCH METHODOLOGY

Research Objectives

- To identify integrated elements for analysing the effect of E-Consumer behaviour on company's value chain.
- To construct an interpretive structural model of the identified variables.
- To do a MICMAC analysis for studying the interrelationship between factors.

Research Design

Phase 1 - Identifying Integrated Elements

In this phase, the researcher has identified the relevant factors which establish the impact of E-Consumer behaviour on company's value chain:

- Review of literature.
- Nominal Group Technique (NGT) workshop.

Phase 2 - Development of Hierarchical Structural Model

In this Phase 2, the researcher has developed the interaction matrix amongst identified factors and developed hierarchical structural model under relevant contextual relations of impact of E-Consumer behaviour on company value chain.

- Creating SSIM matrix and deploying VAXO framework for identifying the relationship amongst factors of E-Consumer behaviour affecting company value chain.
- ISM technique being deployed to develop hierarchical model of identified factor of E-Consumer behaviour affecting company value chain.

Phase 3 – Classifying Variables Based on the Strength of Interaction

The researcher has deployed MICMAC method, a cross-impact matrix multiplication applied to classify variables in a structural, by developing a graph that classifies factors based on driving power and dependence power. It identifies and distinguishes these four categories of the variables/factors, thereby explaining the entire system in a more comprehensive and understandable manner.

Sampling Plan

In the above phases, various set of respondents were contacted for data collection, the respondent demographic profile are as follows:

- Policy Maker from Government-01.
- Academia-10.
- Industry-10.

The number of respondents in all the workshops was between 10 and 15. The sampling technique adopted was non-probability Judgement Sampling.

FINDING AND ANALYSIS

Objective 1

The first objective has been achieved in two phases. First phase being an exhaustive review of literature in which various papers and articles are studied and after a thorough content analysis a list of initial variables (n=16) was made. These factors have been listed below in Table B.

Table B

Sr. No.	Variables
1	Social Media Tracking
2	Search History
3	Historical Data & Trends
4	Customer Online Tracking
5	Surveys & Feedbacks
6	E-Database
7	Repetitive Searches
8	Algorithmic Patterns
9	Less Time Consuming Solution Delivery
10	Search Suggestions
11	Personalised Information Delivery
12	New Pattern Recognition
13	Online Customer Service
14	E – CRM
15	E – Consumer Patterns
16	E – Logistics

In the second phase, a NGT workshop was conducted with expert using the trigger question of the impact of E-Consumer behaviour on company's value chain. In the first round, experts were asked to list one factor for each problem. These factors were listed and the panel was opened for discussion, after providing experts with a list of variables generated from secondary data. The group discussed the interrelationship among the variables. Weighted average mean technique was employed to enlist the final factors, which listed in Table C.

Table C

Sr. No.	Variables
1	Social Media Tracking
2	Search History
3	Customer Online Tracking
4	Surveys & Feedbacks
5	E – Database
6	Repetitive Searches
7	Less Time Consuming Solution Delivery
8	Search Suggestions Personalised Information Delivery
9	New Pattern Recognition
10	Online Customer Service and Relationship Management
11	E – Logistics

Objective 2

In constructing interpretive structural model, the process includes formulation of SSIM, reachability tables and level partitions. The initial construction of SSIM requires a symbolic representation using "VAXO" framework. The symbols and their interpretation are listed in Table D.

Table D

If i is driving j	iVj
If i is being driven by j	iAj
If both are driving each other	iXj
If no relation is present.	iOj

The identified variables from Objective 1, were presented to the experts, who were then asked to define the contextual relationship among variables using the principle of Table D, the entries for cells where i=j are left blank and only the upper triangle is considered while filling the table, which generated the SSIM table (Table 1).

Table 1: SSIM

VAXO Table

i \ j	1	2	3	4	5	6	7	8	9	10	11
1		V	V	X	V	A	V	V	V	X	X
2			V	A	V	A	V	V	X	V	V
3				X	V	A	V	V	V	X	X
4					V	A	V	V	X	X	V
5						A	V	V	V	V	X
6							X	X	V	V	V
7								A	X	X	A
8									A	X	A
9										X	V
10											X
11											

The entries in the initial reachability table were computed using the concept as presented in Table E (INSERT TABLE E HERE), which resulted in the conversion of SSIM into binary form as shown in Table 2. The binary entry for all cells with i=j was kept '1'. In the next step, the final reachability table was constructed, using Warshall's algorithm in Microsoft Excel, to check for transitivity closure, which is shown in Table 3. In the end, the driving power and dependence power were calculated by adding '1' in the rows and columns.

Table 2: Initial Reachability Matrix

Initial Reachability Table

	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	0	1	1	1	1	1
2	0	1	1	0	1	0	1	1	1	1	1
3	0	0	1	1	1	0	1	1	1	1	1
4	1	1	1	1	1	0	1	1	1	1	1
5	0	0	0	0	1	0	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1	1	1
7	0	0	0	0	0	1	1	0	1	1	0
8	0	0	0	0	0	1	1	1	0	1	0
9	0	1	0	1	0	0	1	1	1	1	1
10	1	0	1	1	0	0	1	1	1	1	1
11	1	0	1	0	1	0	1	1	0	1	1

Table 3: Final Reachability Matrix

Final Reachability Table

	1	2	3	4	5	6	7	8	9	10	11	DRIVING
1	1	1	1	1	1	1	1	1	1	1	1	11
2	0	1	1	1	1	1	1	1	1	1	1	10
3	0	0	1	1	1	1	1	1	1	1	1	9
4	1	1	1	1	1	1	1	1	1	1	1	11
5	0	0	0	0	1	1	1	1	1	1	1	7
6	1	1	1	1	1	1	1	1	1	1	1	11
7	0	0	0	0	0	1	1	0	1	1	0	4
8	0	0	0	0	0	1	1	1	0	1	1	5
9	0	1	0	1	0	0	1	1	1	1	1	7
10	1	0	1	1	0	0	1	1	1	1	1	8
11	1	0	1	0	1	0	1	1	0	1	1	7
DEPENDENCE	5	5	7	7	7	8	11	10	9	11	10	

The structural hierarchy of the variables were established using the method of level partition, the application of which requires formulation of a reachability set, an antecedent set, an intersection set and a level partition as defined below:

- Reachability Set – All rows in the final reachability table are checked for '1'.
- Antecedent Set – All columns in the final reachability table are checked for '1'.
- Intersection Set – The intersection of the reachability set and antecedent set.
- Level Partition – Where the reachability set is the same as the intersection set.

Once the level has been established, the procedure of level partition requires, cancellation of the elements for which the reachability set is same as the intersection set. This process requires successive iterations, until no further levels can be established, which has been depicted in Table 4–10 in succession below.

Table 4: Iteration 1 for Level Partition

	REACHABILITY SET	ANTECEDENT SET	INTERSECTION SET	
1	1 2, 3 4 5 6 7 8 9 10 11	1 4 6 10 11	1 4 6 10 11	
2	2 3 4 5 6 7 8 9 10 11	1 2 4 6 9	2 4 6 9	
3	3 4 5 6 7 8 9 10 11	1 2 3 4 6 10 11	3 4 6 10 11	
4	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 6 9 10	1 2 3 4 6 9 10	
5	5 6 7 8 9 10 11	1, 2 3 4 5 6 11	5 6 11	
6	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8	1 2 3 4 5 6 7 8	
7	6 7 9 10	1 2 3 4 5 6 7 8 9 10 11	6 7 9 10	1
8	6 7 8 10 11	1 2 3 4 5 6 8 9 10 11	6 8 10 11	
9	2 4 7 8 9 10 11	1 2 3 4 5 6 7 9 10	2 4 7 9 10	
10	1 3 4 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11	1 3 4 7 8 9 10 11	1
11	1 3 5 7 8 10 11	1 2 3 4 5 6 8 9 10 11	1 3 5 8 10 11	

Table 5: Iteration 2 for Level Partition

	REACHABILITY SET	ANTECEDENT SET	INTERSECTION SET	
1	1 2 ,3, 4, 5, 6, 8, 9, 11	1, 4, 6, 11	1, 4, 6, 11	
2	2, 3, 4, 5, 6, 8, 9, 11	1, 2, 4, 6, 9	2, 4, 6, 9	
3	3, 4, 5, 6, 8, 9, 11	1, 2, 3, 4, 6, 11	3, 4, 6, 11,	
4	1, 2, 3, 4, 5, 6, 8, 9, 11	1, 2, 3, 4, 6, 9	1, 2, 3, 4, 6, 11	
5	5, 6, 8, 9, 11	1, 2, 3, 4, 5, 6, 11	5, 6, 11	
6	1, 2, 3, 4, 5, 6, 8, 9, 11	1, 2, 3, 4, 5, 6, 8	1, 2, 3, 4, 5, 6, 8	
8	6, 8, 11	1, 2, 3, 4, 5, 6, 8, 9, 11	6, 8, 11	2
9	2, 4, 8, 9, 11	1, 2, 3, 4, 5, 6, 9	2, 4, 9	
11	1, 3, 5, 8, 11	1, 2, 3, 4, 5, 6, 8, 9, 11	1, 3, 5, 8, 11	2

Table 6: Iteration 3 for Level Partition

	REACHABILITY SET	ANTECEDENT SET	INTERSECTION SET	
1	1 2 ,3, 4, 5, 6, 9	1, 4, 6	1, 4, 6	
2	2, 3, 4, 5, 6, 9	1, 2, 4, 6, 9	2, 4, 6, 9	
3	3, 4, 5, 6, 9	1, 2, 3, 4, 6,	3, 4, 6	
4	1, 2, 3, 4, 5, 6, 9	1, 2, 3, 4, 6, 9	1, 2, 3, 4, 6, 9	
5	5, 6, 9	1, 2, 3, 4, 5, 6	5, 6	
6	1, 2, 3, 4, 5, 6, 9	1, 2, 3, 4, 5, 6	1, 2, 3, 4, 5, 6	

Table 7: Iteration 4 for Level Partition

	REACHABILITY SET	ANTECEDENT SET	INTERSECTION SET	
1	1 2 ,3, 4, 5, 6	1, 4, 6	1, 4, 6	
2	2, 3, 4, 5, 6	1, 2, 4, 6	2, 4, 6	
3	3, 4, 5, 6	1, 2, 3, 4, 6	3, 4, 6	
4	1, 2, 3, 4, 5, 6	1, 2, 3, 4, 6	1, 2, 3, 4, 6	
5	5, 6	1, 2, 3, 4, 5, 6	5, 6	4
6	1, 2, 3, 4, 5, 6	1, 2, 3, 4, 5, 6	1, 2, 3, 4, 5, 6	4

Table 8: Iteration 5 for Level Partition

	REACHABILITY SET	ANTECEDENT SET	INTERSECTION SET	
1	1, 2 ,3, 4	1, 4	1, 4	
2	2, 3, 4	1, 2, 4	2, 4	
3	3, 4	1, 2, 3, 4	3, 4	5
4	1, 2, 3, 4	1, 2, 3, 4	1, 2, 3, 4	5

Table 9: Iteration 6 for Level Partition

	REACHABILITY SET	ANTECEDENT SET	INTERSECTION SET	
1	1, 2	1	1	
2	2	1, 2	2	6

Table 10: Iteration 7 for Level Partition

	REACHABILITY SET	ANTECEDENT SET	INTERSECTION SET	
1	1	1	1	7

The interpretive structural model generated from the procedure above, has been depicted in Fig. 2.

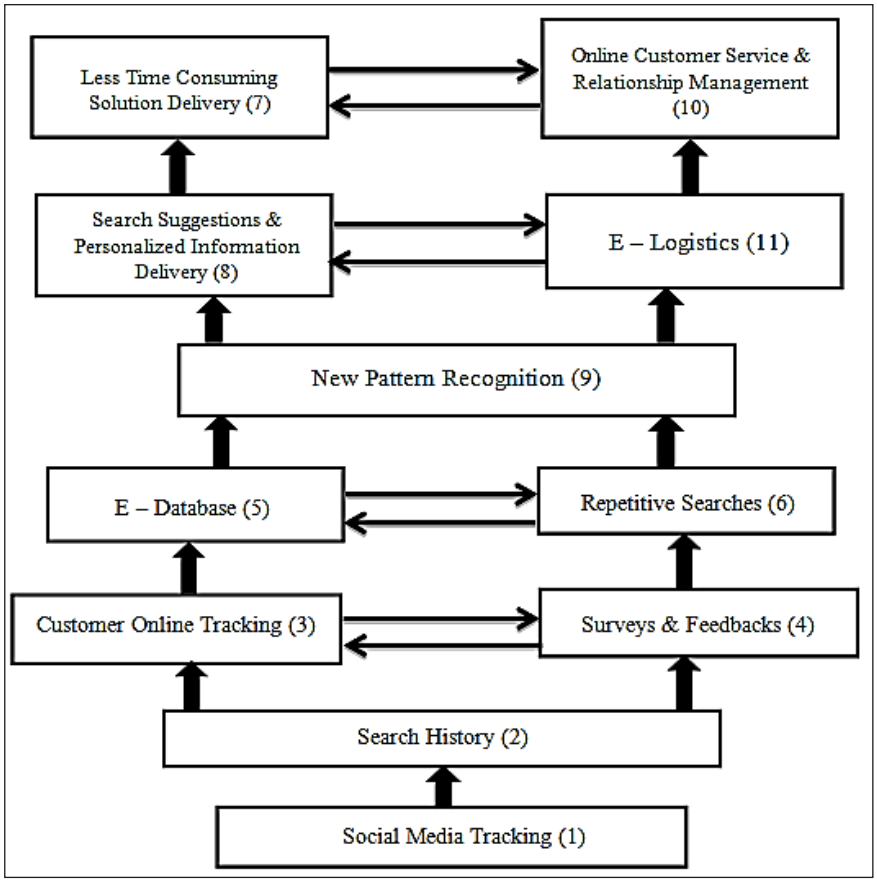

Fig. 2: Interpretive Structural Modelling

Objective 3

MICMAC Matrice d'impacts croisés multiplication appliqué e á un classment, Cross-Impact Matrix Multiplication applied to Classification) analyses the driving and dependence powers of the variables, and help to identify the main drivers of the system, the linking elements of the system, the autonomous or independent variables of the system and the dependent variables/ factors of the system. It identifies and distinguishes these four categories of the variables/factors, thereby explaining the entire system in a more comprehensive and understandable manner.

A graph plotted with the coordinates of dependence and driving powers provide the:

- *Drivers* – These factors are known as the "key factors" that have a very high/strong driving power and low/weak dependence power.
- *Linkage Factors* – The driving and dependence powers of these factors are of the same strength magnitude, that is, high/strong.
- *Autonomous Factors* – These factors are low/weak driving as well as dependence power. These factors are relatively disconnected and independent from the system.
- *Dependent Factors* – These factors have low/weak driving power but a high/strong dependence power.

Fig. 3 shows the graph of MICMAC analysis, obtained by defining the axes as the dependence and the driving power.

	X Axis	Y Axis	
VARIABLE	DEPENDENCE POWER	DRIVING POWER	TYPE
1	5	11	Driver
2	5	10	Driver
3	7	9	Linkage
4	7	11	Linkage
5	7	7	Linkage
6	8	11	Linkage
7	11	4	Dependent
8	10	5	Dependent
9	9	7	Linkage
10	11	8	Linkage
11	10	7	Linkage

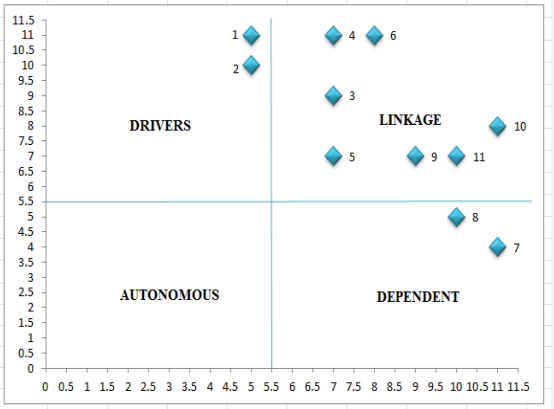

Fig. 3: MICMAC Analysis and Graph

CONCLUSION

Social media tracking and search history are the two base variables as per the structural model and also contribute as drivers of the system as per MICMAC analysis. Hence, companies should focus on social media tracking and search history of E-Consumers to make appropriate modifications in their value chain. Digital footprints are very useful for all companies as they can leverage this information to identify and target the right user. The logical flow of information is also captured in the hierarchy as social media tracking provides information regarding the search history of E-Consumers, thereby, improving the accuracy of the recorded information. This information provided by social media has given a completely new reference area for the marketers and companies which they did not have before. Every action on the social media that an individual performs; be it is a conversation, a site visit, a post or a like/react, shows a piece of information about that individual. "*This data goes beyond simple demographic information to robust details like preferences, intent, sentiment, activities and social networks" (Source: http://snaptrends.com/social-media-software/data-collection/)*.

The next level of the structural model contains customer online tracking and surveys and feedback variables, which are in a reinforcing loop. This relationship is justified as effective online tracking will help in conducting surveys, and survey information regarding what a customer expects or likes/dislikes after a particular transaction or interaction with a website, results in effective online tracking. These variables are part of linkage factors as per the MICMAC analysis, as they collect information from social media tracking and provide the input for E-database. The next level of hierarchy contains E-database and repetitive searches, which also form a reinforcing loop as both positively, contribute to each other. The more a person searches an information, website, etc., the E-database gets enlarged, the larger the database the better search results can be provided for E-user. They are also linkages factor of the model as they are built upon a previous layer of the model to seek inputs in the form of requisite information and can be utilised for analysing the E-behaviour of a user for any deviation from previous searches.

Improvements in the E-database and repetitive searches will lead to better and systematic understanding of the new patterns that E-Consumers have developed, which has been called as new pattern recognition in the present study. E-logistic, the set of activities involved in the logistics of a company through internet-based technologies, responds to the changes in the expected consumer behaviour and provides optimised search suggestion as per the new information. E-logistic also falls in the category of linkage factors as per MICMAC analysis, which justify the fact that, agile E-logistic activities are dependent on factors such as social media tracking, E-database, new pattern recognition and offer the opportunity to companies to stay relevant by offering personalised information delivery to the E-Consumer.

The interpretive structural modelling established here shows that this system contains drivers, linkage factors and dependent factors but has no autonomous factors. There are a number of linkage factors in the model. All these linking variables prove that the entire system is interrelated and interdependent. Surveys and feedbacks

and customer online tracking leads to information regarding repetitive searches, thereby, enhancing the E-database of a company. Finally, all the above efforts of companies will lead to a less time-consuming solution and better online customer service and relationship management.

Social media and search history tracking are the main drivers of this entire system as they help a company for tracking its customers online. Tracking the customers online not only shows their behaviour but also their perceptions and habits. Companies also track repetitive search habits of the people. Another useful source of information for the companies, are the surveys and feedbacks collected. This entire bulk of information collected by the companies improves to their E-database.

Through this enhanced E-database, the companies can recognise the new patterns that the customers or potential customer have/can form, thereby, modifying their business practices. All these efforts of the companies, together, will enable them to deliver better search suggestions and personalised information. E-logistics being a relatively novel area has a lot of scope of modifications and improvements. Managing the online customer service and relationship is in turn linked with all the other practices done by the companies. Finally, these efforts will lead to less time-consuming solution delivery to the people, thereby, improving the holistic working of the companies.

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