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An Analysis of Post COVID-19 Scenario using Data Science in Digital Marketing

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Abstract
The Purpose of the study is to analyze the uses of data science in digital marketing in post COVID-19 scenario. General design of the study includes survey of relevant research literature, primary data collection, structural modeling and critical analysis**.** The study uses Interpretive Structural Modeling (ISM) for structural modeling and Matriced' Impacts Croise's Multiplication Appliquée a UN Classement (MICMAC) for analysis. Introducing new products, personalizing customers' online experience and improve user experience occupy top (*Level I)* and tracking social media commentary/interactions occupies bottom (*Level IX)* of ISM model. Analyzing user generated content, tracking social media commentary/interactions, analysis of online sales data, analyzing social media trends, analyzing product recommendations and reviews and analyze real-time big data are categorized as independent uses. Optimize customers' preferences, optimize stock levels in e-commerce businesses, introducing new products, improve user experience and identify fake news & false content are categorized as dependent uses but others are categorized as linkage uses and no one is categorized in autonomous. It is an original study because it uses real time market survey data the findings of which are useful for folks of its stakeholders. It is particularly useful for marketers. It has serious implications for businesses since nowadays there is influx of data generation that has become a type of a noise for businesses. Use of data science not only converts this data noise into useful information but also an opportunity. This study provides lot of information about uses of data science particularly for marketing.
Keywords: COVID-19, data science, digital marketing, ISM, MICMAC, Pakistan, uses of data science

1. Introduction

With unprecedented development in information communication technology, data generation has exponentially increased unwantedly (Islam et al., 2020; Audi et al., 2021). It has become literally a data noise for businesses. This data generation is increasing beyond expectations that have raised the complexity of businesses to great extent (Liu et al., 2021). The smart stakeholders of this phenomenon are trying to benefit from the analytics of this big data. Big data analytic tools over the complex software are being introduced day by day. There is an array of stakeholders to this reality that includes data scientists/analysts, data engineers, IT personnel, government/regulators, business analysts/industry, customers, suppliers, competitors, unions, media, and the community at large (Ali et al., 2023). The marketers from the business community are the most hopeful stakeholders trying to make some sense of the benefits of data science, particularly in digital marketing (Bai et al., 2021). In the era of digitalization, the use of data science in marketing is not only beneficial, easy, or better but also provides a competitive advantage as well. There is a lot of effort present in contemporary literature that covers a wide variety of aspects of uses of data science in business practices that vary on the continuum of very simple to very complex. In fact, it is now inevitable to use the tools of big data analytics for reaping the benefits from the data sets. To this extent, a few studies viz: Bai et al. (2021) claimed that Micro and Small Enterprises (MSEs) in developing countries are the major victims of the COVID-19 pandemic due to the limited use of digital technologies. They further argued that the digital transformation of MSEs particularly in post-COVID-19 is crucial for business continuity. Burhan et al. (2021) explored factors (formal planning, affable relationships with stakeholders, government support, and self-determination of entrepreneurs) susceptible during the COVID-19 pandemic and buttressed that innovating marketing strategies and social media should be used as promotion to get out of economic shocks. Gupta et al. (2021) identified substantial gaps in conventional decision-making systems and proposed a model to demonstrate how big data enhances firms' strategic and operational decisions for improved marketing performance. Liu et al. (2021) used big data to examine the impact of a luxury brand's social media marketing strategies on consumer engagement by way of analyzing 3.78 million tweets (having the highest number of Twitter followers) from the top 15 luxury brands. The results affirmed that interaction, entertainment, and trendiness dimensions of social media marketing activities significantly increase customer engagement. Luo (2021) proposed a model to examine the effect of social behavior and social networks on e-business during the COVID-19 pandemic. The results revealed that the proposed model enhances the profitability ratio to 98.5%, the accuracy ratio of 96.7%, and the prediction ratio of 97.9%, the performance ratio of 97.5%, and less error rate of 11.3% as compared to other existing methods. Modgil et al. (2021) proclaimed that COVID-19 has surged to provide digital solutions for the survival of businesses. Therefore, digital entrepreneurship requires four pre-requisites such as i) entertainment (social media, gaming), ii) technology (FinTech, EdTech, and cyber security), iii) e-commerce (contactless delivery, payment methods, augmented reality) and iv) healthcare (virtual care, diagnostics, fitness). There is a research gap in literature particularly about the uses of data science in digital marketing. The research work has been found on the identification of uses of data science in digital marketing and the framework thereof, but neither has it been explored for the underlying structures of the contributory factors of uses of data science nor for quantification of intra-factor relations (Saura, 2021; Audi et al., 2023). Admittedly data generation, utilization of big data are one of the hot topics among marketers. Therefore, this study is aimed to impose hierarchy and direction on complex relations of the uses of data science as identified by Saura (2021). It develops a structural graphical model and classifies the uses of data science in digital marketing. It also enlightens upon its usefulness qua reality. The specific research questions which this study addresses include: i) which issues need high priority? ii) Which issues are relatively less important?

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iii) What is the contextual relationship between variables? For achieving these objectives and answering the research questions a set of methodological choices is considered viz: analytic network process, fuzzy analytic network process, analytic hierarchical process, preference ranking organization method for enrichment evaluations, technique for order of preference by similarity to ideal solution, Vlsekriterijumska Optimizacija I KOmpromisno Resenje, interpretive structural modeling, Matriced' Impacts Croise's Multiplication Appliquée a UN Classement and interpretive ranking process (Shaukat et al., 2021; Valmohammadi & Dashti, 2016). ISM augmented with MICMAC is considered to be the most appropriate method. ISM and MICMAC are standalone structural methodologies using the inductive approach that have the capability of representing poorly articulated complex relations into a simple and useful structural model (Warfield, 1973 and 1974; Sushil, 2017). This methodology is preferred over other statistical methodologies particularly in exploratory studies (Chidambaranathan et al., 2009; Shaukat et al., 2021; Fu et al. 2022a; Abbass et al., 2022a; Fu, et al., 2022b; Abbass, et al., 2022b; Basit, et al., 2021; Abbass, et al. 2021; Shaukat, et al., 2021a). It uses limited primary data and by exploiting the elementary concepts of Boolean algebra, set theory, and directed graph theory provides a lot of new insights into the phenomenon (Abbass et al., 2021; Basit et al., 2021). The rest of the paper is organized as literature review, methodology, modeling/analysis/results/discussion and conclusion.

2. Literature Review

The review of the literature is always helpful to justify the work within the contemporary literature. It also helps to avoid objectionable duplication. With the information communication technology and development of the web and internet, it has become convenient for the researchers to set the context of the studies. For this purpose, we explored various databases namely IEEE Explore, Science Direct, Web of Sciences, Association of Computing Machinery, Emerald, Springerlink, Taylor & Francis Journals, Wiley-Blackwell Journals, JStor, etc. Using Google as a search engine, the keywords like data sciences, digital marketing, data mining, online marketing**,** knowledge discovery and internet marketing are used. An avalanche of literature on the phenomenon is extracted and examined. The relevant studies are reported here with brevity. Alaimo et al. (2020) analyzed the impact of COVID-19 outbreak on online food shopping behavior in Italy. Apuke and Omar (2020) concluded that self-promotion, altruism and instant news sharing during COVID-19 pandemic among social media users in Nigeria predicted fake news sharing. Baicu et al. (2020) examined the effect of COVID-19 pandemic on consumer behavior retail marketing in Romania. Islam et al. (2020) attempted to recognize knowledge workers' behavior towards COVID-19 information sharing using WhatsApp in Pakistan. Jaman et al. (2020) presented comparative sentiment analysis on utilizing online transportation of Indonesian consumers using tweets in pre-COVID-19 and during COVID-19 pandemic. Kayakuş and Çevik (2020) assessed the number of visitor of e-commerce website during COVID-19 in Turkey by way of neural networks. Korankye (2020) suggested the integrated marketing strategy by evaluation of COVID-19 pandemic impact on small and media enterprises in Ghana. Liu (2021) discussed the intelligent marketing information service of agricultural products in China. Mejía-Trejo (2021) examined purchase intention of online consumer behaviors of Mexican's COVID-19 ads. Strotmann et al. (2021) devised marketing strategy using digital technology to prevent food waste in German food service sector during COVID-19 pandemic. Saura et al. (2021) classified types of Customer Relationship Management (CRM) and explore the efficient use of artificial-based CRM systems in B2B digital marketing as a communication and sales channel. Verma et al. (2021) carried a comprehensive systematic review of literature on the importance of artificial intelligence in marketing using intellectual, conceptual and bibliometric analysis of extant published literature (i.e. one thousand five hundred and eighty published research articles) during the period of 1982-2020. From the survey of the literature, we found a study by Saura (2021) that has worked on "using data sciences in digital marketing: framework, methods, and performance metrics". It is a theoretical study based on an extensive review of literature on uses of data science in digital marketing. It contributed theoretical frameworks and list of uses of the data science in digital marketing. We fine it appropriate and representative of the phenomenon under study, therefore, have adopted the same for building the study. The uses include: "analyzing user generated content (U1), optimize customers' preferences (U2), tracking customer behaviors online (U3), tracking social media commentary/interactions (U4), optimize stock levels in e-commerce businesses (U5), analysis of online sales data (U6), introducing new products (U7), analyzing social media trends (U8), analyzing product recommendations and reviews (U9), personalizing customers' online experience (U10), building recommender systems (U11), measure and predict clicks online for social and paid Ads (U12), measure and predict user's behavior (U13), improve user experience (U14), analyze real-time big data (U15), identify online communities (U16), identify fake news and false content (U17)" (Saura, 2021).

3. Methodology

This study is based on the philosophy of interpretivism using induction as a generalization approach. The overall research design of the study comprises of literature review to explore the uses of data science, primary data collection methods and use of qualitative mathematical techniques for modeling and analysis. The population under study is folk of stakeholders of the phenomenon. Non-probability-based purposive sampling is used and fifteen experts are selected as sample size because no predefined set of population frames is available. To collect data from experts face to face, a one-to-one interview is used (Abbass et al., 2021). The study uses ISM for modeling and MICMAC for data analysis that has the capability of using small set of qualitative data and providing relatively more insights (Wafield, 1973; Shaukat, et al., 2021b; Niazi, et al., 2020a; Niazi, et al., 2020b; Niazi, et al., 2020c; Niazi, Qazi, & Basit, 2020; Audi et al., 2021; Qazi, et al., 2019).

3.1. Panel of Experts

A panel of experts is used for the elicitation of data for this study as firsthand information on the phenomenon under study was not available (Sushil, 2017). A panel consisting of seven to twelve experts is considered appropriate for a heterogeneous group of experts whereas a homogenous panel may comprise of twelve to twenty-five members, where 25 members are considered optimum for a homogenous group of panel of experts (Clayton, 1997; Khan & Khan, 2013). There are more benefits of eliciting data from expert groups than from statistical groups as experts have more in-depth knowledge and provide reliable, authentic and realistic information (Clayton, 1997; Niazi, et al., 2019; Niazi, Qazi, Basit, & Khan, 2019; Niazi, Qazi, & Sandhu, 2019; Niazi, Qazi & Basit, 2019a; Niazi, Qazi & Basit, 2019b; Niazi, Qazi & Basit, 2019c). The formal criteria for recruiting the experts for the study are: having theoretical, technical and practical knowledge about the phenomenon under study, marketing experience (more than 10 years), education (university graduates), willingness to participate and having appropriate quotient of research. The panel of this study is heterogeneous i.e. one consisting of three data scientists, three digital marketers, three business analysts, four academicians/researchers, one policymaker and one expert from cyber security. Initially, we approached 25 experts through emails, phone calls, and personal visits and developed a rapport for briefing the background of the study and inviting them to participate. Only 15 have successfully participated in this study. The profile of the experts is given as *Annexure I*. Therefore, the actual size of the panel on which the study is built is the panel of fifteen experts. The panel was approached two times once for data collection and second for logical, theoretical, conceptual, and directional verification of the model. It took us approximately 3.5 months to contact and collect data from a panel of experts in the field setting. Various methods to elicit data from experts are considered viz: Delphi Method, discussion session, matrix type questionnaire, one-to-one, face-to-face in-depth interview, and approval voting on alternatives (*VAOX*) for every pair of relations through software/questionnaire. For this study, the matrix type questionnaire in combination with one-to-one, face-to-face in-depth interview and approval voting on alternatives (*VAOX*) for every pair of relations through questionnaire is used (Alawamleh & Popplewell, 2011; Niazi et al., 2019). The data is converted into a matrix using the majority rule (Li et al., 2019).

4. Modeling/Analysis/Results & Discussion

4.1. ISM Modeling

Following the stepwise classical procedure of applying ISM (Warfield, 1973), the data collected from the individual experts are aggregated by majority rule and a matrix (Table 1) is constructed below.

Table 1: Structural Self- Interaction Matrix (SSIM)

Code	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17
U1		V	V	X	V	O	V	X	V	V	V	V	V	V	A	V	V
U2			A	A	V	O	V	A	A	O	A	O	A	V	A	A	O
U3				A	V	O	V	V	A	V	O	O	X	V	A	V	O
U4					V	O	V	V	V	V	V	V	V	V	V	V	V
U5						A	O	A	A	O	A	O	A	V	A	A	O
U6							V	O	A	V	V	O	V	V	V	V	O
U7								A	A	A	A	O	A	V	A	A	O
U8									V	V	O	V	V	V	O	O	O
U9										V	V	V	V	V	V	V	V
U10											A	A	X	X	A	A	A
U11												V	V	V	V	V	V
U12													V	V	A	O	O
U13														V	A	X	O
U14															A	A	A
U15																V	V
U16																	V
U17																	

Using the classical rules of converting SSIM into reachability matrix (Table 2) is constructed as initial reachability matrix (Attri et al., 2013).

Table 2: Initial Reachability Matrix

Code	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17
U1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1
U2	0	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0
U3	0	1	1	0	1	0	1	1	0	1	0	0	1	1	0	1	0
U4	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
U5	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
U6	0	0	0	0	1	1	1	0	0	1	1	0	1	1	1	1	0
U7	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0
U8	1	1	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0
U9	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1
U10	0	0	0	0	0	0	1	0	0	1	0	0	1	1	0	0	0
U11	0	1	0	0	1	0	1	0	0	1	1	1	1	1	1	1	1
U12	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	0	0
U13	0	1	1	0	1	0	1	0	0	1	0	0	1	1	0	1	0
U14	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
U15	1	1	1	0	1	0	1	0	0	1	0	1	1	1	1	1	1
U16	0	1	0	0	1	0	1	0	0	1	0	0	1	1	0	1	1
U17	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1

For incorporating the transitivity in the initial reachability matrix every 0 is evaluated and all the possible transitive relations are incorporated (Attri et al., 2019). In this way a fully transitive matrix (Table 3) is obtained.

Table 3: Final Reachability Matrix

Code	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17
U1	1	1	1	1	1	1*	1	1	1	1	1	1	1	1	1*	1	1
U2	0	1	0	0	1	0	1	0	0	1*	0	0	0	1	0	0	0
U3	1*	1	1	0	1	0	1	1	1*	1	0	1*	1	1	0	1	1*
U4	1	1	1	1	1	1*	1	1	1	1	1	1	1	1	1	1	1
U5	0	0	0	0	1	0	0	0	0	1*	0	0	0	1	0	0	0
U6	1*	1*	1*	0	1	1	1	0	0	1	1	1*	1	1	1	1	1*
U7	0	0	0	0	0	0	1	0	0	1*	0	0	0	1	0	0	0
U8	1	1	1*	1*	1	1*	1	1	1	1	1*	1	1	1	1*	1*	1*
U9	1*	1	1	0	1	1	1	1*	1	1	1	1	1	1	1	1	1
U10	0	1*	1*	0	1*	0	1	0	0	1	0	0	1	1	0	1*	0
U11	1*	1	1*	0	1	0	1	0	0	1	1	1	1	1	1	1	1
U12	0	1*	1*	0	1*	0	1*	0	0	1	0	1	1	1	0	1*	0
U13	0	1	1	0	1	0	1	1*	0	1	0	0	1	1	0	1	1*
U14	0	0	0	0	0	0	1*	0	0	1	0	0	1*	1	0	0	0
U15	1	1	1	1*	1	0	1	1*	1*	1	1*	1	1	1	1	1	1
U16	0	1	1*	0	1	0	1	0	0	1	0	0	1	1	0	1	1
U17	0	0	0	0	0	0	1*	0	0	1	0	0	1*	1	0	0	1

Using the classical iteration method of partitioning the binary matrices, transitive matrix (Table 3) is partitioned as Table 4-12 (Sushil, 2017; Warfield, 1973).

Table 4: Level Partitioning - Iteration 1

Code	Reachability Set	Antecedent Set	Set Product	Level
U1	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,3,4,6,8,9,11,15	1,3,4,6,8,9,11,15	
U2	2,5,7,10,14	1,2,3,4,6,8,9,10,11,12,13,15,16	2,10	
U3	1,2,3,5,7,8,9,10,12,13,14,16,17	1,3,4,6,8,9,10,11,12,13,15,16	1,3,8,9,10,12,13,16	
U4	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,4,8,15	1,4,8,15	
U5	5,10,14	1,2,3,4,5,6,8,9,10,11,12,13,15,16	5,10	
U6	1,2,3,5,6,7,10,11,12,13,14,15,16,17	1,4,6,8,9	1,6	
U7	7,10,14	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17	7,10,14	*I*
U8	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,3,4,8,9,13,15	1,3,4,8,9,13,15	
U9	1,2,3,5,6,7,8,9,10,11,12,13,14,15,16,17	1,3,4,8,9,15	1,3,8,9,15	
U10	2,3,5,7,10,13,14,16	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	2,3,5,7,10,13,14,16	*I*
U11	1,2,3,5,7,10,11,12,13,14,15,16,17	1,4,6,8,9,11,15	1,11,15	
U12	2,3,5,7,10,12,13,14,16	1,3,4,6,8,9,11,12,15	3,12	
U13	2,3,5,7,8,10,13,14,16,17	1,3,4,6,8,9,10,11,12,13,14,15,16,17	3,8,10,13,14,16,17	
U14	7,10,13,14	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	7,10,13,14	*I*
U15	1,2,3,4,5,7,8,9,10,11,12,13,14,15,16,17	1,4,6,8,9,11,15	1,4,8,9,11,15	
U16	2,3,5,7,10,13,14,16,17	1,3,4,6,8,9,10,11,12,13,15,16	3,10,13,16	
U17	7,10,13,14,17	1,3,4,6,8,9,11,13,15,16,17	13,17	

Table 5: Level Partitioning - Iteration 2

Code	Reachability Set	Antecedent Set	Set Product	Level
U1	1,2,3,4,5,6,8,9,11,12,13,15,16,17	1,3,4,6,8,9,11,15	1,3,4,6,8,9,11,15	
U2	2,5	1,2,3,4,6,8,9,11,12,13,15,16	2	
U3	1,2,3,5,8,9,12,13,16,17	1,3,4,6,8,9,11,12,13,15,16	1,3,8,9,12,13,16	
U4	1,2,3,4,5,6,8,9,11,12,13,15,16,17	1,4,8,15	1,4,8,15	
U5	5	1,2,3,4,5,6,8,9,11,12,13,15,16	5	*II*
U6	1,2,3,5,6,11,12,13,15,16,17	1,4,6,8,9	1,6	
U8	1,2,3,4,5,6,8,9,11,12,13,15,16,17	1,3,4,8,9,13,15	1,3,4,8,9,13,15	
U9	1,2,3,5,6,8,9,11,12,13,15,16,17	1,3,4,8,9,15	1,3,8,9,15	
U11	1,2,3,5,11,12,13,15,16,17	1,4,6,8,9,11,15	1,11,15	
U12	2,3,5,12,13,16	1,3,4,6,8,9,11,12,15	3,12	
U13	2,3,5,8,13,16,17	1,3,4,6,8,9,11,12,13,15,16,17	3,8,13,16,17	
U15	1,2,3,4,5,8,9,11,12,13,15,16,17	1,4,6,8,9,11,15	1,4,8,9,11,15	
U16	2,3,5,13,16,17	1,3,4,6,8,9,11,12,13,15,16	3,13,16	
U17	13,17	1,3,4,6,8,9,11,13,15,16,17	13,17	*II*

Table 6: Level Partitioning - Iteration 3

Code	Reachability Set	Antecedent Set	Set Product	Level
U1	1,2,3,4,6,8,9,11,12,13,15,16	1,3,4,6,8,9,11,15	1,3,4,6,8,9,11,15	
U2	2	1,2,3,4,6,8,9,11,12,13,15,16	2	*III*
U3	1,2,3,8,9,12,13,16	1,3,4,6,8,9,11,12,13,15,16	1,3,8,9,12,13,16	
U4	1,2,3,4,6,8,9,11,12,13,15,16	1,4,8,15	1,4,8,15	
U6	1,2,3,6,11,12,13,15,16	1,4,6,8,9	1,6	
U8	1,2,3,4,6,8,9,11,12,13,15,16	1,3,4,8,9,13,15	1,3,4,8,9,13,15	
U9	1,2,3,6,8,9,11,12,13,15,16	1,3,4,8,9,15	1,3,8,9,15	
U11	1,2,3,11,12,13,15,16	1,4,6,8,9,11,15	1,11,15	
U12	2,3,12,13,16	1,3,4,6,8,9,11,12,15	3,12	
U13	2,3,8,13,16	1,3,4,6,8,9,11,12,13,15,16	3,8,13,16	
U15	1,2,3,4,8,9,11,12,13,15,16	1,4,6,8,9,11,15	1,4,8,9,11,15	
U16	2,3,13,16	1,3,4,6,8,9,11,12,13,15,16	3,13,16	

Table 7: Level Partitioning - Iteration 4

Code	Reachability Set	Antecedent Set	Set Product	Level
U1	1,3,4,6,8,9,11,12,13,15,16	1,3,4,6,8,9,11,15	1,3,4,6,8,9,11,15	
U3	1,3,8,9,12,13,16	1,3,4,6,8,9,11,12,13,15,16	1,3,8,9,12,13,16	*IV*
U4	1,3,4,6,8,9,11,12,13,15,16	1,4,8,15	1,4,8,15	
U6	1,3,6,11,12,13,15,16	1,4,6,8,9	1,6	
U8	1,3,4,6,8,9,11,12,13,15,16	1,3,4,8,9,13,15	1,3,4,8,9,13,15	
U9	1,3,6,8,9,11,12,13,15,16	1,3,4,8,9,15	1,3,8,9,15	
U11	1,3,11,12,13,15,16	1,4,6,8,9,11,15	1,11,15	
U12	3,12,13,16	1,3,4,6,8,9,11,12,15	3,12	
U13	3,8,13,16	1,3,4,6,8,9,11,12,13,15,16	3,8,13,16	*IV*
U15	1,3,4,8,9,11,12,13,15,16	1,4,6,8,9,11,15	1,4,8,9,11,15	
U16	3,13,16	1,3,4,6,8,9,11,12,13,15,16	3,13,16	*IV*

Table 8: Level Partitioning - Iteration 5

Code	Reachability Set	Antecedent Set	Set Product	Level
U1	1,4,6,8,9,11,12,15	1,4,6,8,9,11,15	1,4,6,8,9,11,15	
U4	1,4,6,8,9,11,12,15	1,4,8,15	1,4,8,15	
U6	1,6,11,12,15	1,4,6,8,9	1,6	
U8	1,4,6,8,9,11,12,15	1,4,8,9,15	1,4,8,9,15	
U9	1,6,8,9,11,12,15	1,4,8,9,15	1,8,9,15	
U11	1,11,12,15	1,4,6,8,9,11,15	1,11,15	
U12	12	1,4,6,8,9,11,12,15	12	*V*
U15	1,4,8,9,11,12,15	1,4,6,8,9,11,15	1,4,8,9,11,15	

Table 9: Level Partitioning - Iteration 6

Code	Reachability Set	Antecedent Set	Set Product	Level
U1	1,4,6,8,9,11,15	1,4,6,8,9,11,15	1,4,6,8,9,11,15	*VI*
U4	1,4,6,8,9,11,15	1,4,8,15	1,4,8,15	
U6	1,6,11,15	1,4,6,8,9	1,6	
U8	1,4,6,8,9,11,15	1,4,8,9,15	1,4,8,9,15	
U9	1,6,8,9,11,15	1,4,8,9,15	1,8,9,15	
U11	1,11,15	1,4,6,8,9,11,15	1,11,15	*VI*
U15	1,4,8,9,11,15	1,4,6,8,9,11,15	1,4,8,9,11,15	*VI*

Table 10: Level Partitioning - Iteration 7

Code	Reachability Set	Antecedent Set	Set Product	Level
U4	4,6,8,9	4,8	4,8	
U6	6	4,6,8,9	6	*VII*
U8	4,6,8,9	4,8,9	4,8,9	
U9	6,8,9	4,8,9	8,9	

Table 11: Level Partitioning - Iteration 8

Code	Reachability Set	Antecedent Set	Set Product	Level
U4	4,8,9	4,8	4,8	
U8	4,8,9	4,8,9	4,8,9	*VIII*
U9	8,9	4,8,9	8,9	*VIII*

Table 12: Level Partitioning - Iteration 9

Code	Reachability Set	Antecedent Set	Set Product	Level
U4	4	4	4	*IX*

Table 13: Level Partitioning Results' Summary

Code	Reachability Set	Antecedent Set	Set Product	Level
U1	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,3,4,6,8,9,11,15	1,3,4,6,8,9,11,15	*VI*
U2	2,5,7,10,14	1,2,3,4,6,8,9,10,11,12,13,15,16	2,10	*III*
U3	1,2,3,5,7,8,9,10,12,13,14,16,17	1,3,4,6,8,9,10,11,12,13,15,16	1,3,8,9,10,12,13,16	*IV*
U4	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,4,8,15	1,4,8,15	*IX*
U5	5,10,14	1,2,3,4,5,6,8,9,10,11,12,13,15,16	5,10	*II*
U6	1,2,3,5,6,7,10,11,12,13,14,15,16,17	1,4,6,8,9	1,6	*VII*
U7	7,10,14	1,2,3,4,6,7,8,9,10,11,12,13,14,15,16,17	7,10,14	*I*
U8	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	1,3,4,8,9,13,15	1,3,4,8,9,13,15	*VIII*
U9	1,2,3,5,6,7,8,9,10,11,12,13,14,15,16,17	1,3,4,8,9,15	1,3,8,9,15	*VIII*
U10	2,3,5,7,10,13,14,16	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	2,3,5,7,10,13,14,16	*I*
U11	1,2,3,5,7,10,11,12,13,14,15,16,17	1,4,6,8,9,11,15	1,11,15	*VI*
U12	2,3,5,7,10,12,13,14,16	1,3,4,6,8,9,11,12,15	3,12	*V*
U13	2,3,5,7,8,10,13,14,16,17	1,3,4,6,8,9,10,11,12,13,14,15,16,17	3,8,10,13,14,16,17	*IV*
U14	7,10,13,14	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	7,10,13,14	*I*
U15	1,2,3,4,5,7,8,9,10,11,12,13,14,15,16,17	1,4,6,8,9,11,15	1,4,8,9,11,15	*VI*
U16	2,3,5,7,10,13,14,16,17	1,3,4,6,8,9,10,11,12,13,15,16	3,10,13,16	*IV*
U17	7,10,13,14,17	1,3,4,6,8,9,11,13,15,16,17	13,17	*II*

The summary of partitioning is represented as Table 13.

Having determined the levels from partitioning of transitive matrix (Table 3) and using the concept of permutation/rearrangement of matrix a conical matrix (Table 14) is obtained. Level numbers are italicized to maintain clarity from within text.

Table 14: Rearranged Matrix

Sr. no	U7	U10	U14	U5	U17	U2	U3	U13	U16	U12	U1	U11	U15	U6	U8	U9	U4	Driving
U7	1	1*	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
U10	1	1	1	1*	0	1*	1*	1	1*	0	0	0	0	0	0	0	0	8
U14	1*	1	1	0	0	0	0	1*	0	0	0	0	0	0	0	0	0	4
U5	0	1*	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
U17	1*	1	1	0	1	0	0	1*	0	0	0	0	0	0	0	0	0	5
U2	1	1*	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	5
U3	1	1	1	1	1*	1	1	1	1	1*	1*	1	1	1	1	1*	1	13
U13	1	1	1	1	1*	1	1	1	1	0	0	0	0	0	1*	0	0	10
U16	1	1	1	1	1	1	1*	1	1	0	0	0	0	0	0	0	0	9
U12	1*	1	1	1*	0	1*	1*	1	1*	1	0	0	0	0	0	0	0	9
U1	1	1	1	1	1	1	1	1	1	1	1	1	1*	1*	1	1	1	17
U11	1	1	1	1	1	1	1*	1	1	1	1*	1	1	0	0	0	0	13
U15	1	1	1	1	1	1	1	1	1	1	1	1*	1	0	1*	1*	1*	16
U6	1	1	1	1	1*	1*	1*	1	1	1*	1*	1	1	1	0	0	0	14
U8	1	1	1	1	1*	1	1*	1	1*	1	1	1*	1*	1*	1	1	1*	17
U9	1	1	1	1	1	1	1	1	1	1	1*	1	1	1	1*	1	0	16
U4	1	1	1	1	1	1	1	1	1	1	1	1	1	1*	1	1	1	17
Dependence	16	17	17	14	11	13	12	14	12	9	8	7	7	5	7	6	4	

Some of the 0s are changed into 1* that means there exists a transitive relationship among the elements of the system (uses in this case). In this way a directed graph is drawn which being optional is not reported here for sake of brevity (Sushil, 2012). The ISM model (Figure 1) is constructed from the hierarchical partitioning and replacing the nodes of directed graph with descriptions.

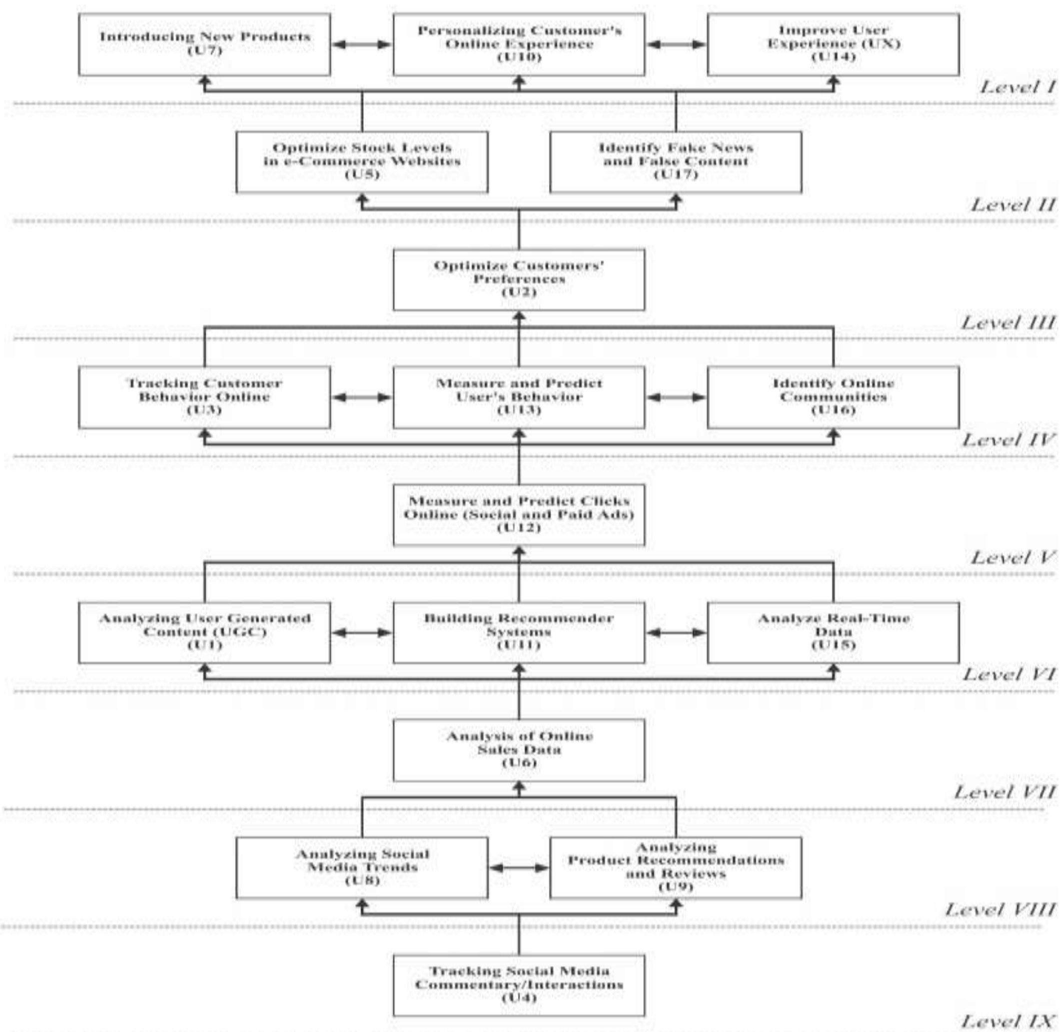

Figure 1: ISM Model - Hierarchical Structure of Uses

The uses coded as U7, U10 & U14 occupy *Level I*, U5 & U17 *Level II*, U2 *Level III*, U3, U13 & U16 *Level IV*, U12 *Level V*, U1, U11 & U15 *Level VI*, U6 *Level VII*, U8 & U9 *Level VIII* and U4 occupies *Level IX* of ISM model. All multiple uses at any one level have two way relations at levels except U5 & U17 at *Level II.* These uses have no relationships at level.

4.2 MICMAC Analysis

MICMAC is a structural methodology commonly used for augmenting and corroborating the results of ISM (Godet, 1986). Following the classical format of MICMAC analysis (Figure 2) the study proceeded to categorize the uses into four (autonomous, independent, dependent and linkage) clusters using scale centric approach.

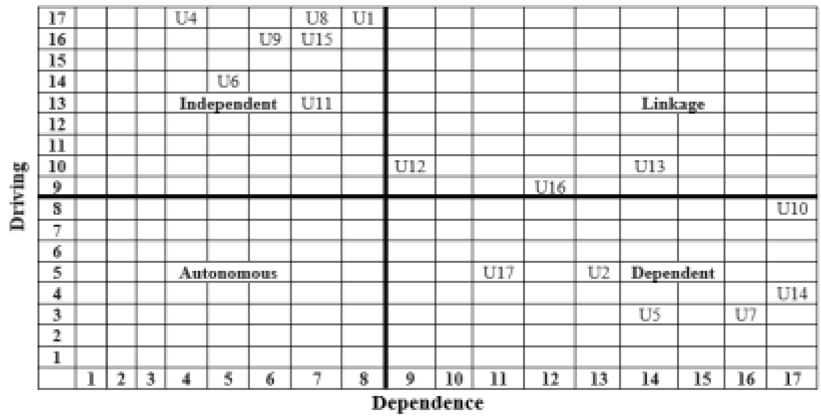

Figure 2: Driving and Dependence Diagram

The uses coded as U1, U4, U6, U8, U9, U11 and U15 are categorized as *independent*, U2, U5, U7, U10, U14 and U17 are categorized as *dependent*, U3, U12, U13 and U16 are categorized as *linkage,* whereas, there is no use categorized in autonomous.

4.3. Results

There is an outburst of increased use of data generation with the recent development in the field of information communication technology. In the recent post-COVID-19 scenario when most of the businesses around the world had shifted online. This increased data generation increased the complexities of the businesses. A lot of efforts have been made in the recent past to benefit more and more from the analytics of big data by its stakeholders.

Table 15: Summarized Results

Code	Results of MICMAC Analysis				ISM Results	Comments
	Driving	Dependence	Effectiveness	Cluster	Level	
U1	17	8	9	Independent	*VI*	
U2	5	13	-8	Dependent	*III*	
U3	13	12	-1	Linkage	*IV*	
U4	*17*	*4*	*13*	*Independent*	*IX*	*Major Use*
U5	3	14	-11	Dependent	*II*	
U6	14	5	9	Independent	*VII*	
U7	3	16	-13	Dependent	*I*	
U8	17	7	10	Independent	*VIII*	
U9	16	6	10	Independent	*VIII*	
U10	8	17	-9	Dependent	*I*	
U11	13	7	6	Independent	*VI*	
U12	9	9	0	Linkage	*V*	
U13	10	14	-4	Linkage	*IV*	
U14	4	17	-13	Dependent	*I*	
U15	16	7	9	Independent	*VI*	
U16	9	12	-3	Linkage	*IV*	
U17	5	11	-6	Dependent	*II*	

Therefore, it has become imperative to examine the uses of data science in digital marketing. The study uses seventeen factors extracted by Saura (2021) to which we have applied ISM and MICMAC. The results of ISM show that introducing new products (U7), personalizing customers' online experience (U10), and improve user experience (U14) occupy *Level I* of the ISM model. Optimize stock levels in e-commerce businesses (U5) and identify fake news and false content (U17) occupy *Level II*. Optimize customers' preferences (U2) at *Level III*. Tracking customer behaviors online (U3), measure and predict user's behavior (U13) and identify online communities (U16) occupy *Level IV*. Measure and predict clicks online for social and paid ads (U12) occupy *Level V*. Analyzing user generated content (U1), building recommender systems (U11), and analyzes real-time big data (U15) occupy *Level VI*. Analysis of online sales data (U6) occupies *Level VII*. Analyzing social media trends (U8) and analyzing product recommendations and reviews (U9) occupy *Level VIII*. Tracking social media commentary/interactions (U4) occupies *Level IX* of the ISM model. Results of MICMAC show that analyzing user generated content (U1), tracking social media commentary/interactions (U4), analysis of online sales data (U6), analyzing social media trends (U8), analyzing product recommendations and reviews (U9), and analyze real-time big data (U15) are categorized as *independent* uses. Optimize customers' preferences (U2), optimize stock levels in e-commerce businesses (U5), introducing new products (U7), improve user experience

(U14) and identify fake news & false content (U17) are categorized as *dependent* uses. Tracking customer behaviors online (U3), measure and predict clicks online for social and paid ads (U12), measure and predict user's behavior (U13) and identify online communities (U16) are categorized as *linkage* uses No use is categorized in *autonomous.* The results aforementioned are abridged in Table 15.

U4 is the key factor that is marked as grey and italicized to distinguish it from within the multitude. It is the most critical use of the data science in digital marketing since it has high effectiveness. It independent factor and have maximum driving power and minimum dependence power.

4.4. Discussion

With reiterating the objectives of this study i.e. the development of a structural model representing the uses of data science in digital marketing and the classification of these uses. The discussion qua reality is divided into five sections i.e. discussion on results, contrasting the study with contemporary literature, implications, limitations, and recommendations of the study.

i) Discussion on results: By way of ISM modeling, we obtained nine different levels where the factors occupying top-level are dependent factors and relatively least important. The factors occupying the bottom level are considered as independent and important particularly for policy stakeholders, whereas, the middle of the model runs along on the continuum of less severe to moderate-severe (top-bottom). In this study, tracking social media commentary/interactions (U4) occupies *Level IX* of the ISM model; therefore, it is the most critical use of data science and deserves a high degree of attention from the stakeholders. Accordingly, three uses i.e. introducing new products (U7), personalizing customers' online experience (U10), and improve user experience (U14) occupy *Level I* of the ISM model and are least critical and driven by the other uses. MICMAC classifies the factors (uses of data science in digital marketing) into four different clusters on the basis of their relevance, driving and dependence. Relevance is determined through the autonomous cluster. Any factor(s) that is/are classified as autonomous is indicative of the fact that it is not relevant or pertinent to the system under study and thus can be eliminated. And no factor being classified as autonomous means that all the factors are contributing towards the system under study. In this case, there is no such factor classified in autonomous that necessarily tantamount to the fact that all factors are very much elements of the system under study. Some of the factors may be independent, others may be dependent and yet others may be having the potential of both being independent- dependent. Independent factors have high driving but low dependence power, dependent factors have low driving and high dependence power, whereas linkage factors have high driving and high dependence power. With this reasoning the results of the study entail that uses coded as U1, U4, U6, U8, U9, and U15 are categorized as *independent* uses. U2, U5, U7, U14, and U17 are categorized as *dependent* uses. U3, U12, U13, and U16 are categorized as *linkage* uses. No use is categorized as *autonomous.*

ii) Discussion on contrasting the study with contemporary literature: It is always important to contrast the results of a research study with contemporary literature that can provide justification and adjust the contributions of the study within the existing literature. As aforementioned, there is a plethora of literature using a wide variety of contexts, methodologies, and data sets resulting in a range of different results. The overall literature is dominated by empirical and statistical studies. Few qualitative studies are found in this regard. The current study is a qualitative study conducted in different contexts, uses different data sets, different methodology, and provides different new insights into the phenomenon but at the same time it is built on existing literature and its results are aligned with existing studies. It is not out of context to juxtapose the current study as against some contemporary studies (Table 16).

Table 16: Contrasting Results of the Study with Some Studies from Existing Literature

Sr.	Studies	Focus	Variables	Methodology	Results
1	Current	Uses of data science in digital marketing post COVID-19 scenario	17	ISM and MICMAC	Tracking social media commentary / interactions is the key factor.
2	Mejía-Trejo (2021)	Design a framework based on purchase intention of online consumer behavior as a business innovation activity to generate marketing strategies	39	Delphi panel-focus group, AHP, CFA, co-variance based SEM	Results revealed eight variables, four underlying factors and twenty seven indicators that collectively formed a model to gain consumers online buying intention and respond accordingly by way of devising marketing strategy.
3	Saura (2021)	Using data science in digital marketing	Data sets	Systematic literature review	Results provide a holistic overview of the main applications data science to digital marketing and create insights related to the creation of innovative knowledge discovery techniques and data mining.

Mejía-Trejo (2021) focuses on purchase intention of online consumer behavior while considering thirty-nine variables extracted from Delphi panel-focus group, AHP, CFA, and co-variance based SEM and concluded that eight variables, four underlying factors, and twenty-seven indicators collectively formed the model that can provide insights to online buying intentions of customers. On the other hand, Saura (2021) conducted a systematic literature review to give a list of uses of data science and provided new acumens towards discovery techniques and data mining. The present study focuses on the uses of data science in digital marketing in the post-COVID-19 scenario by analyzing seventeen uses and modeling and classifying them by using ISM and MICMAC respectively. It concludes that tracking social media commentary is the most critical use of data science in post-COVID scenario.

iii) Discussion on implications: The study has both practical and theoretical implications some of which are discussed in the following section.

- **Practical implications:** Discussion on implications of the study is divided into nine parts i.e. data scientists/analysts: data engineers, IT personnel, government/regulators, business analysts/industry, customers, suppliers, competitors, unions, media and community:
  - **a. Data scientists/analysts:** Data scientists can use this study to analyze the data and give recommendations to different organizations or policymakers on making better decisions.
  - **b. Data engineers:** Since data engineers are the practitioners who design and build systems for data collection, storage and analysis, therefore, the study is useful for them because it provides a framework helpful in designing such systems.
  - **c. IT personnel:** IT personnel of business organizations can use the information provide this in identifying the trends on social media and make updated reports available for quick and better decision making.
  - **d. Government/regulators:** Government can use this study to protect the general public by giving due consideration to the most critical factors identified in this study. Analyzing social media trends can help the government in formulating policies that can protect the public from any calamitous incident or protect them from scams of organizations using digital platforms.
  - **e. Business analysts/industry:** This study is helpful for the business community as their marketing strategies can be developed in accordance to the findings of this study because it provides framework related information about charismatic uses of data science for marketing.
  - **f. Customers:** This study can be used by customers in increasing awareness on how marketing strategies are directed towards them using data science and the important factors companies analyze, so they can contribute their opinions by initiating new trends to shift the company's focus.
  - **g. Unions, media and community:** For these stakeholders, this research is extremely helpful in understanding the factors that are of prime importance in post-COVID-19 scenario on the basis of which most of the digital marketing strategies are based.
  - **h. Competitors:** By focusing on the most influential uses of data science and considering the findings of the study the competitors can keep an eye on trends on the basis of which marketing strategies of their competitors have been formed and act accordingly/promptly.
  - **i. Suppliers:** This study contains information for software suppliers and the hardware suppliers and using that information they can set their priorities.
- **Theoretical implications:** This study has a lot of theoretical implications as well. The researchers can use this study to quantify the relations among various uses of data science by conducting quantitative research. This study has contributed to the body of literature by introducing an ISM model depicting the most critical to least critical factors of uses of data science along with MICMAC diagram portraying these uses on the basis of their driving and dependence power.

iv) Discussion on limitations: This study has some limitations as well. Since it is based on qualitative analysis with limited data set and few experts on the panel, therefore, its generalizability is accordingly limited. ISM is helpful in identifying the relations among different factors but the quantification of relationships among them cannot be obtained. This model lacks statistical testing and validation. The list of the uses of data science is not comprehensive/meticulous and some important factors may have been overlooked. The model is developed and classified on the basis of a small set of exerts which may give a biased opinion. The results are based on the context of Pakistan only which is also considered as a factor limiting its generalizability.

v) Discussion on recommendations for future research to overcome limitations: Future researchers can increase the data set by adding more stakeholders. Other techniques like ANP, AHP, IRP, etc. can be used to overcome the scope and generalizability issues. To quantify the relationships among factors other statistical techniques like GRA, PCA, ANP, AHP, or TOPSIS can be used. It is recommended to have a more comprehensive list of uses of data science by either extending the literature survey or using other techniques like PCA. The contribution of the research can be increased by conducting the same research in different contexts/countries.

Contribution of the study: The study contributes ISM model, MICMAC diagram, discussions on the model/MICMAC diagram qua reality and new simplified information regarding complex relations of uses of data science in digital marketing.

5. Conclusion

The momentum of data analytics alongside the continuum of developments in information communication technology, particularly in post-COVID scenario, has made use of data science for the benefits of business extremely important. The phenomenon of the use of data science is an emerging field of marketing. Understanding different uses and their relatedness is a complex problem and is the call of the day. The study takes this topic as an object and used ISM augmented with MICMAC to solve the problem. It starts with the list of seventeen uses from the aforementioned literature and applied the classical procedure of ISM on the primary data collected from a panel of experts. Results of literature discourse show that there are a total of seventeen major uses of data science in digital marketing. Results of ISM show that the uses coded as U7, U10 & U14 occupy *Level I*, U5 & U17 *Level II*, U2 *Level III*, U3, U13 & U16 *Level IV*, U12 *Level V*, U1,U11 & U15 *Level VI*, U6 *Level VII*, U8 & U9 *Level VIII* and U4 occupies *Level IX* of ISM model. Results of MICMAC show that the uses coded as U1, U4, U6, U8, U9, U11, and U15 are categorized as *independent*, U2, U5, U7, U10, U14, and U17 are categorized as *dependent*, U3, U12, U13 and U16 are categorized as *linkage* whereas the is no use categorized in autonomous. The overall conclusion is introducing new products, personalizing customers' online experience, and improve user experience occupy the top (*Level I),* and tracking social media commentary/interactions occupies the bottom (*Level IX)* of the ISM model. Analyzing user generated content, tracking social media commentary/interactions, analysis of online sales data, analyzing social media trends, analyzing product recommendations and reviews, and analyze real-time big data are categorized as independent uses. Optimize customers' preferences, optimize stock levels in e-commerce businesses, introducing new products, improve user experience, and identify fake news & false content are categorized as dependent uses but others are categorized as linkage uses and no use is categorized as autonomous.

References

Abbass, K., Asif, M., Niazi, A. A. K., Qazi, T. F., Basit, A., & Al-Muwaffaq Ahmed, F. A. (2022a). Understanding the interaction among enablers of quality enhancement of higher business education in Pakistan. *PloS One*, *17*(5), e0267919.

Abbass, K., Basit, A., Niazi, A. A. K., Mufti, R., Zahid, N., & Qazi, T. F. (2022b). Evaluating the social outcomes of COVID-19 pandemic: empirical evidence from Pakistan. *Environmental Science and Pollution Research*, 1-13.

Abbass, K., Niazi, A. A. K., Qazi, T. F., Basit, A., & Song, H. (2021). The aftermath of COVID-19 pandemic period: barriers in implementation of social distancing at workplace. *Library Hi Tech*.

Alaimo, L. S., Fiore, M., & Galati, A. (2020). How the COVID-19 pandemic is changing online food shopping human behavior in Italy. *Sustainability*, *12*(22), 9594.

Alawamleh, M., & Popplewell, K. (2011). Interpretive structural modelling of risk sources in a virtual organization. *International Journal of Production Research*, *49*(20), 6041-6063.

Ali, A., Hasan, Z. U., Abbasi, Q., & Sulehri, F. A. (2023). Business or Politics: Exploring the Determinants of Policy Mix in South Asia. *Bulletin of Business and Economics (BBE)*, *12*(3), 114-123.

Apuke, O. D., & Omar, B. (2020). User motivation in fake news sharing during the COVID-19 pandemic: an application of the uses and gratification theory. *Online Information Review*, *45*(1), 220-239.

Attri, R., Dev, N., & Sharma, V. (2013). Interpretive structural modelling (ISM) approach: An overview. *Research Journal of Management Sciences*, *2319*, 1171.

Audi, M. Poulin, M. Ali, A. (2023). Determinants of Human Wellbeing and its Prospect Under the Role of Financial Inclusion in South Asian Countries. *Journal of Applied Economic Sciences* 18 (4(82)), 296-311.

Audi, M., Ali, A., & Al-Masri, R. (2022). Determinants of Advancement in Information Communication Technologies and its Prospect under the role of Aggregate and Disaggregate Globalization. *Scientific Annals of Economics and Business*.

Audi, M., Ali, A., & Roussel, Y. (2021). The Advancement in Information and Communication Technologies (ICT) and Economic Development: A Panel Analysis. *International Journal of Innovation, Creativity and Change*, 15(4), 1013-1039.

Bai, C., Quayson, M., & Sarkis, J. (2021). COVID-19 Pandemic Digitization Lessons for Sustainable Development of Micro-and Small-Enterprises. *Sustainable Production and Consumption*, *27*, 1983-2001.

Baicu, C. G., Gârdan, I. P., Gârdan, D. A., & Epuran, G. (2020). The impact of COVID-19 on consumer behavior in retail banking. Evidence from Romania. *Management & Marketing*, *15*(1), 534-556.

Basit, A., Khan Niazi, A. A., Qazi, T. F., Rao, Z. U. R., & Shaukat, M. Z. (2021). Structural Modeling on the Determinants of Effectiveness of SOPs Containing COVID-19 in Mass Gatherings. *Frontiers in Psychology*, 4754.

Basit, A., Scholz, M., Niazi, A. A. K., Qazi, T. F., Shaukat, M. Z., Rao, Z. U. R., & Mahmood, A. (2021). Structural Modeling on the Determinants of Effectiveness of SOPs Containing COVID-19 in Mass Gatherings. *Frontiers in Psychology*, *12*.

Burhan, M., Salam, M. T., Abou Hamdan, O., & Tariq, H. (2021). Crisis management in the hospitality sector SMEs in Pakistan during COVID-19. *International Journal of Hospitality Management*, *98*, 103037.

Chidambaranathan, S., Muralidharan, C., & Deshmukh, S. G. (2009). Analyzing the interaction of critical factors of supplier development using Interpretive Structural Modeling-An empirical study. *The International Journal of Advanced Manufacturing Technology*, *43*(11-12), 1081-1093.

Clayton, M. J. (1997). Delphi: A technique to harness expert opinion for critical decision-making tasks in education. *Educational Psychology*, *17*(4), 373-386.

Fu, H., Abbass, K., Qazi, T. F., Niazi, A. A. K., & Achim, M. V. (2022a). Analyzing the barriers to putting corporate financial expropriations to a halt: A structural modeling of the phenomenon. *Frontiers in Environmental Science*, 967418.

Fu, W., Abbass, K., Niazi, A. A. K., Zhang, H., Basit, A., & Qazi, T. F. (2022b). Assessment of sustainable green financial environment: The underlying structure of monetary seismic aftershocks of the COVID-19 pandemic. *Environmental Science and Pollution Research*, 1-15.

Godet, M. (1986). Introduction to la prospective: Seven key ideas and one scenario method. *Futures*, *18*(2), 134-157.

Gupta, S., Justy, T., Kamboj, S., Kumar, A., & Kristoffersen, E. (2021). Big data and firm marketing performance: Findings from knowledge-based view. *Technological Forecasting and Social Change*, *171*, 120986.

Islam, T., Mahmood, K., Sadiq, M., Usman, B., & Yousaf, S. U. (2020). Understanding knowledgeable workers' behavior toward COVID-19 information sharing through WhatsApp in Pakistan. *Frontiers in Psychology*, *11*.

Jaman, J. H., Abdulrohman, R., Suharso, A., Sulistiowati, N., & Dewi, I. P. (2020). Sentiment analysis on utilizing online transportation of indonesian customers using tweets in the normal era and the pandemic covid-19 era with support vector machine. *Adv. Sci. Technol. Eng. Syst.*, *5*(5), 389-394.

Kayakuş, M., & Çevik, K. K. (2020). Estimation the Number of Visitor of E-Commerce Website by Artificial Neural Networks During Covid19 in Turkey. *Electronic Turkish Studies*, *15*(4), 615-631

Khan, S., & Khan, M. S. A. (2013). Conceptualized Model of Green It Purchasing Enablers–An Application of Delphi Technique and Interpretive Structural Modeling. *Business Sciences International Research Journal*, *1*(1), 24-37.

Korankye, B. (2020). The Impact of Global Covid-19 Pandemic on Small and Medium Enterprises in Ghana. *International Journal of Management, Accounting and Economics*, *7*(6), 320-341.

Li, G., Huang, D., Sun, C., & Li, Y. (2019). Developing interpretive structural modeling based on factor analysis for the water-energy-food nexus conundrum. *Science of the Total Environment*, *651*, 309-322.

Liu, X. Y. (2021). Agricultural products intelligent marketing technology innovation in big data era. *Procedia Computer Science*, *183*, 648-654.

Liu, X., Shin, H., & Burns, A. C. (2021). Examining the impact of luxury brand's social media marketing on customer engagement : Using big data analytics and natural language processing. *Journal of Business Research*, *125*, 815-826.

Luo, C. (2021). Analyzing the impact of social networks and social behavior on electronic business during COVID-19 pandemic. *Information Processing & Management*, *58*(5), 102667.

Mejía-Trejo, J. (2021). COVID-19 ads on purchase intention of online consumer behavior as business innovation activity: A contribution to the uses and gratification theory. *Electronic Commerce Research and Applications*, *49*, 101086.

Modgil, S., Dwivedi, Y. K., Rana, N. P., Gupta, S. & Kamble, S. (2021). Has Covid-19 accelerated opportunities for digital entrepreneurship? An Indian Perspective. *Technological Forecasting & Social Change.*

Niazi, A. A. K., Qazi, T. F. Khan, K. S., Basit, A. and Ahmad, R. (2020c). Identification and Ranking of Employees' Physical Behaviors Critical to Mergers. *International Journal of Management and Emerging Sciences*, *10*(4), 1-10.

Niazi, A. A. K., Qazi, T. F., & Basit, A. (2019). An Interpretive Structural Model of Barriers in Implementing Corporate Governance (CG) in Pakistan. *Global Regional Review*, *4*(1), 359-375.

Niazi, A. A. K., Qazi, T. F., & Basit, A. (2019a). What Hinders to Promote Tourism in Pakistan? Using Binary Matrices for Structuring the Issue. *Review of Economics and Development Studies, 5*(4), 881-890.

Niazi, A. A. K., Qazi, T. F., & Basit, A. (2019b). Expounding the Structure of Slyer Ways of Tunneling in Pakistan. *Global Regional Review*, *4*(2), 329-343.

Niazi, A. A. K., Qazi, T. F., & Basit, A. (2019c). An Interpretive Structural Model of Barriers in Implementing Corporate Governance (CG) in Pakistan. *Global Regional Review*, *4*(1) 359-375.

Niazi, A. A. K., Qazi, T. F., & Sandhu, K. Y. (2019). Uncovering the Myths of TQM in Readymade Garment Sector of Pakistan: An Interpretive Structural Modeling Approach. *Review of Economics and Development Studies, 5*(3), 531-540.

Niazi, A. A. K., Qazi, T. F., Ali, I., & Ahmad, R. (2020a). Prioritizing Determinants of Effective Whistle Blowing (WB): An Interpretive Structural Modeling Approach. *International Journal of Law and Management*, *62*(3), 213-230.

Niazi, A. A. K., Qazi, T. F., Basit, A., & Khan, K. S. (2019). Curing Expensive Mistakes: Applying ISM on Employees' Emotional Behaviors in Environment of Mergers. *Review of Economics and Development Studies, 5*(1), 79-94.

Niazi, A. A. K., Qazi, T. F., Basit, A., & Khan, R. A. (2019). Expounding Complex Relations among Criticisms on Islamic Banking through Interpretive Structural Modeling. *Paradigms*, *13*(2), 151-159.

Niazi, A. A. K., Qazi, T. F., Hameed, R., & Basit, A. (2020b). How They Get Stuck? Issues of Women Entrepreneurs: An Interpretive Structural Modeling Approach. *Paradigms*, *14*(1), 73-80.

Niazi, A.A.K., Qazi, T.F. and Basit. A. (2020). Investigating Critical Resemblances of Islamic Banking with Conventional: Binary Matrices as Solution Methodology. *Journal of Business and Social Review in Emerging Economies*, *6*(1), 351-366.

Qazi, T. F. Niazi, A. A. K. Basit, A. Rehman, A. and Nazir, A. (2019). The Jostle of Workplace Pressures on Credit Managers: Interpretive Structural Modeling to Underpin the Severity. *Bulletin of Business and Economics, 8*(3), 155-163.

Saura, J. R. (2021). Using data sciences in digital marketing: Framework, methods, and performance metrics. *Journal of Innovation & Knowledge*, *6*(2), 92-102.

Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2021). Setting B2B digital marketing in artificial intelligence-based CRMs: A review and directions for future research. *Industrial Marketing Management*, *98*, 161-178.

Shaukat, M. Z., Niazi, A. A. K., Qazi, T. F., & Basit, A. (2021). Analyzing the Underlying Structure of Online Teaching During the COVID-19 Pandemic Period: An Empirical Investigation of Issues of Students. *Frontiers in Psychology*, *12*.

Shaukat, M. Z., Niazi, A. A. K., Qazi, T. F., & Basit, A. (2021a). Analyzing the Underlying Structure of Online Teaching during the COVID-19 Pandemic Period: An Empirical Investigation of Issues of Students. *Frontiers in Psychology*, 12.

Shaukat, M. Z., Scholz, M., Fiaz Qazi, D., Khan Niazi, A. A., Basit, A., & Mahmood, A. (2021b). Analyzing the Stressors for Frontline Soldiers Fighting against COVID-19 Pandemic. *Frontiers in Psychology*, 4904.

Shaukat, M. Z., Scholz, M., Qazi, T. M., Niazi, A. A. K., Basit, A., & Mahmood, A (2021). Analyzing the Stressors for Frontline Soldiers Fighting against COVID-19 Pandemic. *Frontiers in Psychology*, 4904.

Strotmann, C., Baur, V., Börnert, N., & Gerwin, P. (2021). Generation and prevention of food waste in the German food service sector in the COVID-19 pandemic-Digital approaches to encounter the pandemic related crisis. *Socio-Economic Planning Sciences*, 101104.

Sushil, A. (2017). Modified ISM/TISM Process with Simultaneous Transitivity Checks for Reduced Direct Pair Comparisons. *Global Journal of Flexible Systems Management*, *18*(4), 331-351.

Sushil, S. (2012). Interpreting the interpretive structural model. *Global Journal of Flexible Systems Management*, *13*(2), 87-106.

Valmohammadi, C., & Dashti, S. (2016). Using interpretive structural modeling and fuzzy analytical process to identify and prioritize the interactive barriers of e-commerce implementation. *Information & Management*, *53*(2), 157-168.

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*, 100002.

Warfield, J. N. (1973). Binary matrices in system modeling. *IEEE Transactions on Systems, Man, and Cybernetics*, (5), 441-449.

Warfield, J. N. (1974). Toward interpretation of complex structural models. *IEEE Transactions on Systems, Man, and Cybernetics*, (5), 405-417.

Annexure I
Profile of Respondent Participants of the Study

Expert	Designation	Organization	Experience	Qualification
1	Director	NetSol	23 years	MS in IT
2	Director	PRGTTI	20 years	PhD in Marketing
3	Associate Professor	A Large Public Sector University	20 years	PhD in CS
4	Data Scientist	SaevolGO	18 years	MS in IT
5	Associate Professor	A Large Public Sector University	15 years	PhD in Marketing
6	Security Solution Architect	SaevolGO	17 years	MS in CS
7	Chief Data Analyst	OZI Technology	18 years	MS in IT
8	Data Engineer	Teradata	19 years	MS in Software Engineering
9	Content Marketing Specialist	Digibulls	16 years	MS in Mass Communication
10	Machine Learning Engineer	Datum Brain	19 years	PhD in Deep Learning & Machine Learning
11	Marketing Head	Brawon	16 years	M.Com.
12	Senior Data Scientist	TKXEL	17 years	MS in Software Engineering
13	Chief Marketing Officer	Digital Otters	20 years	MBA in Marketing
14	Marketing Manager	Commtel Digital	17 years	MS in Management
15	Data Engineer	NorthBay	18 years	MS in CS