A conceptual framework for the adoption of Big Data Analytics by e-commerce startups: A case-based approach

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Abstract

E-commerce start-ups have ventured into emerging economies and are growing at a significantly faster pace. Big Data has acted like a catalyst in their growth story. Big Data Analytics (BDA) has attracted e-commerce firms to invest in the tools and gain cutting edge over their competitors. The process of adoption of these BDA tools by e-commerce start-ups has been an area of interest as successful adoption would lead to better results. The present study aims to develop an interpretive structural model (ISM) which would act as a framework for efficient implementation of BDA. The study uses hybrid multi criteria decision making processes to develop the framework and test the same using a real-life case study. Systematic review of literature and discussion with experts resulted in exploring 11 enablers of adoption of BDA tools. Primary data collection was done from industry experts to develop an ISM framework and fuzzy MICMAC analysis is used to categorize the enablers of the adoption process. The framework is then tested by using a case study. Thematic clustering is performed to develop a simple ISM framework followed by fuzzy analytical network process (ANP) to discuss the association and ranking of enablers. The results indicate that access to relevant data forms the base of the framework and would act as the strongest enabler in the adoption process while the company rates technical skillset of employees as the most important enabler. It was also found that there is a positive correlation between the ranking of enablers emerging out of ISM and ANP. The framework helps in simplifying the strategies any e-commerce company would follow to adopt BDA in future.

Keywords: Big Data Analytics; Interpretive Structural Modelling; fuzzy MICMAC; Analytical Network Process; E-commerce; Start-ups

1 Introduction

Data mining is an essential process for businesses, individuals, and society at large. While its importance always existed in industries, recent advancements have made this information accessible to common man as well. The digital revolution which is an after effect of the growth of data has impacted every industry irrespective of its size (Ramamurthy et al., 2008). One of its most important and significant versions is Big Data Analytics (BDA) which has been widely used, and the credit goes to accessibility to internet. The wide reach of internet has also made companies reach their customers easily, frequently, which is why the electronic version has replaced the physical forms of interactions. Kwon et al. (2014) defines BDA as combination of techniques and technologies that any organization can adopt to analyse large volume of data which could be complex and diverse. The analysis of complex data offers clear understanding of the phenomenon for firms and it helps in improving the decision-making process (Manyika et al., 2011). Komioka et al. (2016) also asserted that BDA has helped companies to gain a competitive advantage over others especially in an emerging market setting.

The developed nations have witnessed the use of advanced tools to handle big data (Ramamurthy et al., 2008; Alshamila et al., 2013) while the emerging markets are still advancing gradually in the process of adoption and adoption of BDA tools (Dubey et al., 2015; Saffu et al., 2007). World Economic Forum (2014) also discussed the growth potential which would drive the business of BDA industry in the developing nations. It makes the developing economies an unquestionable choice to be studied and explored in terms of adoption of BDA. India is one of the emerging economies which has promising digital revolution and has grown twice as fast as its peers (Ernst & Young, 2016). The wave of digital revolution is driven by rate of increase of usage of internet and smartphones which has resulted in generation of big data for companies. The companies are extensively using BDA tools to gain competitive advantage (Dubey et al., 2015; Agarwal, 2013). Survey results published by International Data Corporation confirms adoption and deployment of BDA by only 15 percent firms in India (Maru, 2014) and most of them are business giants. Studies also confirm that the growth of these companies on average is around 6% higher than the ones not adopting it. Although the statistics cannot be generalized for every company, yet the process of adoption has shown significantly better results (Mikalef et al., 2017).

Studies have also explored factors for successful adoption of data analytics tools in companies in the past (Low et al., 2011), most of which are for firms which were well established and therefore the chances of failure in adoption significantly reduced. Studies have also positively correlated the financial stability and rate of success after adoption of data analytics (Gandomi and Haider, 2015; Kwon et al., 2014). Some factors which were also explored as enablers in the success of the firms adopting BDA were existing data analytics environment of firms (Davenport and Dyché, 2013), and perceived usefulness of analytical tools to convert unstructured data to structured and meeting their clients requirements (Mahrt and Scharkow, 2013). Shin (2016) listed some enablers in the process of adoption of BDA in firms which were mainly categorized into constructs like security and employee involvement, quality, perceived ease of use, perceived usefulness, etc. Although past studies have tried exploring the key enablers, the studies lack uniformity of sample selection which makes the study results too generic (Shareef et al., 2014). The rate of adoption would be relatively quicker as the decision making of larger firms has lesser risks and uncertainty. The adoption of BDA by firms is also driven by the enthusiasm of the firm's management and compatibility between nature of BDA and firm's business process (Esteves and Curto, 2013; Dubey et al., 2015).

The adoption of BDA is largely discussed in any firms while start-ups have a different organizational structure than established firms. One of the prominent differences which makes start-ups different is the degree of risks involved into decision making especially in situations where the investment is high and the results are uncertain (Loukis et al., 2017). The recent advent of BDA in the information technology space is one such technology which has of late gained traction by e-commerce firms. Shin (2016) has pointed that BDA falls into a high-risk category and thus its adoption, especially by an e-commerce startup, needs attention.

Shin (2016) also confirmed that post BDA adoption, benefits have been higher for companies which had a larger customer base and were financially sound while the chances of failure were higher for startups. Studies also confirm that e-commerce startups face challenges in managing data and adopting data analytics which are mainly managerial, organizational, environmental and technology oriented (Loukis et al., 2017; Kwon et al., 2014; Shin, 2016; Dubey et al., 2015).

The objectives of the study can be listed as under:

1. to identify the enablers for adoption of BDA tools in e-commerce start-ups in India;
2. to develop a theoretical framework using Interpretive Structural Modelling for understanding the linkage and hierarchy of enablers;
3. to categorize the enablers and discuss the attributes of enablers using fuzzy MICMAC analysis;
4. to validate the theoretical framework using a case study with fuzzy analytical network process (FANP).

The studies related to BDA have been done earlier in various contexts using resource-based view theory, stakeholders theory, contingent theory, graph theory and many more, but most of the theories were used in contexts where the firms have already adopted the technology. There is a dearth of studies which explores the factors for adoption of BDA in a start-up environment which is different from established firms and has been discussed earlier. The study would contribute in understanding the systematic approach in the process of adoption which is often missing in most of the theory-based studies. A systematic approach would also enable a higher chance of success in the post adoption phase.

Therefore, it becomes all the more important to explore the adoption process systematically using an alternative approach to theory. Extensive survey of existing literature also confirms that multi criteria decision making (MCDM) techniques have not been used to address such issues which will help in addressing the first objective.. The study uses interpretive structural modelling (ISM) along with fuzzy MICMAC analysis to develop a generalized conceptual framework for adoption of BDA which in turn would contribute towards second and third objective. Lastly, validation of the framework using fuzzy analytical network process (FANP) in a real time situation would help in sufficiently address the last objective as well.

A combination of ISM and fuzzy MICMAC followed by fuzzy ANP to address issues related to process of adoption of BDA tools is the uniqueness of this study. The combined MCDM techniques would help in achieving robust results with practical implications.

The remaining sections of the papers are as follows. Section 2 elaborates the literature review and discusses the enablers of adoption of Big Data Analytics. Section 3 discusses the research design and presents an overview of Interpretive Structural Modelling and discusses the ISM framework in detail. Section 4 elaborates on MICMAC analysis which categorizes the enablers into four categories followed by discussion on their individual properties. Section 5 validates the developed ISM framework using a case study by using fuzzy analytical hierarchy process. Lastly, Section 6 concludes the study and presents the managerial implications.

2 Literature Review

Maity and Dass (2014) define e-commerce startups as human driven organizations that create/sell innovative products and services on an online platform and aim for sustainable business models under uncertainty (Hashem et al., 2015). It is also witnessed that the rate of success in this field is relatively low and studies have tried to analyze the situation from various theoretical and empirical viewpoints. The prominent and significantly discussed reasons include lack of knowledge about competition and uncertainty about future competition. The success factors of e-commerce startups are driven by increasing customer base and booking profits to sustain competitiveness (Gubela et al., 2017). A prerequisite for success is data, its accuracy and its relevance to take correct decisions. While the criticality of data is widely acknowledged, generalized finding concerning the antecedents of BDA adoption are lacking, especially for e-commerce startups (Akter and Wamba, 2016; Qi et al., 2016). The changing business environment has also infused analytics and its variants to understand the present and predict the future. The complexity of analytical skillset has turned out to be the saviour for a lot of e-commerce startup companies. The business environment of e-commerce startups is dynamic and therefore needs critical assessment. The e-commerce startup market has also transformed into an arena where players are aiming for competitive advantage, and analytics have proved to be a vital resource.

Recent studies have also recorded that the rate of adoption for BDA in e-commerce is highest (Akhter and Wamba, 2016). The challenge facing firms is to adopt the right kind of analytics and at the right time to deal with structured and unstructured data. Also, the diversity of data which is generated in the e-commerce business makes it more challenging to decipher results and provide decision making support dynamically. Thus, the need for strategic adoption of right tools of BDA is important (Khajouei et al., 2017).

As BDA is an innovative way of looking at variety of data, its adoption by firms would have roots in IT adoption and theories supporting the same (Sun et al., 2016). Theories supporting adoption include resource-based view theory, stakeholder theory and strategic competitive theory (Akhter and Wamba, 2016). Studies have confirmed that adoption of technology and its variants have mostly been carried out in western developed countries (Ngai et al., 2017), while there is paucity of research conducted in the emerging markets (Wamba et al., 2015). Emerging economies therefore qualify for conducting experiments, developing theoretical models and testing their validation (Zhao et al., 2014).

The process of adoption and usage of technology in any industry has been widely studied and applied in academia and industry. There are multiple theories which have explored the process of adoption of technology, the prominent one being unified theory for acceptance and use of technology, theory of reasoned action, theory of planned behaviour, technology acceptance model and many more. While these theories have mainly discussed the outcome as of behavioural intention of adoption of technology, many studies among them explain the role and importance of the constructs in a given setting. Studies have also criticized these theories under the lens of risk and uncertainty. The empirical validations of these theories have not used time series data which makes it difficult to explain the actual intention of adoption over a span of time. There have been debates and discussions regarding the application of such theories for adoption and, more importantly, adaptation of them (Chen and Nath, 2018). The present study aims to take a step beyond the contemporary discussion of extension of theories of testing the relationship in a different setting. The reasons to make a trail into a different direction is because of the nature and attributes of process of adoption of big data which is less similar to a technology due to its evolving nature with time and requirements. A systematic review of literature although highlights the enablers of the process of adoption highlighted by various studies, but theoretical underpinning of them is missing. As discussed by earlier studies, the usage and the variety of big data analytics is dynamic and needs to therefore be studied by developing a framework which could be specific to industry.

Earlier studies have also debated that the adoption of technologies is dependent largely on culture of the organization and fundamentally governed by the geography of operations of the firm (Khajouei et al., 2017). BDA is one of such technology which involves huge capital and the rate of success depends largely on stakeholders and organizational culture. Unlike other technologies where the consumers are mostly large in number, BDA has limited audience as the adopters are firms (Ngai et al., 2009). More so, it becomes important to understand that e-commerce startups have risk concerns while taking financial decisions in investing on technologies. Thus, it becomes a peculiar case to understand what enables BDA adoption process in an emerging economy. Thus, relying purely on theory to explain the interlinkages would not offer a holistic view of the adoption process. The present study therefore explores enablers from both systematic review and discussion of experts.

The study explores the enablers of adoption of BDA by performing a systematic review of literature along with the discussion and validation of the identified constructs by industry professionals. The selection of industry professionals was based on two criteria. First, they were working in an e-commerce start-up mostly from the beginning of the startup and have direct or indirect control in buying or upgrading a technology. Second, they should have significant amount of overall work experience where more than 3 years of their experience would be related to big data technology. A total of 52 professionals were contacted out of which 44 agreed to share their response. Based on their response and literature review, eleven enablers were finalized which are discussed as below:

- **Technical support from vendor (V1):** The decision of adoption of any technology or technological service is driven by the availability and regularity of updates and technical support offered by the vendor. The growth of the e-commerce startup would need higher technical support in future and would need customized platforms with constant technical backup (Olszak, 2016; Sharma et al., 2014; Jagdish et al., 2014). Technical support also gets stronger depending upon the selection of vendor and its reputation with its clients (Martin, 2015). The process of adoption would also be influenced by quality of technical support offered during adoption phase (Kambatla et al., 2014; Minelli et al., 2012).

- **Attitude of top management (V2):** The top management which usually constitutes the foundation of a startup has a major say in the company affairs. Studies have argued that understanding the need of adoption of BDA tools and assessing the requirement and return on investment to adopt it needs strategic decisions taken by the top management (Kauffman et al., 2012; Akter and Wamba, 2016). Entrepreneurial theories also support the argument that the vision of top management brings in changes in the organization which is true in the current setting as well (Taylor et al., 2014; Hsinchun et al., 2012)

- **Competitiveness (V3):** The process of adoption of technologies is usually driven by two factors: intrinsic and extrinsic. Studies have discussed role of competitiveness as a key enabler for bringing a change in an organization (Ngai et al., 2009). Competitiveness also contributes towards improving the quality of firms and this has been one of the prime reasons which the studies have discussed about adoption of BDA by e-commerce startups as well. While the startups compete on similar products and services, competitiveness acts a fuel for attracting customers and offering better services.

- **IT infrastructure (V4):** The adoption of BDA also requires technically sound infrastructure which has been the strength of most of the firms which have adopted it. While it is an enabler for information technology led firms, marketing firms lack them due to the minimal usage (Jagdish et al., 2014). It is also discussed that startups, especially in developing nations, use third parties' infrastructure or share IT services in their initial years (Koutsabasis et al., 2008; Nelson et al., 2005). Some of the firms adopt these tools with their current IT configuration and then expand with time as per the requirement and funds (Woudstra et al., 2017; Boja et al., 2012).
- **Training and development of employees (V5):** Studies have discussed that training employees on new technology or tool is one of the biggest challenges and BDA adoption also encompasses the same (Riggin and Wamba, 2015; Taylor et al., 2014). As the tools and techniques would be used by handful of employees, it is important to train them theoretically with enough exposure to hands on experience. While some studies debate that learning technology has become easier with time, understanding context of the same still remains a challenge and an efficient and regular training would act as an enabler (Goes, 2014). It has been also projected that on the job training and hands on experience, if given to the employees, would ease up the process of diffusion (Barton and Court, 2012).
- **Access to skilled workforce (V6):** The adoption of BDA is more complex and tedious for firms which have lesser workforce and they have their operations only in a city. One of the important enablers is accessibility of skilled manpower at an optimum experience (Taylor et al., 2014). The boom of BDA has also created more educational courses in the market and studies have proved that education in analytics has been growing at fastest pace (George et al., 2014; Gandomi and Haider, 2015). This ensures availability of skilled workforce which would be available in plenty for these e-commerce startups. The process of adoption is dependent on the availability of such human resources in the company or in third party firms where some of the processes are outsourced (Provost and Fawcett 2013).
- **Access to capital (V7)**: The deployment of BDA in an e-commerce startup is driven by investment of funds. While startups face challenges related to capital as they are mostly funded, it has been discussed that investment of capital on analytics has been a major investment by most of the firms (Ohlhorst, 2012; Minelli et al., 2012). The rate of investment by firms ranges from 20-50% of their profit share (Mohanty et al., 2013). Although, the relationship between successful adoption of BDA and investment made by companies has not been proved significant yet, Koirala (2012) proposed that capital can be considered as fuel to the BDA chariot.
- **Quality of data (V8):** Data forms the base for adoption of BDA tools in any firm. While some studies debate on the definition of big data, it has been widely discussed that e-commerce business churn the maximum data (Vossen, 2014; Zhou et al., 2014; Constantiou and Kallinikos, 2015). Thus, the adoption of BDA tools would be effective for e-commerce startups which have grown in size and eventually with respect to data, and have expanded operations and business across various territories and business units (Wixom et al., 2013; Kwon et al., 2014).
- **Access to relevant data (V9)**: Data forms the prerequisite for any analysis, while it is argued that most of the successful companies have focused on accessibility of relevant data rather than just data (Barrett et al., 2015). The success of adoption of BDA is further more driven by identifying relevant data. Studies have argued upon ownership of data which makes it easier for firms to access them as an enabler (Agarwal and Dhar, 2014; Ramaswamy, 2013). Therefore, accessibility is higher if the firm owns the data while relatively low if the data is handled by a third party (Mithas et al., 2013).
- **Perceived usefulness (V10):** Studies related to adoption of technology have used perceived usefulness as an important enabler in context of technology (Wamba et al., 2015). While BDA is a tool which is technology driven, this variable also plays an important role in explaining the rate of adoption in an e-commerce setting (Ngai et al., 2009). The perception of employees of the company, including the management, about the importance and usefulness of BDA would enable the rate of exploration they would perform during the adoption process (Zhou et al., 2014). It has also been proved that perception about benefits is usually developed by success or failure, and the principle also applies in adoption of BDA in e-commerce startups (Davenport, 2012; Devraj et al., 2002)

- **Technical skillset of employees (V11):** The knowledge and understanding of BDA is a prerequisite to extract maximum potential of the tool. The success of adoption also lies in the technical background and experience of the employees who would be the end users of the tool (Vossen, 2014). Gandomi and Haider (2015) argue that most of the employees are sound with their daily work profile but face challenges to adapt to work on updated technologies. The analytical acumen of the employees plays a significant role in understanding the degree of adoption of BDA in any e-commerce startup (Boja et al., 2012; Hsinchun et al., 2012)

The presentation of the eleven enablers highlights that while each of them is contributing towards the success of adoption process, the challenge is to understand their importance and more than that to build a framework where the thematic structure gets interlinked.

3 Research Design

The adoption of big data analytics as a tool or technique by marketing firms seeks in-depth analysis rather than a generalized model. Generalized models would be best as they holistically discuss the challenges and solutions for majority of the firms; but those would be highly likely when there is an underlying theory that has been discussed and debated under various situations over time. Interpretive Structural Modelling (ISM) approach does not follow a dominance approach which is usually followed by other MCDM techniques like TOPSIS, ANP, AHP, etc. Therefore, this study uses ISM to develop a hierarchical model for the enablers and combines it with fuzzy MICMAC analysis to categorize variables into dependent, independent, autonomous and linkage variables. The next section discusses ISM and fuzzy MICMAC approach in detail and relevance of the same in the study. A brief overview of the flow of research design can be referred from Figure 1 which was developed after extending the framework offered by Attri et al. (2013).

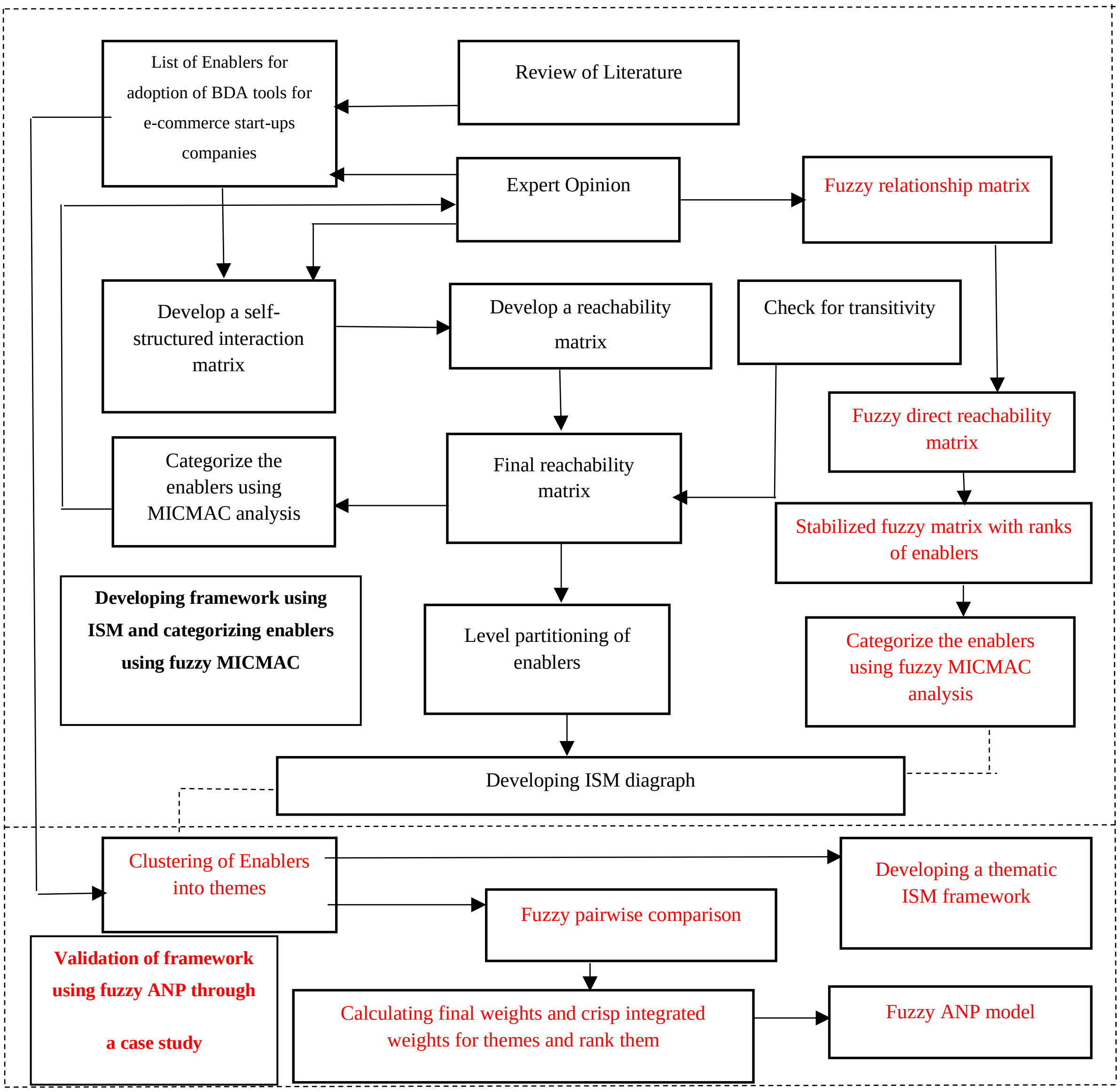

Figure 1. A brief overview of the flow of research design (Extended framework of Attri et al. (2013))

Interpretive Structural Modelling is one of widely used grounded theory methods to develop theoretical frameworks. The study is an amalgamation of graph theory, discrete mathematics, social science, computer assistance and decision-making approach. There have been various studies which have used Interpretive Structured Modelling (ISM) to develop theory or theoretical models in instances where there is dearth of literature or in situations where they explicate relationships between the constructs, but it has not been reflected in the literature or hypothesized by existing theory. The primary objective lies in understanding the interaction between the constructs derived from unorganized literature which is mostly interdisciplinary. The complexity of the relationship is higher due to paucity of discussions made by earlier studies to link the constructs. Barve et al. (2007) emphasized that ISM provides clear understanding of hierarchical relationships between the constructs which could be used to strategize and implement planning. It does not use a contemporary method of data collection rather it uses the comparative ranking methods (Morgado et al., 1999) which conjoint analysis uses to measure utility. Thus, ISM model helps the managers to ponder upon the linkages between the variables which helps in emerging the model. Various studies have highlighted the use and importance of ISM to discuss complex issues which are applicable in industries and/or in real life (Behl et al., 2015; Dubey et al., 2016; Sachdeva et al., 2015).

The primary objective of using ISM is that it uses both existing literature and opinions from experts to arrive at factors which are contextually more relevant rather than approaches like factor analysis. While factor analysis offers solutions with empirical data, it does not account for relationships between the variables/constructs and more than that it does not develop a hierarchy which is often required when problems like adoption of a new technology is concerned. In such situations, a systematic approach would be more useful than exploring the prominent factors only. Another advantage of ISM over other MCDM techniques is that it also does not explicitly ask the respondents to mark their understanding on arranging the factors in a comparative scale. This in turn reduces the chances of committing human errors (Sushil, 2002). Keeping the advantages of ISM in the context of the present study, the present study followed the following steps for developing ISM:

Step 1: Exploring the enablers of adoption of BDA in e-commerce startups in India.

Step 2: Determine the contextual relationship between the possible pairs of enablers using viewpoints of experts from different e-commerce startups and develop a Self-Structured Interaction Matrix (SSIM).

Step 3: Develop an initial and final reachability matrix by incorporating possible transitivity linkages between the enablers.

Step 4: Form level partitions using the driving power and dependence of the enablers and build the hierarchical framework.

Step 5: Classify enablers using graph theory through MICMAC analysis and incorporate fuzziness in the classification.

The first step is to explore the enablers of adoption of big data in e-commerce companies. The data collection for the study is done in India. India is one of the fastest growing economies for e-commerce. A recent report by Indian Brand Equity Foundation in 2019 highlights that revenue from the e-commerce sector is growing at a rate of 51%, which is highest in the world. It makes India one of the countries where e-commerce start-ups would flourish. Thus, the study and the related data for it is collected from Indian context.

Data collection is done in two phases. A list of enablers of adoption of BDA in any firm was derived from systematic search of literature. The systematic search was done using keyword approach from journals indexed in reputed indices like Scopus, Australian Business Dean Council (ABDC), and Association of Business School (ABS) etc. The initial list of enablers was 28 in number which were drawn by performing systematic review of literature. It was also found that most of the studies have used variables whose scope were overlapping. Thus, in order to make them heterogeneous in nature, in the second phase, the list was further reduced by removing the enablers which were overlapping or had similar orientation. The list was also shared with experts/decision makers from e-commerce startups which are either in the process of adoption or have successfully adopted and adapted BDA for their functionality. Every expert was asked to check the appropriateness and applicability of enablers.

The list was collated and finalized only if the enabler was selected by more than 50% of the reviewers. The list of enablers was finalized and a detailed version of the same has been presented in the literature review section (Section 2).

The second step involved developing a contextual relationship matrix after consulting the experts. The study consulted 44 experts from various domains and related areas of adoption of BDA in a firm. The same experts were again contacted for data collection which helped in uniformity of knowledge amongst in the study. The experts were asked to fill the Self-Structured Interaction Matrix (SSIM) by using any of the 4 symbols to denote the relationship between the variables. These symbols indicate the degree of association between the pairs of the variables and are denoted by 'p' and 'q' (referring to serial number of a barrier in row and column respectively).

V – There is a need to address barrier "p" before barrier "q"

A – There is a need to address barrier "q" before barrier "p"

X – There is a need to address both "p" and "q" simultaneously and

O – There is no relationship between "p" and "q" which results in a void relationship between them.

The SSIM matrix denoted by V, A, X and O are represented in the Table 1 (Appendix). This helps in designing an upper triangular matrix with a diagonal running from the top right corner to the bottom left corner. The other half of the matrix is intentionally left blank as the results are always represented from i to j and not vice-versa. The primary objective of developing SSIM was to understand the contextual linkages of the enablers. Some of the important linkages highlighted from the study are the forward linkages of V1 to V11 which essentially denotes how technical support of vendors help in empowering technical know-how of employees. Similarly, each of the corresponding values can be interpreted as the first level of preliminary analysis.

The next step is to complete the remaining half of the matrix and this operation is performed by converting the letter notations to binary values where each of the four notations will represent a binary combination of 0 and 1 and the order of which is defined earlier (Table 2- Appendix).

The substitution of the rows and columns is done using a specific order and it is as follows:

Every (p,q) entry in SSIM matrix as "V" should be replaced with 1 for (p,q) and as 0 for its corresponding pair of (q,p).

Every (p,q) entry in SSIM matrix as "A" should be replaced with 0 for (p,q) and as 1 for its corresponding pair of (q,p).

Every (p,q) entry in SSIM matrix as "X" should be replaced with 1 for (p,q) as well as its corresponding pair of (q,p).

Every (p,q) entry in SSIM matrix as "O" should be replaced with 0 for (p,q) as well as its corresponding pair of (q,p).

As a next step, it is important to also introduce the concept of transitivity to some of the cells of the matrix. This principle of transitivity is used as a basic assumption in interpretive structural model and is used in most of the studies using this technique (Farris and Sage, 1975). The revised and the final reachability matrix therefore comprise some entries which are modified with respect to the effect of principle of transitivity. The rows and columns are also added to calculate "dependence" and "driving power" (Table 3- Appendix).

The reachability and the antecedent set are derived from final reachability matrix and their interaction is also derived. Every antecedent should have a corresponding value written and the same can be seen in Table 4 (Appendix). This information is then used to define the hierarchy and therefore to develop the graph. After the top level of the hierarchy is achieved, it is important to remove the elements of it from the table and the process is repeated for further levels of hierarchy. The iterative process is repeated till every element has been assigned a level against it.

The last step is to develop the diagraph for the Interpretive Structural Model. This exercise is done by using Table 4 (Appendix) which highlights the various levels of the diagraph. The directional graph or the diagraph represents the graph connecting the enablers in a directional setting. The diagraph is drawn by stacking the enablers at various levels and joining them with directional arrows drawn from their relationship from SSIM. The diagraph for the present study is shown in Figure 2. It is also discussed that ISM is used to obtain parallel structural models which could be a result of modifications and enhancement in the relationship between the enablers placed at various levels (Austin and Burns, 1985).

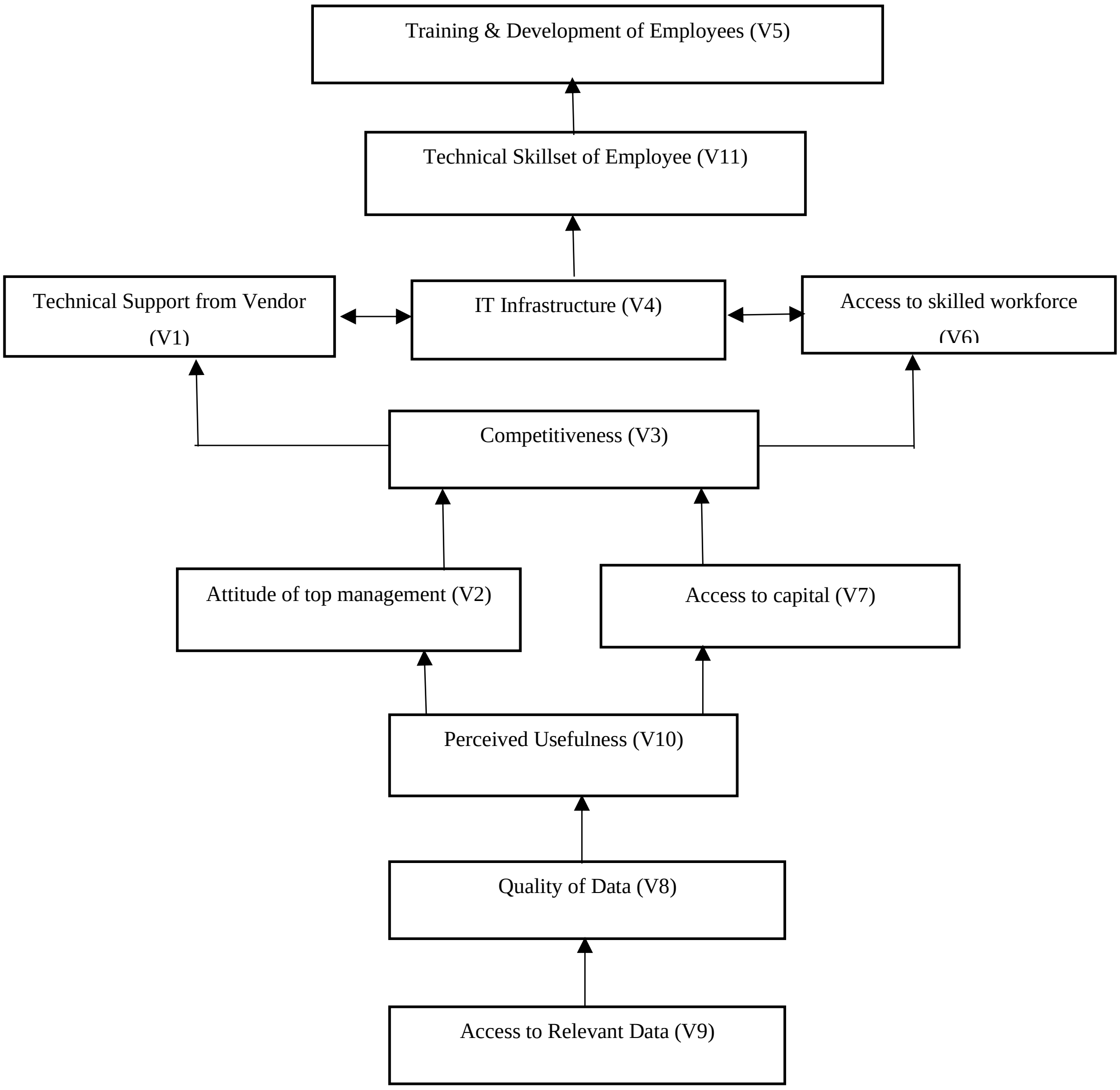

Figure 2: ISM framework for enablers of adoption of BDA

3.1 Discussion of Results of ISM

The most important enabler identified is “technical expertise of internal staff” and “training of employees” which makes the process of adoption easier for the firm as their reliability on third party analytics firms to analyze data would reduce. The existence of internal resources with the company makes it analytically strong as it becomes easier for them to understand the sources of data and how well can they use to develop business. Thus, technical expertise of internal resources forms the most important enabler in the adoption process. The results are consistent with Agarwal et al. (2011) wherein they studied the importance of internal resources using a resource-based view theory. The results are also in close proximity with Benedettini and Neely (2012) wherein proposal of using and training internal staff is a reliable and an effective move by e-commerce firms rather than outsourcing it. While the previous studies were conducted in a different geographic and time setting, the utilization of internal resources was highlighted and proposed to be an important factor in the adoption process.

Other key elements, which gained importance, were technical support offered by the vendors, IT infrastructure of the e-commerce companies and access to skilled workforce. The nature of startups makes it difficult to get a cutting edge of the three mentioned factors which is why they are also classified as the independent variables, and are dependent on factors like competitiveness, attitude of top management and access of capital.

The results also highlight the importance of “analytical skillset of top management” as yet another key enabler. As the firm chosen in the present study is simply an online portal which offers services to restaurants to deliver food to customers, their primary business is only offering services. It has been argued in the earlier literature as well that in a service dominated startup, the skillset of the top management, mainly the entrepreneur(s), plays a significant role in expanding business. The present study also affirms the results discussed by earlier studies (Sharma et al., 2014; Constantiou and Kallinikos, 2015).

Results further highlight “consistency of data” as another significant enabler of the implementation process. The company acts as a mediator for the orders placed online by customers and the delivery of food from the restaurant with whom the order was placed. Studies have reported that there is a steep rise in the trend of ordering food in India which leads to high usage of similar services (Kwon et al., 2014). The availability of consistent and regular data also helps in adoption of BDA tools as engaging customers regularly needs dynamically managing their needs and orders. The results go in consonance with Chang et al. (2014) who discussed that usage of BDA tools to its complete potential by startups is usually not done because of lack of availability of regular data. The results also confirm the outcomes highlighted by Brown et al. (2011) who discussed the importance of the size of information and its regularity in adoption of analytical tools in any firm. It also invariably follows the principles of five V’s of big data discussed in literature review section (Beulke, 2011).

The enabler might become irrelevant for e-commerce startups in their beginning phase of implementation and acquiring customers. That would result is acquiring low quality data and irregularity in it. Thus, one of the prerequisites for e-commerce startups is to operationalize the flow of regular data.

Other enablers having significant prominence in the adoption rate of BDA include awareness of the existing companies offering such packages, frequency of upgrades of the tool, and technical support from the vendors. Awareness about vendors forms the base of enablers which further splits into the frequency of upgrades they offer to the e-commerce company that additionally contributes to trust in the vendor. As the application of BDA is usually offered by vendors with background of information technology and statistics, it becomes important to choose a vendor which has reputation in the market and can offer a stable tool with fewer upgrades. The rate of adoption of BDA offered by these vendors is relatively higher as they can customize the tool according to the requirement of the e-commerce company. The stability of the tool also acts as a catalyst to help make decisions with the tool.

4. MICMAC Analysis

The ISM framework was used to develop the interlinkages but it does not discusses the characteristics of each of the enablers. This call for developing a classification approach which would enable us to develop strategies and propose hypothesis in future. The classification is defined as Matriced' Impacts Croise's Multiplication Appliquée a UN Classement (MICMAC) analysis. The next step is to distribute the enablers into various clusters based upon their corresponding values of dependence and driving power. The clustering also helps in defining the properties of these enablers which are also a result of their relative importance and score on the two parameters of driving power and dependence (Dubey and Ali, 2014). The classification categories are independent variables, dependent variables, linkage variables and autonomous variables (Gorane and Kant, 2013). The study also categorized the eleven enablers into the four clusters and found that there are no variables in the autonomous category which is a combination of weak dependence and driving power.

The figure (Figure 3) reveals that the distribution of the variables was only in two categories: dependent and independent ones while there is only one variable in linkage variable and no variable in the autonomous variable. In the study, there is only one variable: 'Competitiveness' in this category.

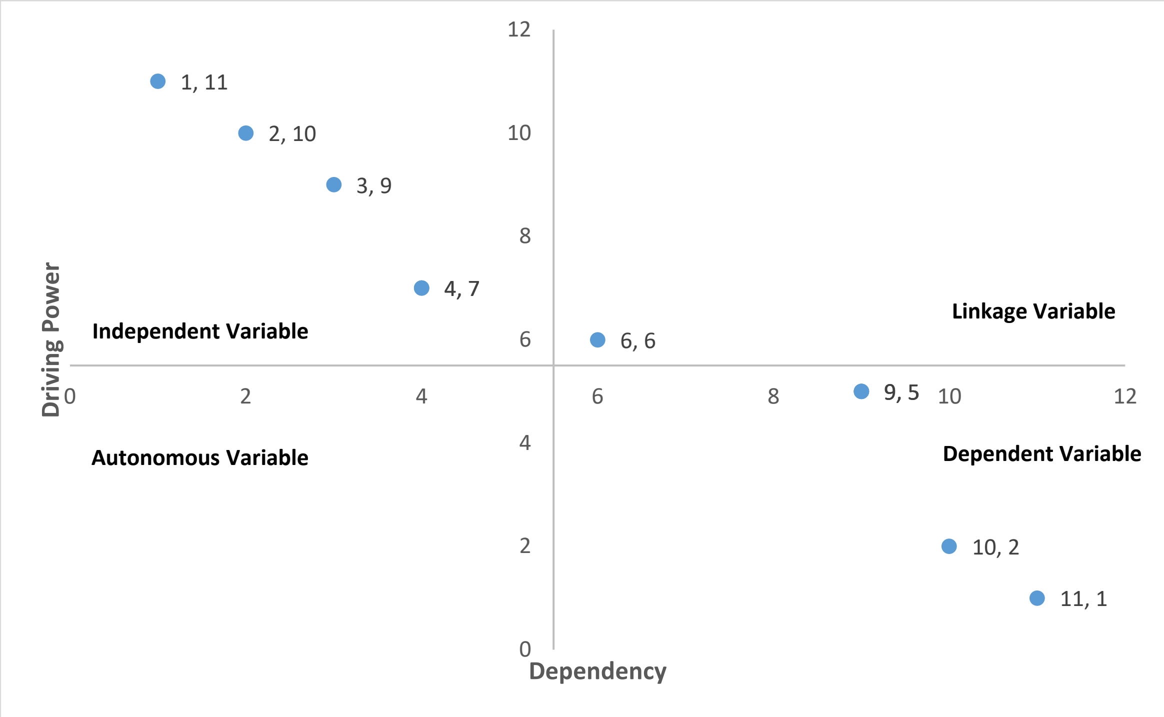

Figure 3: MICMAC Graph

The dependent variables included five variables: technical support by vendors, IT infrastructure, access to skilled workforce, training of employees, technical skillset of employees. A careful assessment of these enablers could also be used to observe a pattern which is that they belong to the initial levels in the level portioning process and are placed in the top of the diagraph. The reaming five are the independent variables and they lie in the top left of the diagraph.

4.1 Extending ISM and MICMAC using fuzzy set theory

The results of ISM and MICMAC analysis have discussed the importance of enablers by arranging in a hierarchical setup and classifying them into four clusters. Saxena et al. (1992) debated that there is a possibility of suppressing impact and association of the enablers in a direct linkage setup which ISM and MICMAC have predominantly presented. Also, there is a chance that the latent enablers have some impact on the model. These indirect linkages and relationships of the enablers could be clarified by repetitive discussion with the stakeholders and iterating the process as much as possible. The integration of ISM with fuzzy MICMAC attempts to incorporate the uncertain latent relationships between the enablers using a looped feedback mechanism.

Mandal and Deshmukh (1994) discussed the primary objective of using MICMAC analysis which was mere classification of variables. The process also takes into consideration transitivity at every level unlike ISM which only takes care of it at one level. The advantage of incorporating transitivity at every level makes the diagraph more stable as it would convert the unsteady state of the relationship into a steady state. The key steps of performing fuzzy MICMAC analysis are as follows:

The first step is development of binary direct reachability matrix. It is developed by using relationships between all the possible enablers and ISM framework. The matrix does not include transitivity and converts all the diagonal elements into 0 instead of 1 as in the case of ISM. The revised version of the matrix can be referred to from Table 5 (Appendix).

The next step is to develop a fuzzy direct relationship matrix. Most of the studies using MICMAC analysis have used binary type of relationship between the variables, but they lack sensitivity in their relationship which could be increased by considering fuzziness in the system. The dichotomous binary options in MICMAC are further broken down into a continuous scale at varied intervals. The interval scale can be referred to from Table 6 (Appendix).

The next step is to develop fuzzy direct relationship matrix which is obtained by superimposing the final reachability matrix by fuzzy relationship. The idea is to convert the dichotomous values into more robust and varied scale of values. The revised tables can be referred to Table 7- Appendix.

The fuzzy direct relationship matrix would now be used to perform fuzzy MICMAC analysis. The final stabilized matrix is then calculated by iteratively multiplication of the matrix with itself. This process is done to stabilize the hierarchies of driving power and dependence of the matrix. The process in multiplication follows a process described by Kandasamy (2007) instead of Boolean multiplication. The stabilized fuzzy matrix is used to calculate the revised driving power and dependence (Table 8 - Appendix).

The steps for constructing the diagraph are repeated again to understand the revised level and interrelationship of the enablers. The revised diagraph has five levels unlike the previous one which had eight. Lastly, the enablers are re-classified into four factors in order to understand their orientation (Figure 4).

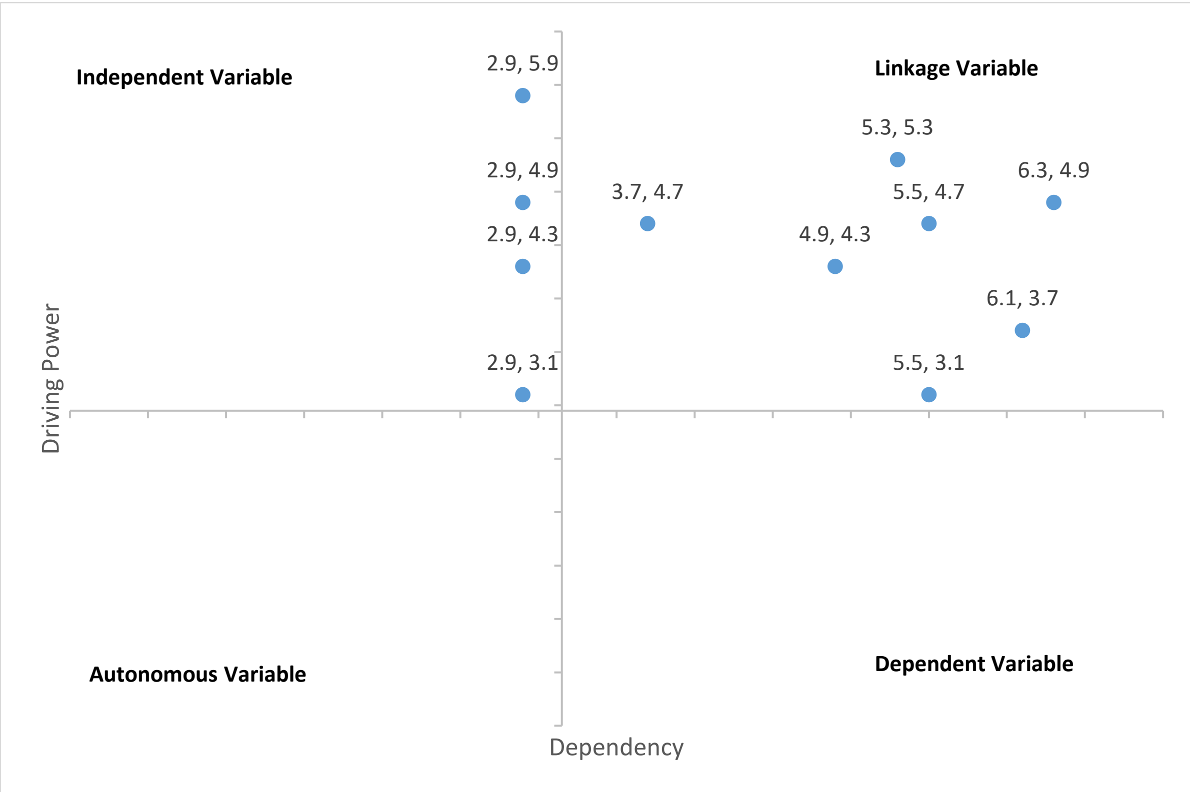

Figure 4: Classification of enablers using fuzzy MICMAC analysis

4.2 Discussion of Results from fuzzy MICMAC

The schematic diagram helps in understanding the most important enabler which have high values of driving power. This exercise has helped in reconfirming the importance of variables in an uncertain environment of e-commerce startups. The process also helps in giving robust results in developing a hierarchical arrangement of enablers in installing BDA in e-commerce startups in India. The usage of fuzzy techniques increases the robustness and validity of the framework.

The fuzzy MICMAC diagram (Fig 4) classifies the eleven enablers in four categories similarly like that of MICMAC analysis (Bhosale and Kant, 2016). The advantage with fuzziness in the process is that the classification becomes more stable which adds to the reliability of the classification (Shukla and Mattar, 2019; Dubey and Ali, 2014). The study explored that there are no variables in the dependent and the autonomous category and the distribution of them is in independent and linkage category. It can be inferred that all the variables have more or less similar driving power and therefore have a very low variance. This confirms that the properties of the variables in terms of their ability to drive other variables is more or less similar which indicates the heavy dependence on each other. The results also indicate that there are only four independent variables and those too are marginally in the bracket of independent category. The implementation of BDA would therefore be driven by four major variables: "attitude of top management"; "access to capital"; "access to relevant data" and "perceived usefulness". Therefore, they can be clubbed up broadly into two categories: perceptual behaviour of stakeholders and accessibility of resources. This also indicates that theories measuring perception and linkage to resources could be used to perform future analysis with adoption of BDA in e-commerce start-ups.

It would be worthwhile to explore the relationship between the linkage variables and check their combined effect on independent variable by collecting empirical data from the e-commerce startups from diverse background (Sachdeva et al., 2015). The study also confirmed existence of seven linkage variables which would impact the relationship between the dependent and independent variables the most. These are technical support from vendors; competitiveness; IT infrastructure; training and development of employees; access to skilled workforce; quality of data and technical skillset of employees. All the seven factors are high on dependence and driving power. These enablers would be most interesting ones to explore in terms of their impact on the overall relationship. Competitiveness which is a result of pressure and success rate of peers would result in testing theoretical models in the process of adoption of BDA. Although, competitive theory is usually applied in established settings, it would be interesting to look at its impact in the newbies in this area. This also calls for understanding the behavioral impact in the process of adoption which would be studied by applying theoretical support from "Theory of Planned Behavior" and its variants. The other two linkage variables: "quality of data" and "access to capital" have close connections with "resource-based view theory" and "resource dependence theory" (Jones et al., 2018; Whalen et al., 2016).

The study gives a blueprint of the importance, classification and probable linkages between the enablers of adoption of BDA in e-commerce startups. The study opens doors for both empirical researchers and theorists to explore this area in order to reduce the time of adoption and move towards adaptation of BDA in due course of time.

5. Case Study

The adoption of big data analytics as a tool by e-commerce startup firms seeks in-depth analysis rather than a generalized model. Generalized models would be best as they holistically discuss the challenges and solutions for majority of the firms; but those would be highly likely when there is an underlying theory which has been discussed and debated under various situations over time. As the field is relatively new and there is dearth of literature explaining the causal relationships between explanatory variables, case study approach would fit better in such a situation. Yin (2013) has suggested case study analysis to be suitable under theoretically uncertain situations. Case studies are epistemologically justifiable under theoretically uncertain situations or with issues which need explorations rather than validation. Adoption of BDA is also one such phenomenon which lacks theoretical underpinning and more so, needs an in-depth study with respect to firms which adopt them. Thus, extending the arguments made by Valmohammadi and Servati (2011), case study methodology is applied to evolve theory and discuss relationships between constructs. Case study approach aims at analytical generalization which is apt for adoption of BDA in e-commerce companies as the primary objective is not to statistically generalize results for the population, rather discuss in detail each of the constructs and focus on development of relationships between them. As the present study aims to address issues regarding adoption which is a dynamic process and is variable across different firms, case study approach would give robust results.

The study uses a case study of a company which delivers food from different restaurants to the customers through a mobile application and/or website having its operations only in India. The firm was used because of its recent transformation towards adoption of big data tools to improve their operations in multiple cities in India. The enablers identified in Section 2 were explained to the team members and key decision makers of the company to test the validity of them. The company decided to drop one construct “Competitiveness” as there are no other firms in the same business which have adopted or in the process of adoption of big data tools to manage their business. Thus, the further study would continue with ten enablers which are categorized into four themes based on the functional roles and nature of behavior. Thus, these enablers would act as sub-categories to the four broad themes. The reason for putting them into categories is to understand the linkages between the broad functional heads and link them together using appropriate modelling.

One of the primary reasons for extending the analysis of ISM using a fuzzy ANP analysis using a case study is to validate the framework in a practical setting. Most of the studies using ISM usually end up with proposing the framework and rarely validate the same in the real setting. This study uniquely uses data from a company and tests if such a framework would give meaningful results or not. It remains a debate in literature that companies don’t practically use these as a regular exercise, which is primarily because of unorganized process of adoption of any technology. This integrated approach would also help the e-commerce start-ups a window to ponder upon how interlinkages between enablers would help them organize the adoption process.

The presentation of the ten enablers and their categorization into thematic clusters (Table 9 - Appendix) depicts that while each of them is contributing towards the success of adoption process, the challenge is to understand their importance and more than that to build a framework where the thematic structure gets interlinked. The study aims to address the gap of linking the themes and assign weights to them to understand their relative importance.

Thus, the primary objective for the firm was to develop a theoretical framework for the clusters and assign weights to them for understanding the importance while administering the level of uncertainty in the entire process. The study uses interpretive structural modelling to develop a hierarchical model for the clusters of enablers and combines it with fuzzy analytic network process to understand the prioritization of enablers for adoption of BDA for the firm. As the study has already discussed ISM in depth, the next section discusses briefly about fuzzy ANP.

5.1 Fuzzy Analytical Network Process

The evolution and development of fuzzy set theory was primarily meant to address issues of uncertainty which were a result of ambiguous results from judgments, evaluations and decisions made by process and humans. The ambiguity in the relationship is also a function of their relationship with each other and more importantly their changing properties in a research environment. It is also important to understand that every decision-making process is not hierarchical because of the interactions of constructs at various levels. Analytical Network Process caters to this problem of complex interrelationship among constructs between levels which may or may not be directly linked. The primary idea of ANP is replacement of hierarchical model with a network model in order to reduce ambiguity. It is also important to understand that while ISM is a hierarchical model building exercise, there is a possibility that constructs are often interdependent at various levels which is not considered in the development of model.

Zadeh (1965) proposed a fuzzy set theory whose primary objective was to address the problem of uncertainty which could be a result of human judgement coupled with complex phenomenon affecting them. The theoretical underpinning of fuzzy numbers is discussed by various studies in different contexts.

The present study uses triangular fuzzy numbers which are operationally defined as p,q,r such that $p<q<r$ and p,q,r denote the smallest value, the most probabilistic value and the highest value that significantly describes the fuzzy process. The output function of the fuzzy triangular function can be referred to in Table 10 (Appendix).

While ANP comes as a savior, the fuzzy version of the same reduces the error much further. The development of a fuzzy ANP gets its inspiration from fuzzy analytical hierarchical process (AHP). The pattern of distribution of local weights and construction of pair wise comparisons is same as that of fuzzy AHP. The weights are arranged in a matrix structure which is then used to derive the importance or priorities. The concept was proposed and discussed initially by Satty (1988). While ANP is a widely used technique in the area of research, the present study adds a degree of fuzziness because of the ambiguous and stochastic nature of decision making. Studies have used fuzzy theory in various decision-making processes including ANP. This study also employed a fuzzy ANP technique to allot the priorities of the enablers for adoption of big data analytics in the firm. The primary objective of using fuzzy ANP was to incorporate the uncertainties in the hierarchy and of the enablers.

Data was collected by circulating a questionnaire to decision making authorities and analysts at various levels. The sample sizes of such were 23 which included 17 analysts and 6 top management members which were directly involved in the decision making and adoption process. The questionnaire was also pretested with academic experts and researchers who have published quality publications using fuzzy ANP, to ensure content validity of the instrument. The relevant and required changes were made to remove probable chances of commitment errors while doing data collection. The respondents were also given scales and related fuzzy triangular fuzzy number tables (Table 4) to perform a pairwise comparison and evaluate relative importance of network nodes between each of the possible pairs. To ensure consistency of the results obtained from the experts, Consistency Rate (CR) was calculated in the fuzzy importance matrix. As proposed by Satty (1988), Random Index (RI) is also calculated which is simply the average Consistency Index (CI) over numerous random entries of the same order reciprocal matrices which is dependent on the number of related criteria in the decision matrix. Table 11 (Appendix) presents random index.

The next step is to calculate CR which a ratio of CI and RI. While, RI has been calculated above,

Consistency Index (CI) is calculated using the following formula:

$$CI = \frac{\tau_{max} - n}{n-1}$$

$$CR = \frac{CI}{RI}$$

Studies have highlighted that if the value of CR is less than 0.1, the results are acceptable; else a new comparison matrix should be developed. The study uses CFCS method of defuzzification proposed by Opricovic and Tzeng (2003). The process is repeated iteratively till consistency test is passed of the CFCS method and the corresponding results are found for each of the evaluator. The last step is to then calculate the geometric mean of all crisp values of the calculated evaluators.

$$X_{ij}^* = [x_{ij}^*]$$

whereX_{ij}^* is an aggregated crisp judgment matrix, and x_{ij}^* is the aggregated crisp assessments of criterion i and criterion j of k experts, i, j = 1, 2, . . ., n. k is the number of experts. In the next step, the final weight W of the nodes from the pairwise comparisons are calculated as below.

$$W_i = \frac{\left(\prod_{j=1}^{n} x_{ij}^*\right)^{1/n}}{\Sigma\left(\prod_{j=1}^{n} x_{ij}^*\right)^{1/n}} \text{ where i, j = 1,2,3…….. n}$$

5.2 Development of ISM Framework for the Firm

The steps were followed as mentioned in Section 3 and ISM framework was developed. The first step of developing a SSIM is mentioned in order to replicate the process. The SSIM matrix denoted by V, A, X and O are represented in the table as under (Table 12- Appendix). The interpretive model is developed from the final reachability matrix (Fig. 5)

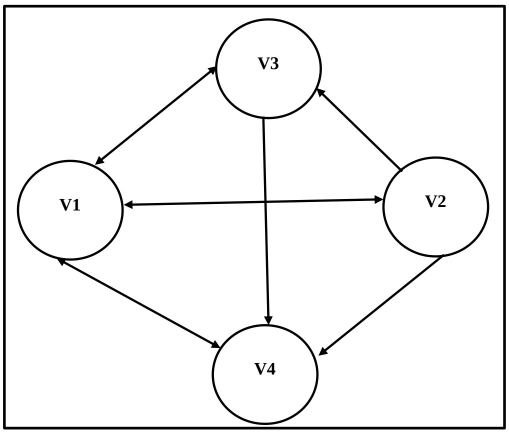

Figure5: ISM framework for thematic enablers of adoption of BDA

The next step was to develop the pairwise comparison matrix using the priority relationship between the enablers and convert them into fuzzy numbers based on network relationships and responses collected from experts.

Following this, the next step was to check the consistency for which matrix was developed using the middle number of the triangular matrix (Csutora and Buckley, 2001). As per the recommendation by Csutora and Buckley (2001), the consistency of the fuzzy matrix was evaluated based on the consistency of middle number of triangular fuzzy numbers (Table 13- Appendix).

$$\begin{vmatrix} 1-\lambda & 0.3 & 3 & 0.5 \\ 3 & 1-\lambda & 5 & 2 \\ 0.3 & 0.2 & 1-\lambda & 0.33 \\ 2 & 0.5 & 3 & 1-\lambda \end{vmatrix} = 0 \quad [\text{Ref: } \det(A-\lambda I) = 0]$$

The value of $\lambda = 4.07$. We would now use it to calculate CI and therefore CR which comes down to 0.031. Results show that the value of CR is less than 0.1, it is concluded that there exists a consistency, henceforth the judgment is acceptable. Similar results were found out for each of the 23 experts.

The next step is to defuzzify the matrices using CFCS method and calculate weights proposed in the methodology section. Results confirm that the consistency test for each of the five enablers was passed. The aggregate consistency judgment was then worked around and the process of defuzzification and calculation of weights was again performed followed by calculation of their geometric mean (Valmohammadi and Dashti, 2016). The final weights and crisp integrated values of the pairwise comparison results from the 23 experts are shown in the Table 14 and Table 15 respectively (refer to Appendix). The final weights of the relevant enablers with respect to the primary enabler and their interaction were calculated based upon the responses collected from the experts.

The last step was to finalize weighted, unweighted and limited super-matrix to identify the enablers of BDA in the firm. The process includes development of unweighted super-matrix of ANP by substituting the weights of main enabler rating under the goal node of the super-matrix. The weights of the main enabler identified from the process and its interaction with relevant sub enablers or items are then plugged in the super-matrix along with their interaction weights. The normalization of the first column of the unweighted super-matrix is also done to ensure the sum of the column to be 1. The transformed weighted super-matrix could be referred for further analysis.

The weighted matrix is then raised to the power of 2n+1 where n is a random number and the process is repeated iteratively to achieve convergence. The converged matrix is called limited super-matrix. The priorities of the elements could be now derived from the limited super-matrix which has the required weights assigned to each of them. The final set of linkages is obtained from limited super-matrix which is presented in Table 16 (Appendix).

5.3 Results and its implications for the firm

The study has discussed the enablers of adoption of BDA in an e-commerce company. It projects the relationship between the enablers and their degree of association. The study also considers the level of uncertainty and its complexity in understanding the process of implementation and adoption of BDA in an e-commerce company. It is worthwhile to note that the discussion of success factors for adoption and implementation would act as a starting point to understand the relationship and linkages between them and it would benefit other e-commerce firms in the process of adoption. While it is known that adoption is one of the preliminary stages which is followed by adaptation and usage, the study helps to decipher the importance of success factors and how are they linked to others (Jao, 2013). Earlier studies have discussed the barriers in adoption of technologies in companies, and have also incorporated the level of uncertainty and complexity, but very few have discussed adoption of BDA in an e-commerce setup (Fisher et al., 2012; Dinev and Hart, 2006). This proves to be a starting point for e-commerce companies who would prefer to adopt similar tools to enhance their understanding about business. The present study forms a starting point for e-commerce firms to run a similar analysis to understand the linkage and importance of enablers when they would plan to adopt BDA. The integration of interpretive structural modelling and fuzzy analytical network process has helped in developing a structural model for linking enablers and providing a level of priority to each of the set of constructs. The integration approach would also help e-commerce firms in developing their own conceptual model and prioritizing their constructs in the process of adoption. As the process of adoption is a dynamic process, it is also important to understand that such a model could be tested under a simulated environment to ensure its robustness and validity.

The most important enabler established from the study is “technical expertise of internal staff” which makes the process of adoption easier for the firm as their reliability on third party analytics firms to analyze data would reduce. The existence of internal resources with the company makes it analytically strong as it becomes easier for them to understand the sources of data and how well can they use to develop business. Thus, technical expertise of internal resources forms the most important enabler in the adoption process. The results are consistent with Agarwal et al. (2011) wherein they studied the importance of internal resources using a resource-based view theory. The results are also in close proximity with Benedettini and Neely (2012) wherein proposal of using and training internal staff is a reliable and an effective move by e-commerce firms rather than outsourcing it. While the previous studies were conducted in a different geographic and time setting, the utilization of internal resources was highlighted and proposed to be an important factor in adoption process.

The results also highlight the importance of “analytical skillset of top management” as yet another key enabler. As the firm chosen in the present study is simply an online portal which offered delivery services to restaurants to deliver food to their customers their primary business is only offering services. It has been argued in the earlier literature as well that in a service dominated startup, the skillset of the top management, mainly the entrepreneur(s), plays a significant role in expanding business. The present study also affirms the results discussed by earlier studies (Sharma et al, 2014; Constantiou and Kallinikos, 2015).

Results further highlight “consistency of data” as another significant enabler of the implementation process. The company acts as a mediator for the orders placed online by customers and the delivery of food from the restaurant with whom the order was placed. Studies have reported that there is a steep rise in the trend of ordering food in India which leads to high usage of similar services (Kwon et al., 2014). The availability of consistent and regular data also helps in adoption of BDA tools as engaging customers regularly needs dynamically managing their needs and orders. The results go in consonance with Chang et al. (2014) who discussed that usage of BDA tools to its complete potential by startups is usually not done because of lack of availability of regular data. The results also confirm the outcomes highlighted by Brown et al. (2011) who discussed importance of the size of information and its regularity in adoption of analytical tools in any firm. It also invariably follows the principles of five V’s of big data discussed in literature review section (Beulke 2011).

The enabler might become irrelevant for those e-commerce startups which are in their beginning phase of implementation and acquiring customers. That would result is acquiring low quality data and irregularity in it. Thus, one of the prerequisites for e-commerce startups is to operationalize the flow of regular data.

Other enablers having significant prominence in the adoption rate of BDA include awareness of the existing companies offering such packages, frequency of upgrades of the tool, and technical support from the vendors. Awareness about vendors forms the base of enablers which further splits into the frequency of upgrades they offer to the e-commerce company that further contributes to trust in the vendor. As the application of BDA is usually offered by vendors with background of information technology and statistics, it becomes important to choose a vendor which has reputation in the market and can offer a stable tool with fewer upgrades. The rate of adoption of BDA offered by these vendors is relatively higher as they can customize the tool according to the requirement of the e-commerce company. The stability of the tool also acts as a catalyst to help make decisions with the tool.

5.4 Research and Managerial Implications

The study offers guidelines and mechanisms which e-commerce startups can adopt irrespective of geography and sector of application. The systematic approach towards exploring the factors could be used by every e-commerce startup thereby helping them with firstly exploring critical success factors and then developing a relationship based framework with thematic linkages. This study once modelled using dynamic loops can help the e-commerce startups with a dynamic framework which in turn would help them devise strategies easily. The results developed from fuzzy set theory helps in fixing the issues of complexity in decision making. E-commerce firms can find this study as a benchmarking exercise to understand what they need to do in order to aspire what they want to achieve. The additional validation of results in this study using a case based analysis also offers a robust pathway for companies to reorganize the enablers into categories which can be handled by different teams. A fuzzy linkages using ANP also makes the themes looks connected using widely used and tested MCDM technique which makes the results authentic and validated. A similar exercise can therefore be performed across e-commerce firms in different countries and sectors which can help in theory development process as well.

6. Conclusion, limitations and future scope of research

The study has discussed the enablers of adoption of BDA in an e-commerce company. It projects the relationship between the enablers and their degree of association. The study also considers the level of uncertainty and its complexity in understanding the process of implementation and adoption of BDA in an e-commerce company. While it is known that adoption is one of the preliminary stages which are followed by adaptation and usage, the study helps to decipher the importance of success factors and how are they linked to others (Jao, 2013). Earlier studies have discussed the barriers in adoption of technologies in companies, and have also incorporated the level of uncertainty and complexity, but very few have discussed adoption of BDA in an e-commerce setup (Fisher et al. 2012; Dinev and Hart, 2006). This proves to be a starting point for e-commerce companies who would prefer to adopt similar tools to enhance their understanding about business. The present study also forms a starting point for e-commerce firms to run a similar analysis to understand the linkage and importance of enablers when they would plan to adopt BDA. The integration of interpretive structural modelling and fuzzy analytical network process has helped in developing a structural model for linking enablers and providing a level of priority to each of the set of constructs. The integration approach would also help e-commerce firms in developing their own conceptual model and prioritizing their constructs in the process of adoption. As the process of adoption is a dynamic process, it is also important to understand that such a model could be tested under a simulated environment to ensure its robustness and validity.

The study has developed a framework for adoption of BDA for e-commerce start-ups and validated the same for an e-commerce start-up using a case base approach. The validation of the framework would also depend on the nature and structure of the organization and the framework could further be developed and modified after performing similar analysis for multiple firms. Yet, it is worthwhile to test the results with same enablers which have been used in the study as a proxy. The priorities of the enablers might result differently which would depend on functions like nature of business, competitiveness, availability of BDA and years of existence in the business, as well as rate of growth of business. It would be interesting to perform similar analysis for firms which have similar business in Indian context in order to understand the validity and replicability of results. Once the hierarchical model and priorities of enablers are finalized, the study could be then used to empirically test results across the e-commerce startup industry. The application of this framework or similar one would be interesting to discuss due to difference in business, top order management, inflow of data, etc.

The study has some limitations which were mostly driven by operational reasons. The study involved data collection from experts which are currently involved in the adoption process, while a different perspective could also be gathered from the ones which were successfully helped firms to adopt BDA in the firms. There is a scope of developing and testing ISM framework for every company as a dynamic and routine practice which the present study has not encapsulated. Data collection has been done in an Indian context while the same could be done across different geographies where BDA adoption process could be almost similar.

The study could also be done using other tools like decision making trial and evaluation laboratory (DEMATEL) and ANP and an element of fuzziness could be included in each of the two techniques. The integrated technique would help in understanding the functional difference between using interpretive structural modelling and DEMATEL approach in order to develop a hierarchical framework with linkages and defining priorities of the enablers. The adoption of Total Interpretive Structural Modelling (TISM) would be more effective in understanding the reasoning for connecting each and every path. The addition of reasoning in the interpretive structural model would also make it robust which has been argued in previous literature as well (Sushil, 2012).

Another proposal could be empirically testing the model using data from the e-commerce startups and then use techniques like structured equation modelling. It would be helpful in understanding the weights of the internal impact among barriers to e-commerce implementation and the statistical validation of the model. The results could then be generalized and discussed with e-commerce companies and vendors offering similar services. This would help both the stakeholders understand the expectations from the process of adoption and would therefore increase the turn-around time for solving queries and smoothen the process of adoption.

Conflict of interest:

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Appendix

Table 1: SSIM matrix of enablers

	V11	V10	V9	V8	V7	V6	V5	V4	V3	V2	V1
V1	V	A	A	A	A	A	V	X	A	O	
V2	V	A	O	O	O	V	V	V	V		
V3	V	A	A	O	A	V	V	V			
V4	V	A	A	A	A	X	V				
V5	A	O	A	A	O	O					
V6	V	A	A	A	A						
V7	V	A	A	A							
V8	V	V	A								
V9	V	V									
V10	O										
V11											

Table 2: Reachability matrix of the primary enablers

	V11	V10	V9	V8	V7	V6	V5	V4	V3	V2	V1
V1	1	0	0	0	0	0	1	1	0	0	1
V2	1	0	0	0	0	1	1	1	1	1	0
V3	1	0	0	0	0	1	1	1	1	0	1
V4	1	0	0	0	0	1	1	1	0	0	1
V5	0	0	0	0	0	0	1	0	0	0	0
V6	1	0	0	0	0	1	0	1	0	0	1
V7	1	0	0	0	1	1	0	1	1	0	1
V8	1	1	0	1	1	1	1	1	0	0	1
V9	1	1	1	1	1	1	1	1	1	0	1
V10	0	1	0	0	1	1	0	1	1	1	1
V11	1	0	0	0	0	0	1	0	0	0	0

Table 3:Final reachability matrix with transitivity (*)

	V11	V10	V9	V8	V7	V6	V5	V4	V3	V2	V1	Driving Power
V1	1	0	0	0	0	1*	1	1	0	0	1	5
V2	1	0	0	0	0	1	1	1	1	1	1*	7
V3	1	0	0	0	0	1	1	1	1	0	1	6
V4	1	0	0	0	0	1	1	1	0	0	1	5

V5	0	0	0	0	0	0	1	0	0	0	0	1
V6	1	0	0	0	0	1	1*	1	0	0	1	5
V7	1	0	0	0	1	1	1*	1	1	0	1	7
V8	1	1	0	1	1	1	1	1	1*	1*	1	10
V9	1	1	1	1	1	1	1	1	1	1*	1	11
V10	1*	1	0	0	1	1	1*	1	1	1	1	9
V11	1	0	0	0	0	0	1	0	0	0	0	2
Dependence	10	3	1	2	4	9	11	9	6	4	9	

Table 4: Level for developing diagraph

Enablers	Antecedent Set (AS)	Reachability Set (RS)	RS ∩ AS	Level
V1	1,2,3,4,6,7,8,9,10	1,2,5,6,11	1,4,6	Third
V2	2,8,9,10	1,2,3,4,5,6,11	2	Fifth
V3	2,3,7,8,9,10	1,3,4,5,6,11	3	Fourth
V4	1,2,3,4,6,7,8,9,10	1,4,5,6,11	1,4,6	Third
V5	1,2,3,4,5,6,7,8,9,10,11	5	5	First
V6	1,2,3,4,6,7,8,9,10	1,4,5,6,11	1,4,6	Third
V7	7,8,9,10	1,3,4,5,6,7,11	7	Fifth
V8	8,9	1,2,3,4,5,6,7,8,10,11	8	Seventh
V9	9	1,2,3,4,5,6,7,8,9,10,11	9	Eighth
V10	8,9,10	1,2,3,4,5,6,7,10,11	10	Sixth
V11	1,2,3,4,6,7,8,9,10,11	5,11	11	Second

Table 5: Binary direct relationship matrix

	V11	V10	V9	V8	V7	V6	V5	V4	V3	V2	V1
V1	1	0	0	0	0	0	1	1	0	0	0
V2	1	0	0	0	0	1	1	1	1	0	0
V3	1	0	0	0	0	1	1	1	0	0	1
V4	1	0	0	0	0	1	1	0	0	0	1
V5	0	0	0	0	0	0	0	0	0	0	0
V6	1	0	0	0	0	0	0	1	0	0	1
V7	1	0	0	0	0	1	0	1	1	0	1
V8	1	1	0	0	1	1	1	1	0	0	1
V9	1	1	0	1	1	1	1	1	1	0	1
V10	0	0	0	0	1	1	0	1	1	1	1
V11	0	0	0	0	0	0	1	0	0	0	0

Table 6: Fuzzy relationship matrix

Fuzzy relationship	No	Negligible	Low	Medium	High	Very High	Full
Values	0	0.1	0.3	0.5	0.7	0.9	1

Table 7: Fuzzy direct reachability matrix

	V11	V10	V9	V8	V7	V6	V5	V4	V3	V2	V1
V1	0.7	0	0	0	0	0	0.5	0.3	0	0	0
V2	0.3	0	0	0	0	0.3	0.7	0.5	0.9	0	0
V3	0.7	0	0	0	0	0.7	0.5	0.3	0	0	0.5
V4	0.3	0	0	0	0	0.9	0.7	0	0	0	0.7
V5	0	0	0.1	0	0	0	0.3	0	0	0.1	0
V6	0.5	0	0	0	0	0	0	0.7	0	0	0.9
V7	0.5	0	0	0	0	0.7	0	0.3	0.1	0	0.5
V8	0.5	0.7	0	0	0.5	0.3	0.5	0.7	0	0	0.5
V9	0.7	0.5	0	0.3	0.7	0.3	0.5	0.1	0.5	0	0.7
V10	0	0	0	0	0.5	0.7	0	0.5	0.7	0.9	0.3
V11	0	0	0.3	0	0	0	0.9	0	0	0	0

Table 8: Stabilized fuzzy matrix with ranks of enablers

	V11	V10	V9	V8	V7	V6	V5	V4	V3	V2	V1	DP	Rank
V1	0.3	0.3	0.3	0.5	0.3	0.3	0.5	0.3	0.3	0.3	0.3	3.7	6
V2	0.7	0.3	0.3	0.7	0.3	0.7	0.7	0.7	0.5	0.3	0.7	5.9	1
V3	0.7	0.3	0.3	0.7	0.3	0.1	0.5	0.3	0.5	0.3	0.7	4.7	4
V4	0.7	0.5	0.3	0.7	0.3	0.7	0.7	0.3	0.3	0.3	0.5	5.3	2
V5	0.3	0.3	0.1	0.5	0.3	0.3	0.3	0.1	0.1	0.3	0.5	3.1	8
V6	0.7	0.1	0.3	0.3	0.3	0.5	0.5	0.7	0.3	0.3	0.7	4.7	4
V7	0.7	0.3	0.1	0.1	0.3	0.7	0.3	0.5	0.3	0.3	0.7	4.3	5
V8	0.7	0.1	0.3	0.5	0.1	0.5	0.3	0.7	0.3	0.1	0.7	4.3	5
V9	0.7	0.3	0.3	0.3	0.3	0.3	0.7	0.5	0.5	0.3	0.7	4.9	3
V10	0.3	0.1	0.3	0.1	0.1	0.7	0.3	0.5	0.3	0.3	0.1	3.1	7
V11	0.5	0.3	0.3	0.5	0.3	0.7	0.7	0.7	0.3	0.1	0.5	4.9	3
Dependence	6.3	2.9	2.9	4.9	2.9	5.5	5.5	5.3	3.7	2.9	6.1		
Rank	1	7	7	5	7	3	3	4	6	7	2		

Table 9: Thematic clustering of enablers

Themes	**List of enablers**
Technical (V1)	Technical Support from vendor, Technical skillset of employees, IT infrastructure
Organizational (V2)	Access to Capital, Access to skilled workforce, Training and development of employees

Behavioral (V3)	Attitude of top management, Perceived Usefulness
Data oriented (V4)	Access to Relevant Data, Quality of Data

Table 10: Rule for obtaining output from fuzzy triangular matrix

0	x < p
$\frac{x-p}{q-p}$	p <= x < =q
$\frac{x-q}{r-q}$	q < =x <= r
0	x>= r

Table 11: Linguistic scale and corresponding triangular fuzzy numbers

1	Equally important	(1,1,1)
3	Somewhat important	(2,3,4)
5	Essentially important	(4,5,6)
7	Very strongly important	(6,7,8)
9	Absolutely important	(7,8,9)
2 4 6 8	Intermediate values (x)	(x-1, x, x+1)
1/x	Between two adjacent judgements	(1/x-1, 1/x, 1/x+1)

[Source: Valmohammadi and Dashti (2016)]

Table 12: SSIM matrix of enablers

	V1	V2	V3	V4
V1		X	X	X
V2			V	V
V3				V
V4				

Table 13: Fuzzy pairwise comparison table

	V1	V2	V3	V4
V1	(1,1,1)	(1/4, 1/3, ½)	(2,3,4)	(1/3, ½ , 1)
V2	(2,3,4)	(1,1,1)	(4,5,6)	(1,2,3)
V3	(1/4, 1/3, ½)	(1/6, 1/5, ¼)	(1,1,1)	(¼ , 1/3, ½)
V4	(1,2,3)	(1/3, ½ , 1)	(2,3,4)	(1,1,1)

Table 14: Final Crisp values for one evaluator

	V1	V2	V3	V4
V1	1	0.34	3	0.55
V2	3	1	4.94	2.01
V3	0.34	0.2	1	0.34
V4	2.01	0.55	3	1

Table 15: Final weights and crisp integrated weights for themes

	V1	V2	V3	V4	Weight
V1	1	0.327	2.806	0.695	0.172
V2	3.289	1	4.765	2.354	0.482
V3	0.354	0.231	1	0.568	0.115
V4	1.542	0.452	1.546	1	0.231

Table 16: Final weight for each enabler and their ranking

Enablers of BDA adoption	**Weight from limited super-matrix**	**Rank**
Access to relevant data	0.118	3
Access to capital	0.087	8
Attitude of top management	0.129	2
Technical Support from vendor	0.056	10
Technical skillset of employees	0.145	1
IT infrastructure	0.091	7
Access to skilled workforce	0.076	9
Size of Data	0.107	4
Training of employees	0.101	5
Perceived Usefulness	0.097	6