Modelling the Key Enablers and Barriers of Ai-Based Conversational Agents' Adoption: an Ism and Micmac Approach

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ABSTRACT

The purpose of the study is to evaluate and model the influencing factors that act as facilitators and inhibitors for consumers' adoption of conversational agents. The identified variables are then modelled into a hierarchical framework using Interpretive Structural Modelling (ISM) methodology to develop a contextual interrelationship among them. Based on extensive literature review and experts' opinions, the study identifies variables pertaining to the adoption behaviour of AI-based conversational agents. The study proposes a dual approach to establish and explain the behavioural reasons and causal relationship that exists among the identified variables. First, the study employs ISM methodology to examine the interrelationship among the identified fundamental variables, which results in a digraph specifying hierarchical levels. Second, MICMAC analysis has been performed to categorise the corresponding variables based on driving power and dependence power. The six-layered interpretive structural model reveals that social influence plays a pivotal role in the adoption phenomenon. The model further demonstrates that perceived anthropomorphism, perceived intelligence, and perceived personalisation are major drivers for the evaluation of functionality and value of conversational agents. Additionally, MICMAC analysis shows three distinct clusters in which variables are classified based on dependence powers and driving power. The foremost contribution of the current research is the development of the hierarchical model of the variables that shape the adoption decision. The findings may aid practitioners in incorporating human-like qualities and personalized features to ensure prompt functionality and a better experience for the users. This model will help to extend the adoption models by incorporation of contextual variables and also by determination of their dependence and driving power.

Keywords Artificial intelligence. Conversational agents. Communication. Conversation. Adoption behaviour. Human-computer interaction. Interpretive Structural Modelling (ISM). MICMAC. Strengthening variables.

1. Introduction

AI-based conversational agents are one of the emerging technologies which have rapidly gained wider acceptability and popularity among people. Today, as never before, people are more inclined to participate in tangible communication with the conversational agents and are willing to engage frequently while navigating through web pages (Moriuchi, 2020). In general, conversational agents are defined as intelligent software that makes human-computer interaction possible by utilizing natural language processing and a touch-based interface (Paay et al., 2020). They can understand spoken language and use speech communication as user interface

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(Pitardi & Marriott, 2021). Also, these are characterized as personalized systems, encompassing digital assistants, chatbots, voice assistance, and virtually embodied avatars (Araujo, 2018; Balakrishnan et al., 2021). These agents allow for extensive applications to consumers, beginning from personal task management (to schedule appointments, manage calendar, send text messages, make and receive calls, and navigate routes and directions) to highly sophisticated functions and device integrations (healthcare assistance, automated homes, conversational commerce, and customized entertainment) (Baier et al., 2018; Paay et al., 2020). Moreover, this technology also offers businesses a wide array of opportunities to integrate conversational agents into their operations with the aim of achieving productive gains (Baier et al., 2018). Accordingly, conversational agents have been predominantly harnessed in different fields, which include education, banking, healthcare, social media, retail, e-commerce, business, hospitality, and tourism (Beinema et al., 2021; Marikyan et al., 2022; Moriuchi, 2019; Rese et al., 2020; Shamsi, Al-Emran, & Khaled Shaalan, 2022; Trivedi, 2019; Zarouali et al., 2018).

The recent forecast reveals that the conversational agents market size is estimated at USD 6.94 Billion in 2021 and is predicted to grow to USD 54.35 Billion by 2030 (Verified market research, 2022). Owing to its massive demand, conversational agents' adoption has been a focal point of IoT research related to technology adoption (Kasilingam & Krishna, 2020; Pitardi & Marriott, 2021). Researchers have majorly identified and reported antecedents of conversational agent adoption through many theories (Fernandes & Oliveira, 2021).

In particular, the extant literature explores how consumers evaluate and engage with technology and highlight the significance of functionality, design, usage (Balakrishnan & Dwivedi, 2021), humanness perception (Araujo, 2018), and social and personal motivation (Go and Sundar, 2019) in explaining technology adoption. Despite the focus offered on the research of conversational agents and the proliferation of their adoption as well as future growth, there is a need for additional research on AI-based conversational agents since the device and software are constantly improving (Kääriä, 2017).

In this regard, Malodia *et al.* (2022) emphasized the need to cognize the psychological determinants that initiate trust, innovativeness, and risk perception, which may offer potential novel insight about the consumer experience. Further, Vlačić *et al.* (2021) called for the investigation of cognitive and relational elements such as humanness and intelligence of conversational agents because these attributes are crucial to determine usage and adoption patterns.

On the other hand, the literature stands scarce on the possible reasons and outcomes for consumer decision avoidance (Malodia et al., 2022) and deserves more attention from scholars and practitioners. Since conversational agents are relatively new and the research pertaining to their adoption has just commenced, Fernandes and Oliveira (2021) have urged to establish and develop of comprehensive models explaining their adoption phenomenon. In line with this.

Vimalkumar *et al.* (2021) suggested developing a theory-based understanding to research beyond the technological approach to identify the major antecedents that reflect the changing attitude of consumers towards the technological advancement. Therefore, the current study aims to bridge these gaps by identifying the strengthening variables leading to consumer adoption of conversational agents, developing a contextual interrelationship among them, and establishing a hierarchical theoretical framework using ISM methodology. For this purpose, the study has framed research questions which are as follows:

Q1. What are the crucial factors that explain the consumer adoption intention of conversational agents?

Q2. What are the interrelationships among the recognized factors using the MICMAC technique?

Q3. What is the hierarchical framework of the contextual variables that will provide strengthening levels based on dependence and driving power?

The current research is structured as follows: Section 2 describes and highlights the literature pertaining to contextual variables of adoption behaviour. Then, section 3 provides with solution methodology adopted for this paper, and accordingly, section 4 proposes the ISM development and procedural methods. Section 5 presents the MICMAC analysis and resultant ISM model. Lastly, Section 6 discusses results and concludes with the study's limitations and future directions.

2. Literature Review

The exponential growth of human-computer interaction has attracted the attention of both consumer behaviour and information system researchers. Numerous studies reveal the implication of the adoption behaviour of new technologies. Notably, authors have studied the adoption and usage of conversational agents in sales, marketing, and customer service, where they have conceptualized behavioural patterns of consumers. Following the literature review, the study has identified 15 variables that act as the determinants of the adoption behaviour for conversational agents. The identified variables are presented in Appendix A1 and are discussed in the following subsections.

2.1 Value of openness to change

Values are defined as motivational factors that encourage people to strive and achieve the required results (Schwartz, 2006). According to Westaby (2005), the reasons for behaviour do not arise in isolation rather, they emerge from values ingrained in an individual. Thus, values administer a path for an individual to investigate and choose the alternative behaviour. Moreover, past literature evidence that values influence attitude formation towards adopting new technology (Pillai & Sivathanu, 2020; Schwartz, 2012). Besides this, BRT and the theory of explained behaviour advocated that values help explain the adoption behaviour of new innovation (Pennington & Hastie, 1988; Westaby, 2005). Therefore, this construct is of crucial importance for the current study.

2.2 Perceived anthropomorphism

Based on the definition given by Kim and Mcgill (2018), perceived anthropomorphism refers to the human likeness of inanimate objects. More specifically, it is stated as the attribution of humanoid qualities, appearance, and traits to non-human entities (Troshani et al., 2020). Prior research conceptualizes anthropomorphism as a crucial and strengthening factor in creating positive perception and trust in the voice assistants (Pillai & Sivathanu, 2020). Hence, it is pivotal in the creation of attitude toward conversational agents and thereby leads to its adoption (R. Cai et al., 2022). Moreover, several studies have found that higher anthropomorphism leads to better interaction, greater enjoyment, and improved user experience (D. Cai et al., 2022; Moussawi et al., 2021).

2.3 Perceived intelligence

Perceived Intelligence is described as the perception about efficiency with which an assigned role is operated with subsequent commands. Particularly, a conversational agent is perceived as intelligent if it possesses the ability to sense, comprehend, and function as per the user’s requests. In research by Moussawi and Benbunan-fich (2021), perceived intelligence is positively associated with technology usefulness and ease of use. Therefore, it is argued as the determinant characteristic for the acceptance of voice assistants (Ha et al., 2020).

2.4 Performance expectancy

In the literature on human technology interaction, performance expectancy displays the perception of users towards voice assistant’s ability to facilitate greater performance and productivity (Aw et al., 2022; Venkatesh et al., 2003). It is further articulated as a prominent exogenous variable, which relates to users’ evaluation of the cost and benefit of voice assistant usage, ultimately leading to adoption decisions. Based on the UTAUT model, Performance expectancy has been generally found to positively affect perceived benefits and usage intention (Melián-gonzález et al., 2019).

2.5 Social influence

Another vital construct in the UTAUT theory is social influence. Social influence is the extent to which users’ social network guides voice assistants' utility and usage patterns (Lu et al., 2019). Furthermore, social influence is recognized as a source that helps to develop effective negotiation between self and social interest (Dogra and Kaushal, 2021; Howard and Howard, 2012). Many researchers claim that social influence improves consumers' trust and leads to usage intention (Mcknight et al., 2020; Mostafa & Kasamani, 2021). Hereby, this study considers social influence as an important antecedent of technology adoption decisions.

2.6 Perceived usefulness

The construct Perceived usefulness has been developed from the Technology acceptance model (TAM) and concentrates on the creation of subjective perception on individual adoption and usage of voice assistants (Davis, 1989). It is acknowledged to have a direct effect on the creation of attitudes towards adoption decisions (Pillai & Sivathanu, 2020). The extant literature provides evidence supporting the association between usefulness and individuals' behavioural intention (Belanche et al., 2019; Hsieh & Lee, 2021a; Shamsi, Al-Emran, & Shaalan, 2022).

2.7 Perceived ease of use

Perceived ease of use is articulated as the degree to which individuals perceive innovation as free from effort (Davis, 1989). Researchers have established that ease of use strongly impacts attitude and its relative influence on the adoption intention (Shaker et al., 2021). Additionally, researchers claim that behavioural intention increases only when a minimum effort is utilized for using the technology (Coskun-setirek & Sona Mardikyan, 2017; Sorensen & Jorgensen, 2021). Thus, perceived ease of use is considered a determinant for this study.

2.8 Perceived personalization

Perceived personalization is defined as the extent to which the voice assistants are considered competent in fulfilling users' tailored requirements (Wang et al., 2022). As per Lee and Cranage (2011), personalization is the degree to which the voice assistant anticipates the user's behavioural pattern, understands their requirement and provides a necessary output when requested. In addition, prior research demonstrates that perceived personalization generates higher cognitive trust for new technologies, thus positively influencing adoption intention (Chaves & Gerosa, 2021; Shi et al., 2021).

2.9 Perceived enjoyment

Perceived enjoyment is defined as the pleasure and satisfaction the users experience with the usage of the technology (C. Hsu & Lin, 2016). Past literature identifies that enjoyment is influenced by the helpfulness of voice assistants in delivering clear answers and convenience while operating a device (Sorensen & Jorgensen, 2021). Moreover, perceived enjoyment is claimed to have a significant relationship with behavioural intention, provided that the new technology functions effectively and operationalises emotional connection with consumers (Sorensen & Jorgensen, 2021). Thus, perceived enjoyment in this study is poised as a crucial psychological antecedent in the technology adoption context.

2.10 Perceived value

Perceived value is demonstrated as the difference between perceived cost and perceived benefit deriving from a product. A positive change in perceived value is found to significantly influence technology adoption decisions (C. L. Hsu & Lin, 2021). It is also considered as consumers' assessment of quality, usefulness, and conformity of goal achievement. As a result, perceived value shapes attitude formation towards the behavioural intention of new technology, making it a significant and essential variable for the study.

2.11 Perceived risk

Perceived risk is a determinant that entails several kinds of risks like performance risk, time risk, and security risk. It is considered as a major inhibiter to the adoption intention of voice assistants (Hubert et al., 2018). Moreover, it is also indicative of anxiety, discomfort, and fear of loss an individual experiences in an adoption decision (Featherman & Pavlou, 2003). Featherman and Pavlou (2003) argue that increased risk lowers the perceived usefulness of the new technology and thus shapes the attitude towards value accordingly. Thus, making it a strong predictor for the current study.

2.12 Traditional barrier

As per Ram and Sheth (1989), resistance towards innovation is a common instinctive behaviour, whereby consumer experiences psychological conflict in belief structure. Also, it is argued that a behavioural constraint arises when new technology necessitates users to change from accustomed traditions. The greater the change in tradition, the greater the resistance the user will face during the adoption of an innovation. Earlier literature demonstrates the implications of traditional barriers in multiple fields like banking, self–service technologies, IoT, tourism, and hospitality (Featherman & Pavlou, 2003; Vimalkumar et al., 2021). In sum, it substantially influences the adoption intention of the new technology.

2.13 Image barrier

Image barrier as a psychological construct is created due to a lack of information, stereotyped thinking and unfavourable associations (Ram & Sheth, 1989). Shimp and Bearden (1982) has described the image barrier as an extrinsic cue that impacts individual assessment of innovation. Image barrier creates a certain perceptual difficulty and complexity; hence, considered an essential barrier in the adoption intention of new technology.

2.14 Attitude towards conversational agents

Eagly and Chaiken (1998) defines attitude towards adoption as the psychological tendency to evaluate certain innovation with some amount of like or dislike. Moreover, it is considered as the individual's positive or negative notions about a particular behaviour. Owing to this, individuals are determined to undertake and evaluate a specific behaviour when they have positive feelings towards innovation. Therefore, attitude is argued to play a vital role in explaining consumer behaviour. This is confirmed by Kasilingam and Krishna (2020), who state that attitude positively correlates with behavioural intentions.

2.15 Adoption intention of conversational agents

Adoption intention refers to the likeliness of an individual to adopt and use new technology in the future (Coskun-setirek & Sona Mardikyan, 2017; Sorensen & Jorgensen, 2021). In addition, it is considered as the individual's purposeful and conscious action to undertake a particular behaviour. According to Hsu and Lin (2016), perceived value has a strong association with behavioural intention. Moreover, some studies have also found that the high-value perception leads to greater chances of adoption (C. Hsu & Lin, 2016; Johnson et al., 2018). Based on this, it is crucial to consider adoption intention for the current study.

3. Research Methodology

The Interpretative Structural Modelling (ISM) methodology was employed for the current study. The following section presents the meaning, process, and principles to conduct the proposed ISM approach.

3.1 Meaning of ISM

Interpretative Structural Modelling (ISM) is primarily an interpretive learning process that portrays variable order and transforms them into an organized framework (Mathiyazhagan et al., 2013). ISM was conceptualized by John Nelson Warfield (Warfield, 1973), which is fundamentally a systematic application of graph theory (Sindhu et al., 2016). ISM is a qualitative method that transforms complex articulated structural models into well-defined conceptual models illustrating interrelationships among variables (Gupta & Sahu, 2013; Sushil, 2012). The resultant model helps in providing a solution to the defined problem and objectively presents a comprehensible system (Sindhu et al., 2016). ISM follows a structured protocol, which is described below:

(1) Defining the variables and constructing structured self-interaction matrix (SSIM): ISM begins with the identification of variables pertaining to the research agenda or problem from the literature survey. After having a defined set of variables, a pairwise relationship matrix is prepared by a group judgment of experts (Mandal & Deshmukh, 1993; Singh & Samuel, 2018).

(2) Reachability Matrix: Results of SSIM are further replaced by binary numbers to attain the initial reachability matrix. Next, using the approach of transitivity, the final reachability matrix is derived. Transitivity illustrates that if X is associated with Y And Y is associated with Z, then X is certainly associated with Z.

(3) Level Partitioning: From the reachability matrix, the results are then apportioned into distinctive levels.

(4) ISM Model: The results of partitioned levels are then transfigured as a digraph, which is a structured model of the proposed question.

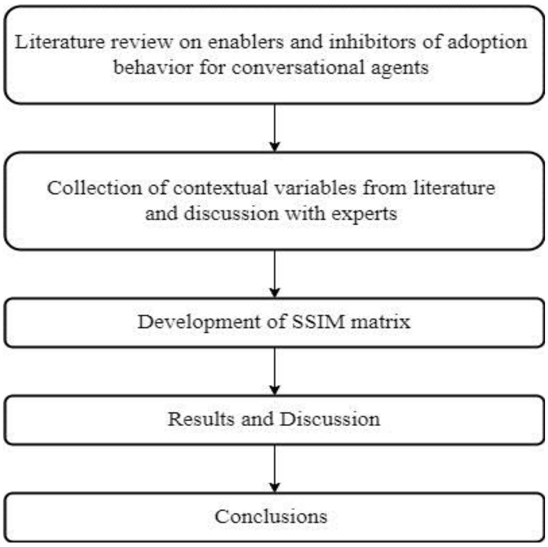

Fig. 1 Conceptual diagram of the methodology

4. Model development

The Process of ISM begins with identifying the variables and determining the contextual relationships among them. The ISM approach utilizes the practical knowledge and understanding of the experts in a particular area (Dubey & Ali, 2014; Yadav & Sagar, 2021). The discussion with experts dispels variables and the interrelationship that exists between them. Several techniques like literature surveys, open brainstorming sessions, questionnaires, open discussion among expert panels, workshops, nominal group techniques, and idea engineering workshops can be opted for the identification process of contextual variables (Ali et al., 2018; Mani et al., 2016).

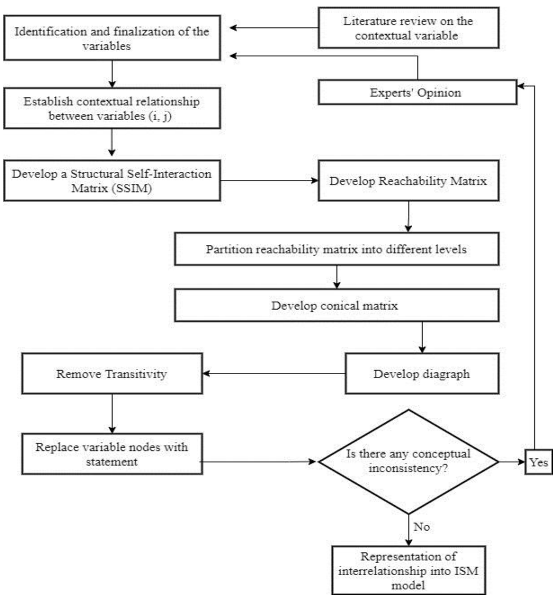

Fig. 2 Flow diagram for ISM

4.1 Structured self-interaction matrix (SSIM)

In accordance with ISM methodology, the contextual relationship between the variables was determined by expert opinion. The SSIM was developed after comparing each row with each column and assigned a code as per the defined set (V, A, X, O). The trajectory of the interrelationship among variables is represented by following the symbolic identifiers:

(1) V – variable i will help to achieve variable j;

(2) A - variable j will help to achieve variable i;

(3) X - variable i and j will help achieve each other; and

(4) O - variable i and j are unrelated.

According to the earlier stated principles, the SSIM was formulated, as presented in Table 1. For the development of SSIM, the number of pairwise comparisons is denoted as ((N)*(N-1)/2), where N is the number of key factors.

4.2 Reachability Matrix

After the formulation of SSIM, the following stage involves the transformation of SSIM into the initial reachability matrix (IRM). IRM is defined as a binary matrix wherein the codes are substituted in the form of 0 and 1. Following are the rules for the transformation of SSIM into IRM.

(1) If the code in the SSIM cell (i, j) is V, then the (i, j) value becomes 1 and the (j, i) value becomes 0 in the IRM.

(2) If the code in the SSIM cell (i, j) is A, then the (i, j) value becomes 0 and the (j, i) value becomes 1 in the IRM.

(3) If the code in the SSIM cell (i, j) is X, then the (i, j) value becomes 1 and the (j, i) value becomes 1 in the IRM.

(4) If the code in the SSIM cell (i, j) is O, then the (i, j) value becomes 0 and the (j, i) value becomes 0 in the IRM.

The IRM is reported in Table 2, which is in accordance with the above-stated principles.

Table 1: Structural self-interaction matrix (SSIM)

Variables	15	14	13	12	11	10	9	8	7	6	5	4	3	2
1. Value of Openness to change	V	V	V	V	V	V	V	V	V	V	V	V	V	V
2. Perceived Anthropomorphism	V	V	V	V	O	O	V	O	V	O	A	O	O	
3. Perceived Intelligence	V	V	V	V	V	V	V	O	O	V	A	V		
4. Performance Expectancy	V	V	V	V	V	V	A	A	A	X	A			
5. Social Influence	V	V	V	V	V	V	V	V	O	V				
6. Perceived Usefulness	V	V	X	X	X	X	V	O	A					
7. Perceived Ease of Use	V	V	X	X	X	V	V	O						
8. Perceived Personalisation	V	V	V	V	O	V	V							
9. Perceived Enjoyment	V	V	X	X	A	X								
10. Perceived Value	V	V	X	X	X									
11. Perceived Risk	V	V	V	X										
12. Traditional Barrier	V	V	X											
13. Image Barrier	V	V												
14. Attitude towards Conversational Agents	V													
15. Adoption intention of Conversational Agents														

Table 2: Initial reachability matrix (IRM)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Driving Power
1. Value of Openness to change	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
2. Perceived Anthropomorphism	0	1	0	0	0	0	1	0	1	0	0	1	1	1	1	7
3. Perceived Intelligence	0	0	1	1	0	1	0	0	1	1	1	1	1	1	1	10
4. Performance Expectancy	0	0	0	1	0	1	0	0	0	1	1	1	1	1	1	8
5. Social Influence	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	13
6. Perceived Usefulness	0	0	0	1	0	1	0	0	1	1	1	1	1	1	1	9
7. Perceived Ease of Use	0	0	0	1	0	1	1	0	1	1	1	1	1	1	1	10
8. Perceived Personalisation	0	0	0	1	0	0	0	1	1	1	0	1	1	1	1	8
9. Perceived Enjoyment	0	0	0	1	0	0	0	0	1	1	0	1	1	1	1	7
10. Perceived Value	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	8
11. Perceived Risk	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	9
12. Traditional Barrier	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	9
13. Image Barrier	0	0	0	0	0	1	1	0	1	1	0	1	1	1	1	8
14. Attitude towards Conversational Agents	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
15. Adoption intention of Conversational Agents	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Dependence Power	1	3	3	8	2	10	6	3	12	12	9	13	13	14	15	

Following this, the IRM is transformed as a final reachability matrix (FRM) post removal of transitivity with the help of specified rules. Firstly, the initial reachability matrix is multiplied by itself to arrive at transitivity. Next, in the resulted matrix the values, which are more than 1 are changed into 1. This procedure is followed up till transitivity is derived, which produces the FRM, reported in Table 3.

Table 3: Final reachability matrix (FRM)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Driving Power
1. Value of Openness to change	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
2. Perceived Anthropomorphism	0	1	0	1*	0	1*	1	0	1	1*	1*	1	1	1	1	11
3. Perceived Intelligence	0	0	1	1	0	1	1*	0	1	1	1	1	1	1	1	11
4. Performance Expectancy	0	0	0	1	0	1	1*	0	1*	1	1	1	1	1	1	10
5. Social Influence	0	1	1	1	1	1	1*	1	1	1	1	1	1	1	1	14
6. Perceived Usefulness	0	0	0	1	0	1	1*	0	1	1	1	1	1	1	1	10
7. Perceived Ease of Use	0	0	0	1	0	1	1	0	1	1	1	1	1	1	1	10
8. Perceived Personalisation	0	0	0	1	0	1*	1*	1	1	1	1*	1	1	1	1	11
9. Perceived Enjoyment	0	0	0	1	0	1*	1*	0	1	1	1*	1	1	1	1	10
10. Perceived Value	0	0	0	1*	0	1	1*	0	1	1	1	1	1	1	1	10
11. Perceived Risk	0	0	0	1*	0	1	1	0	1	1	1	1	1	1	1	10
12. Traditional Barrier	0	0	0	1*	0	1	1	0	1	1	1	1	1	1	1	10
13. Image Barrier	0	0	0	1*	0	1	1	0	1	1	1*	1	1	1	1	10
14. Attitude towards Conversational Agents	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
15. Adoption intention of Conversational Agents	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Dependence Power	1	3	3	13	2	13	13	3	13	13	13	13	13	14	15	

4.3 Level Partitions (LP)

The FRM is used to derive the reachability and antecedent set for each factor (Warfield, 1974). The factors that may assist in attaining the remaining factors are included in each factor's reachability set. A factor solely, plus another factor that could aid in reaching them, together make up the antecedent set. In addition, for each factor, the intersection sets are obtained. The factors for which the reachability and the intersection set are identical occupy the top tier of ISM hierarchical framework. Beyond its own tier, the top-tier factor would not assist in achieving any other factor. Consequently, this top-tier factor is identified and then distinguished and set apart from the other factors. In a similar manner, the subsequent top-tier factors are recognized for the next levels until all the factors obtain a certain level. The final ISM model and the digraph are created using these specified levels.

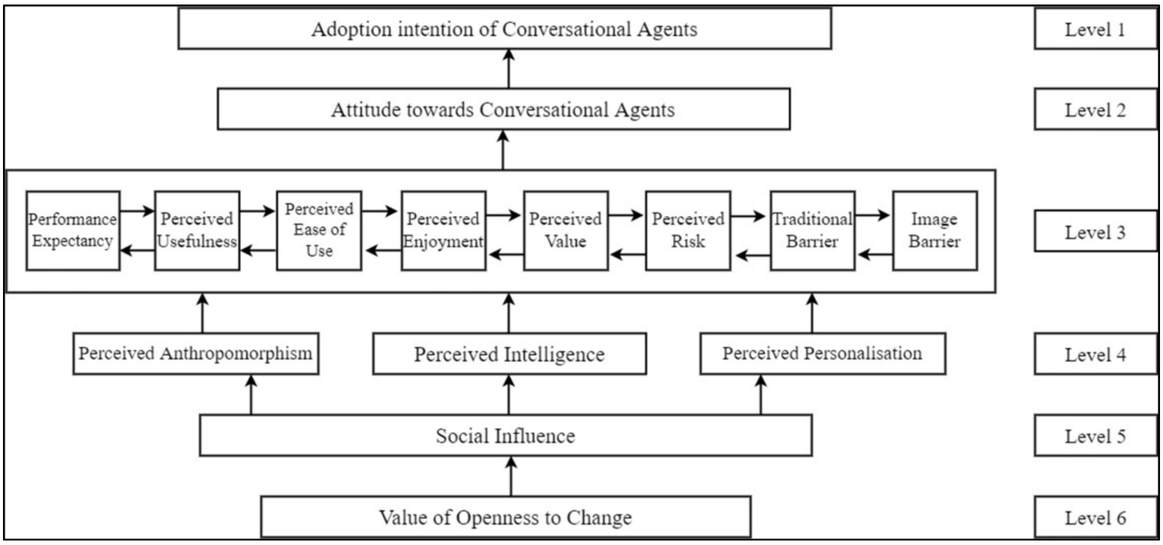

Fig. 3 Interpretative structural model

5. MICMAC analysis

Matrice d'impacts croisés multiplication appliquée á un classment (MICMAC) is a principle approach which is based upon matrix multiplication properties (Nandal et al., 2019). MICMAC investigates the driving power and dependence power of the variables, which assists in identifying and classifying crucial variables, thereby disseminating the adoption enablers of the voice assistants. In the present study, using driving and dependence power, the variables are categorized as follows:

(1) Autonomous variables: Quadrant 1 represents the autonomous variables. These are identified to possess low dependence and low driving power. They are completely independent and fairly disassociated from the arrangement.

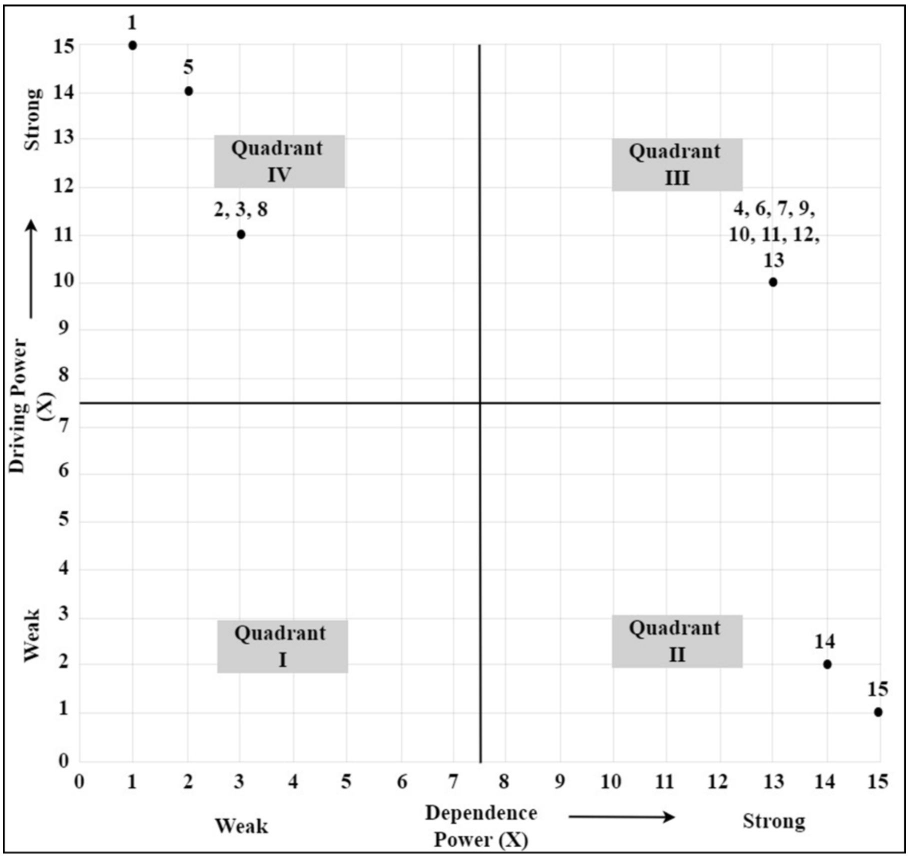

Fig. 4 MICMAC graph

(2) Dependent Variables: Quadrant 2 represents the dependent variables. These are identified to possess high dependence and low driving power.

(3) Linkage Variable: Placed at Quadrant 3, these are represented to possess high dependence and high driving power. They pose to have an effect not only on other variables but can also be dependent on them.

(4) Independent Variables: Quadrant 4 shows independent variables, which possess low dependence and high driving power.

Based on the principles mentioned above, the MICMAC graph (Fig. 4) is generated where x - axis denotes dependence power and y - axis denotes the driving power of the variable. This graph illustrates the hierarchy of variables and generates a conceptual model.

6. Discussions and Conclusions

The present study examines the interrelationship between several factors pertaining to the adoption of conversational agents. For this purpose, the study uses an ISM methodology that provides valuable insights and develops a structured framework of key enablers and barriers to adoption intention. According to the ISM framework (Fig. 3), the value of openness to change is at the sixth level, which posits at the base level of the hierarchical model. The value of openness primarily helps to determine the extent of social influence on individuals. Level fourth of the ISM framework consists of perceived anthropomorphism, perceived personalization, and perceived intelligence. These are arguably critical and encompass the major drivers for the evaluation of functionality and value of conversational agents. Further, all the eight factors at level three are mainly responsible for the formation of attitudes towards conversational agents. Based on the attitudes formed by the customers (Level 2), this then shapes the adoption decision of conversational agents (Level 1).

Subsequently, MICMAC analysis is employed to ascertain the driving and dependence power of different variables in the framework. The resulted MICMAC graph in Fig. 4 presents four quadrants which comprise various clusters based on driving power and dependence power. The first quadrant shows variables characterized by low driving power and low dependence power. Based upon study analysis, there exist no variables that fall in this quadrant, which implies that among the identified variables, none indicate low dependence and low driving power. The second quadrant represents variables which possess low driving power and high dependency and are referred as the dependent variable. These variables drive the topmost level due to their high level of dependency. In the present study, attitude towards conversational agents and adoption intention towards conversational agents capitulate at the topmost level and fall in the second quadrant. The third quadrant reveals linking variables that possess high dependence and high driving power. From the MICMAC diagram, performance expectancy, perceived usefulness, perceived ease of use, perceived enjoyment, perceived value, perceived risk, traditional barrier, and image barrier are ascertained as linkage variables. Lastly, the fourth quadrant reports independent variables, which comprise clusters of variables such as the value of openness to change, social influence, perceived anthropomorphism, perceived personalisation, and perceived intelligence. These variables are recognised to possess low dependence and high driving power. Overall, the resultant model portrays the key strengthening variables that will enable the production of superior operational and serviceable conversational agents redefining the current design configuration.

6.1 Theoretical Contribution

The current study contributes to the adoption literature by identifying prominent variables and determining their corresponding influence on consumer adoption decisions. The study provides context-specific variables instead of broadly construed beliefs. The identified model suggests how these variables are interrelated, which broadens the understanding of the features and functionality of conversational agents. By doing so, the study marks a substantial contribution by conceptualizing contextual variables and conveying their pivotal role in the formation of attitudes towards the decision to adopt conversational agents.

First, using ISM methodology, the findings reveal that perceived anthropomorphism, perceived personalization, and perceived intelligence are the strengthening antecedents of adoption behaviour in the discourse of conversational agents. Consequently, this amplifies the exploratory power of existing technology adoption models like TAM and UTAUT and thereby expands the body of literature. Moreover, models based on psychological theories, i.e., TPB and TRA, have focused primarily on psychological constructs (subjective norm, attitude, behavioural intention) without fully encapsulating other para-social constructs of AI-based technologies. While developing a context-specific framework that inspects not only utilitarian but also social, relational, and technological drivers, the study contributes to the holistic understanding of conversational agents' adoption. Second, the study further postulates social influence as a pertinent antecedent to promote para-social interaction and thus establishing belief and affirming the usefulness of conversational agents. This finding enhances the understanding of the influence of social networks and validates the assertion by Dogra and Kaushal (2021) that social status positively influences behavioural intentions. Third, most prior studies on the technology adoption phenomenon have used a single theoretical model (Dogra and Kaushal, 2021; Sorensen and Jorgensen, 2021), whilst this study has developed an integrated framework that highlights the role of the cognitive constructs and behavioural constructs that determine the technology adoption process. Thus, this study contributes to the literature by underpinning the behavioural mechanism of attitude formation in the context of technology adoption.

Finally, the identification and classification of facilitators and barriers from extensive literature review and expert opinion provide an orientation to future researchers to expedite the research on adoption behaviour and address the barriers that inhibit consumers to adopt AI-based technology. In parallel to this, the SSIM matrix encloses the interrelationship that subsists between the antecedents, which helps outlay their significance. Correspondently, the proliferated variables are classified on the basis of driving power and dependence power which exhibit the prime factors for the adoption phenomenon.

6. 2 Practical Contribution

Whilst this study provides evidence to the extant literature, it also offers additional insight to conversational agent design developers. For companies to benefit, the developers should incorporate human-like characteristics and personalized features, which ensures prompt functionality to the users. Consequently, the aforesaid design features reassure value and usefulness, which diminishes the scope for uncertain outcomes and generates compatibility with users. Hence, the developers should focus upon these factors and provide distinctive offerings to the consumers of this technology. Furthermore, marketing managers should start stimulating social influence and direct their focus on developing an effective marketing strategy which highlights how conversational agents resonates with customers' values, needs, and lifestyle. Sending signals to the customer about the conversational agent's features is crucial to make customers realise its utility and encourage them to use it in daily life. The results are also highly useful for brand managers and practitioners. Since agents are equipped to perform sophisticated functions and device integrations, it broadens the procedural and operational prospects to tailor the agent's functionality as per customers' needs and expectations.

The results would also be helpful for B2C practitioners for customer service organisations. In order to address customers' grievances and redressals, the organisation may consider using conversational agents for business communication and to deliver real-time solutions beyond business hours. This subsequently ensures that AI-powered conversational agents bring forth faster responses, reducing the waiting time of the customer. Moreover, the integration of conversation agents in business operations is expected to minimise customer service overheads. Consequent to the above implications, the findings of the study are also of substantial utility for the consumers as the improvised functionality of agents reduces search cost, provisions autonomy, and outlays potential benefits expected by them. This further ensures to elucidate perceptible benefits by providing the consumer a well-equipped and magnified technology-driven experience.

6.3 Limitations and future research directions

Whilst the study provides evidence of interrelationship among behavioural constructs, it also acknowledges the following limitations. First, the current study primarily focuses on the adoption and evaluation of conversational agents. Additional work might examine post-purchase experience, continuation and repurchase intention to better understand the consumer purchase journey. Second, the current study is an early attempt to explain the relationship between antecedents and outcomes of consumer adoption of conversational agents. Further studies can focus on other behavioural and situational factors and emphasise understanding of conversational agents' usage. Third, the study does not assure the statistical validation of the proposed model. Therefore, future research may extend upon validating the identified model with the help of structural equation modelling (SEM). Also, the analytical hierarchy process (AHP) and analytical network process (ANP) can be used to ascertain the strength of association among variables used in this study. Besides this, the interpretive ranking process (IRP) may be employed to assign ranks to variables concerning conversational agent adoption.

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Appendix A1

Table A1. Enablers and barriers of conversational agents' adoption			
S. No.	Variables	Description	References
1	Value of Openness to change	Values constitute as the initial step towards the adoption process. Values sets and administers the behaviour and guide towards the decisions regarding the adoption of innovation.	Schwartz (2006), Westaby (2005), Schwartz (2012), Pillai and Sivathanu (2020), Pennington and Hastie (1988)
2	Perceived anthropomorphism	Anthropomorphism is the attribution of human qualities and traits to inanimate objects. It ensures efficient interaction and helps in building the feeling of social connections.	Kim and Mcgill (2018), Troshani *et al.* (2020), Pillai and Sivathanu (2020), Cai, Li, *et al.* (2022), Moussawi and Benbunan-fich (2021)
3	Perceived intelligence	Intelligence is defined as the ability with which a device fulfils assigned roles and complete the task requested by the user.	Moussawi and Benbunan-fich (2021), Ha *et al.* (2020)
4	Performance expectancy	It refers to the expectations of an individual towards the technology to assist in the course of completion of the task.	Venkatesh *et al.* (2003), Aw *et al.* (2022), Melián-gonzález *et al.* (2019)
5	Social influence	It refers to the influence of environmental elements on consumer behaviour. Basically, it reflects other beliefs on a particular decision.	Lu *et al.* (2019), Howard and Howard (2012), Dogra and Kaushal (2021), Mcknight *et al.* (2020), Mostafa and Kasamani (2021)
6	Perceived usefulness	It is defined as the degree to which conversational agent is perceived to be functional and advantageous to the user.	Davis (1989), Hubert *et al.* (2018), Pillai and Sivathanu (2020), Shamsi *et al.* (2022), Hsieh and Lee (2021), Belanche *et al.* (2019)
7	Perceived Ease of Use	It refers to the extent to which a conversational device is perceived to be effort free and fulfils the assigned task.	Davis (1989), Shaker *et al.* (2021), Coskun-setirek (2017), Sorensen and Jorgensen (2021)
8	Perceived personalisation	Personalisation is defined as the degree to which the conversational agent intercepts individual usage and operates according to customised needs.	Wang *et al.* (2022), Shi *et al.* (2021), Chaves and Gerosa (2021)
9	Perceived enjoyment	It means the fulfilment, satisfaction, and gratification user experiences with the usage and possession of the technology.	Hsu and Lin (2016), Sorensen and Jorgensen, (2021)
10	Perceived value	Perceived value is defined as the remainder arising from perceived cost and perceived benefit of adoption and usage of a product.	Hsu and Lin (2021)
11	Perceived risk	Perceived risk refers to the probability of loss while in pursuit of a desired outcome during technology usage. It is a cumulation of uncertainty with the possibility of achieving an outcome.	Hubert *et al.* (2018), Featherman and Pavlou (2003)
12	Traditional barrier	It is psychological resistance that arises from cultural change, which inhibits the user from the direction of adoption.	Ram and Sheth (1989)
13	Image barrier	It refers to the perceptual notion that gems from stereotype thinking thus create an unfavorability.	Ram and Sheth (1989), Shimp and Bearden (1982)
14	Attitude towards Conversational Agents	It refers to the tendency of an individual about a certain innovation with a notion of approval or disapproval.	Eagly and Chaiken (1998), Kasilingam and Krishna (2020)
15	Adoption intention of Conversational Agents	It is defined as the subjective probability of user engagement regarding a particular product.	Coskun-setirek (2017), Sorensen and Jorgensen (2021), Hsu and Lin (2016),

Appendix A2

Table A2. Level Partitioning (LP)

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
1	1,	1,	1,	6
2	2,	1, 2, 5,	2,	4
3	3,	1, 3, 5,	3,	4
4	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
5	5,	1, 5,	5,	5
6	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
7	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
8	8,	1, 5, 8,	8,	4
9	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
10	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
11	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
12	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
13	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
14	14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14,	14,	2
15	15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,	15,	1

Appendix A3

Table A3. Level Partitioning Iterations 1

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,	1,	1,	
2	2, 4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 2, 5,	2,	
3	3, 4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 3, 5,	3,	
4	4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
5	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,	1, 5,	5,	
6	4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
7	4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
8	4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,	1, 5, 8,	8,	
9	4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
10	4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
11	4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
12	4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
13	4, 6, 7, 9, 10, 11, 12, 13, 14, 15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
14	14, 15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14,	14,	
15	15,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,	15,	1

Appendix A4

Table A4. Level Partitioning Iterations 2

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14,	1,	1,	
2	2, 4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 2, 5,	2,	
3	3, 4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 3, 5,	3,	
4	4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
5	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14,	1, 5,	5,	
6	4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
7	4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
8	4, 6, 7, 8, 9, 10, 11, 12, 13, 14,	1, 5, 8,	8,	
9	4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
10	4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
11	4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
12	4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
13	4, 6, 7, 9, 10, 11, 12, 13, 14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	
14	14,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14,	14,	2
15		1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14,		1

Appendix A5

Table A5. Level Partitioning Iterations 3

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	1,	1,	
2	2, 4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 5,	2,	
3	3, 4, 6, 7, 9, 10, 11, 12, 13,	1, 3, 5,	3,	
4	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
5	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	1, 5,	5,	
6	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
7	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
8	4, 6, 7, 8, 9, 10, 11, 12, 13,	1, 5, 8,	8,	
9	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
10	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
11	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
12	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
13	4, 6, 7, 9, 10, 11, 12, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,	4, 6, 7, 9, 10, 11, 12, 13,	3
14		1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,		2
15		1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,		1

Appendix A6

Table A6. Level Partitioning Iterations 4

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
1	1, 2, 3, 5, 8,	1,	1,	
2	2,	1, 2, 5,	2,	4
3	3,	1, 3, 5,	3,	4
4		1, 2, 3, 5, 8,		3
5	2, 3, 5, 8,	1, 5,	5,	
6		1, 2, 3, 5, 8,		3
7		1, 2, 3, 5, 8,		3
8	8,	1, 5, 8,	8,	4
9		1, 2, 3, 5, 8,		3
10		1, 2, 3, 5, 8,		3
11		1, 2, 3, 5, 8,		3
12		1, 2, 3, 5, 8,		3
13		1, 2, 3, 5, 8,		3
14		1, 2, 3, 5, 8,		2
15		1, 2, 3, 5, 8,		1

Appendix A7

Table A7. Level Partitioning Iterations 5

Variables	Reachability Set	Antecedent Set	Intersection Set	Level
1	1, 5,	1,	1,	
2		1, 5,		4
3		1, 5,		4
4		1, 5,		3
5	5,	1, 5,	5,	5
6		1, 5,		3
7		1, 5,		3
8		1, 5,		4
9		1, 5,		3
10		1, 5,		3
11		1, 5,		3
12		1, 5,		3
13		1, 5,		3
14		1, 5,		2
15		1, 5,		1

Appendix A8

Table A8. Level Partitioning Iterations 6				
Variables	**Reachability Set**	**Antecedent Set**	**Intersection Set**	**Level**
1	1,	1,	1,	6
2		1,		4
3		1,		4
4		1,		3
5		1,		5
6		1,		3
7		1,		3
8		1,		4
9		1,		3
10		1,		3
11		1,		3
12		1,		3
13		1,		3
14		1,		2
15		1,		1

***