

Factors Impacting Intentions in Adopting Artificial Intelligence- Based Solutions in Agriculture: An Indian Context

A

Thesis

**Submitted in Fulfilment of
the Requirements for the Award of the Degree of
DOCTOR OF PHILOSOPHY**



Submitted by

**Amit Sood
(Registration No. 951913001)**

Under the supervision of

Dr. Amit Kumar Bhardwaj

Associate Professor, L M Thapar School of Management,
Thapar Institute of Engineering & Technology, Patiala

Prof. R. K. Sharma

Vice Chancellor, Jaypee University of Information Technology, Solan

**L M Thapar School of Management
Thapar Institute of Engineering & Technology
Patiala-147004**

Declaration

I hereby declare that the work presented in the thesis entitled “Factors Impacting Intentions in Adopting Artificial Intelligence-Based Solutions in Agriculture: An Indian Context” for the award of degree of Doctor of Philosophy submitted to L.M. Thapar School of Management, Thapar Institute of Engineering and Technology, Patiala is an authentic record of my own research carried out under the supervision of Dr. Amit Kumar Bhardwaj, Associate Professor, L.M. Thapar School of Management, Thapar Institute of Engineering and Technology, Patiala and Dr. R. K. Sharma, Vice Chancellor, Jaypee University of Information Technology, Solan. Any material previously published or written by another author or person in the text is well acknowledged and referred in the thesis.



(Amit Sood)

Registration Number: 951913001

Certificate

This is to certify that the thesis entitled “Factors Impacting Intentions in Adopting Artificial Intelligence-Based Solutions in Agriculture: An Indian Context” is being submitted by Mr Amit Sood (Registration Number: 951913001), in fulfilment of the requirements for the award of degree of DOCTOR OF PHILOSOPHY in MANAGEMENT at L.M. Thapar School of Management, Thapar Institute of Engineering and Technology, Patiala, Punjab. It is a bona fide record of candidate’s original research work carried out under our supervision and guidance. To the best of our knowledge, the matter presented in this thesis has not been submitted to any other University or Institute for the award of any degree or diploma.



Dr. Amit Kumar Bhardwaj
Associate Professor,
L M Thapar School of Management,
Thapar Institute of Engineering & Technology,
Patiala



Prof. R. K. Sharma
Vice Chancellor,
Jaypee University of Information Technology,
Solana

Acknowledgement

With grace of the almighty, I have been able to bring my research work to this stage. I am thankful to the supreme power for giving me enough strength and courage to keep it going throughout the research journey.

I extend my heartfelt thanks to my esteemed supervisors, Dr. Amit Kumar Bhardwaj and Prof. R. K. Sharma, for their unwavering support, invaluable guidance, and constructive feedback throughout this research journey. Their expertise, encouragement, and patience have been instrumental in shaping the direction and quality of this work. I consider myself fortunate to have a long and cherishing association with Prof. R. K. Sharma to get his continued guidance and blessings.

I am also deeply indebted to the faculty members of LM Thapar School of Management and Thapar Institute of Engineering and Technology for their exceptional teaching, mentorship, and dedication to fostering a conducive academic environment. My special thanks to Dr. Harjot Singh and Dr. Inderjit Kaur for their guidance and support right from the start of this journey.

My sincere thanks to all the members of Doctoral Committee Dr. Sonia Garg, Dr. Sandeep Goyal, and Dr. Arunesh Garg for their teaching, direction and motivation that inspired me throughout my studies.

I would like to express my profound gratitude to my parents and all family members for their unending love, understanding, and encouragement. I am thankful to my spouse Dr. Sakshi Kaushal for mentoring, supporting and motivating me at difficult phases of the research work. Her unwavering belief in my abilities and constant support have been my source of strength during the challenging moments of this academic pursuit. I am grateful to my daughter Savi and son Arnav for their cooperation and support during the period of research.

Finally, I extend my thanks to all the participants and respondents who willingly participated in this study. Their valuable insights and contributions have enriched the findings of this thesis.

This thesis represents the culmination of years of dedication, hard work, and collaboration. I am truly grateful to everyone who has played a part in this journey, and I hope that this work contributes meaningfully to the field of digital technologies in agriculture. Thank you all for your unwavering support and encouragement.

Abbreviations used in Thesis

Abbreviation	Full Form
AI	Artificial Intelligence
AGFI	Adjusted Goodness of Fit Index
AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Composite Reliability
DAT	Digital Agriculture Technologies
DF	Degree of Freedom
DoI	Diffusion of Innovation
EFA	Exploratory Factor Analysis
GFI	Goodness of Fit Index
GPS	Global Positioning System
IFI	Incremental Fit Index
IoT	Internet of Things
IS	Information System
IT	Information Technology
ML	Machine Learning
MSV	Maximum Shared Variance
PDA	Personal Digital Assistant
PAT	Precision Agriculture Technologies
RMSEA	Root Mean Square Error Approximation
SEM	Structure Equation Modeling
SFT	Smart Farming Technologies
TAM	Technology Acceptance Model
TLI	Trucker Louis Index
TOE	Technology Organization Environment
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor

Abstract

Earth is now a habitat of eight billion human beings who depend on the limited resources available on the planet to survive. The increasing population is constantly exerting pressure on present agricultural production systems and demands for increased production to ensure food security across the globe. Digital technologies including Artificial Intelligence (AI) enable the farmers and facilitators for making better decisions during crop lifecycle management which in turn leads to lesser damages and increased productivity. Through the use of machine learning algorithms, AI systems can analyze vast amounts of data, including weather patterns, soil conditions, and crop characteristics, to provide valuable insights for farmers. This enables optimized resource allocation, precise irrigation and fertilization techniques, and timely pest detection and control, ultimately increasing crop yields while reducing costs and environmental impact.

Despite the large number of perceived benefits and government plans, the adoption level of AI-based solutions in agriculture is quite low. As a step towards bridging the gap between the present situation of agricultural production and a target of zero hunger identified as sustainable development goal (SDG) by the United Nations, this study empirically evaluates the determinants that influence adoption of AI-based solutions in agriculture. To understand and evaluate the perspectives of farmers (end-users of the solution) and facilitators (enablers in the agricultural system) involved in the diffusion of new agricultural technologies, this study uses an integrated framework built on three eminent theories from Information Systems, namely Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovation (DoI) and Technology-Organization-Environment Framework (TOE Framework). Using survey data of farmers and facilitators from two states in Northern India, this study examines the interaction of independent variables and validates the proposed framework using Structural Equation Model (SEM).

The analysis of farmers' data reveals that user expectations, technology factors, social influence and facilitating conditions are significant factors influencing their intention to adopt AI-based solutions. Farmers recognize the benefits of AI technology in terms of increased productivity, efficiency, and ease of use. Compatibility with existing practices and the availability of resources and information are also important considerations.

In the case of facilitators, the study highlights that facilitating conditions, such as knowledge, resources, and support, plays a crucial role in their intention to adopt AI-based solutions.

Compatibility is also a significant factor influencing adoption intent of facilitators. Facilitators express concerns about the cost, efficiency, and technical risks associated with the new technology.

The given framework significantly explains the adoption intention of farmers and facilitators, hence enhances understanding of researchers and practitioners to increase adoption of AI-based solutions for sustainable agriculture. This study contributes to the understanding of the factors influencing the adoption of AI-based solutions in agriculture and provides practical implications for promoting their adoption. By addressing the specific needs and challenges faced by farmers and facilitators, the study paves the way for the successful integration of AI technology in agriculture, leading to improved productivity, sustainability, and decision-making in the sector.

Table of Contents

Chapter 1 Introduction	1
1.1 Introduction	1
1.2 Role of Technology in Agriculture.....	2
1.3 Artificial Intelligence in Agriculture	5
1.4 Overview of the research	7
1.5 Research Problem	7
1.6 Research Objective	8
1.7 Scope of the Research.....	8
1.8 Rationale for the study	8
1.9 Organization of Thesis.....	9
Chapter 2 Literature Review.....	10
2.1 Introduction	10
2.2 Theoretical Foundation	10
2.2.1 Technology Acceptance Model (TAM)	11
2.2.2 Theory of Reasoned Action (TRA)	11
2.2.3 Theory of Planned Behaviour (TPB)	12
2.2.4 Unified Theory of Acceptance and Use of Technology (UTAUT)	13
2.2.5 Diffusion of Innovation (DoI)	14
2.2.6 Technology-Organization-Environment Framework (TOE Framework).....	15
2.3 Review of Literature	18
2.3.1 Overview of the selected studies	20
2.3.2 Analysis of selected studies.....	30
2.4 Research Gap.....	38
2.5 Development of framework for present study.....	39
2.5.1 Individual characteristics.....	42

2.5.2	Environmental factors	43
2.5.3	Structural factors.....	44
2.5.4	Technology factors.....	45
2.5.5	Demographic factors	46
2.6	Summary of Literature Review	46
Chapter 3 Research Methodology.....		48
3.1	Research Methodology	49
3.1.1	The Methodological Process	50
3.2	Unit of analysis.....	52
3.3	Population and Respondents	53
3.4	Sampling	54
3.5	Measuring Adoption Intent for AI-based Solutions in Agriculture.....	55
3.5.1	Scale Formation.....	56
3.5.2	Data Collection	57
3.6	Reliability and Validity of Research Instruments.....	58
3.7	Data Analysis Methods	58
3.7.1	Descriptive Statistics.....	59
3.7.2	Exploratory Factor Analysis.....	59
3.7.3	Confirmatory Factor Analysis	60
3.7.4	Convergent Validity and Discriminant Validity.....	60
3.7.5	Indices	61
3.7.6	Structural Equation Modeling	61
3.8	Summary	62
Chapter 4 Data Analysis and Results		63
4.1	Data Analysis for Farmers	63
4.1.1	Descriptive Statistics.....	63
4.1.2	Reliability Analysis.....	65

4.1.3	Exploratory Factor Analysis	68
4.1.4	Confirmatory Factor Analysis	72
4.1.5	Research Hypotheses	76
4.1.6	Structural Equation Modeling	77
4.2	Data Analysis for Facilitators.....	80
4.2.1	Descriptive Statistics.....	80
4.2.2	Reliability Analysis.....	83
4.2.3	Exploratory Factor Analysis.....	85
4.2.4	Confirmatory Factor Analysis	89
4.2.5	Research Hypotheses	93
4.2.6	Structural Equation Modeling	93
Chapter 5	Discussions, Contributions and Implications	97
5.1	Discussion on study using Farmers' data.....	97
5.2	Discussion on study using Facilitators' data	100
5.3	Contributions	102
5.4	Implications	103
5.4.1	Theoretical Implications.....	103
5.4.2	Practical Implications.....	104
5.5	Summary	104
Chapter 6	Conclusions and Future Scope.....	106
6.1	Conclusion.....	106
6.2	Limitations	108
6.3	Suggestions for future research	108
	References	110
	Appendix.....	125

Table of Figures

Figure 1.1: Journey of development in agriculture	2
Figure 1.2: Data flow diagram for agricultural process	5
Figure 1.3: Different stages of agriculture and possible use of AI	6
Figure 2.1: Technology Acceptance Model (Davis, 1989)	11
Figure 2.2: Theory of Reasoned Action (Fishbein & Ajzen, 1975).....	12
Figure 2.3: Theory of Planned Behaviour (TPB) (Ajzen, 1991)	13
Figure 2.4: Unified Theory of Acceptance and Use of Technology (Venkatesh, 2003)	14
Figure 2.5: Diffusion of Innovation (Rogers, 2003)	15
Figure 2.6: TOE Framework (Tornatzky et.al. 1990)	16
Figure 2.7: Article selection process.....	19
Figure 2.8: Yearly trend of publications	20
Figure 2.9: Distribution of methods used in the selected studies	29
Figure 2.10: Geographic distribution of selected studies.....	29
Figure 2.11: Analysis of factors from selected articles.....	41
Figure 2.12: Integrated framework based on literature for present study	42
Figure 3.1: Methodological process.....	51
Figure 4.1: Correlation among items from farmers' data.....	67
Figure 4.2: Scree Plot for EFA using data from farmers	69
Figure 4.3: Measurement Model for CFA using data from farmers	74
Figure 4.4: Evolved Model for farmers with latent factors using EFA	76
Figure 4.5: Results of Path Analysis for data from farmers	79
Figure 4.6: Correlation among the items from facilitators' data	84
Figure 4.7: Scree plot for EFA using data from facilitators	87
Figure 4.8 Measurement Model for CFA using data from facilitators	90
Figure 4.9: Evolved Model for facilitators with latent factors using EFA.....	93
Figure 4.10: Results of Path Analysis for data from facilitators	95

List of Tables

Table 2-1: Summary of included studies.....	21
Table 2-2: Theoretical frameworks utilised in studies	28
Table 2-3: Technologies studied in the selected articles.....	30
Table 2-4: Journal, Country, H Index, Citation and Quality evaluation scores (May 2022) ..	32
Table 2-5: Summary of self-reported independent variables (arranged in ascending order) ..	35
Table 3-1: Host Institution-wise distribution of KVKs.....	54
Table 4-1: Respondents profile	64
Table 4-2: Mean, Standard Deviation and Median of the items (N=486).....	65
Table 4-3: Reliability Analysis using Cronbach's alpha.....	66
Table 4-4: Collinearity statistics	68
Table 4-5: Values of KMO	70
Table 4-6: Factor loading	71
Table 4-7: Interpretation of latent factors.....	72
Table 4-8: Calculation of Composite Reliability, Discriminant Validity, AVE and MSV	73
Table 4-9: Cross-loading matrix	75
Table 4-10: Goodness-of-fit indices	76
Table 4-11: Goodness-of-fit indices for Structural Model.....	77
Table 4-12: Regression weights for Structural Model	78
Table 4-13: Hypotheses Substantiation.....	79
Table 4-14: Profile of Respondents	80
Table 4-15: Mean, Standard Deviation and Median of the items (N=198).....	82
Table 4-16: Reliability Analysis using Cronbach's alpha.....	83
Table 4-17: Collinearity statistics	84
Table 4-18: Values of KMO	86
Table 4-19: Factor loading	88
Table 4-20: Interpretation of latent factors.....	89
Table 4-21: Calculation of Composite Reliability, Discriminant Validity, AVE and MSV ...	91
Table 4-22: Cross-loading matrix	92
Table 4-23: Goodness-of-fit indices	92
Table 4-24: Goodness-of-fit indices for Structural Model.....	94
Table 4-25: Regression weights for Structural Model	94

Table 4-26: Hypotheses Substantiation.....	96
--	----

Chapter 1 Introduction

1.1 Introduction

Agriculture has been an essential component of social and economic development of a country as it serves the basic need of living for the human generation. It is a vital sector that plays a crucial role in sustaining human life, ensuring food security, and supporting economic development worldwide. The primary objectives of agriculture include producing an adequate and diverse food supply to meet the nutritional needs of a growing global population, generating income and employment opportunities, and ensuring the sustainability of natural resources. Moreover, agriculture has expanded beyond traditional farming practices to encompass agribusiness, agro-industries, agricultural research, and rural development. It contributes significantly to the economy of many countries, particularly those with a strong agricultural base.

Agriculture includes: (a) cultivating and harvesting crops such as grains (wheat, rice, corn), vegetables, fruits, oilseeds, pulses, and fiber crops (cotton, jute) and includes practices like land preparation, sowing or planting, irrigation, pest control, and harvesting; (b) livestock farming which involves rearing of animals for various purposes, including meat, milk, eggs, wool, and leather. It includes animal husbandry practices such as breeding, feeding, housing, disease control, and management; (c) agriculture value chains encompass the entire process of production, processing, packaging, distribution, and marketing of agricultural products. It includes activities like post-harvest handling, storage, transportation, and market linkages to ensure the smooth flow of products from farms to consumers. Value chains also involve value addition activities such as processing agricultural products into value-added goods like flour, dairy products, canned fruits, and meat products. It plays a vital role in connecting farmers with consumers and ensuring the availability of quality products in the market.

Recently, the world population reached the milestone of eight billion (United Nations, 2022). While it is an obvious outcome of improved health conditions and increased life expectancy across the globe, the experts agree that the overpopulation on the planet is a concern for the limited resources available on the planet. The most essential resource for human beings besides water is the food which is largely produced through agriculture. It is noteworthy that in comparison to increasing world population, the agricultural land has remained at the level of

about 37% during 2000-2016 (World Bank, 2016). This growing trend poses significant challenges and implications for global food security and agricultural production.

With present agricultural production, 8.9% of the total world population is hungry and the target to meet Zero Hunger by 2030 appears to be unachievable as the production levels are below threshold (FAO, 2020). Although agriculture has evolved significantly over the time with the support of technological development to maintain the balance between demand and supply, limited agricultural resources draw the attention of researchers and organizations to enhance productivity for meeting future demand (Elferink & Schierhorn, 2016). Agriculture also faces challenges such as climate change, water scarcity, soil degradation, pests and diseases, and market fluctuations. To address these challenges, sustainable agricultural practices are being promoted, focusing on resource efficiency, environmental conservation, and the well-being of farmers.

1.2 Role of Technology in Agriculture

The journey of agriculture began since the early civilizations and the agricultural practices majorly relied on animal power (Figure 1.1). In economic terms, the agriculture sector used to be highly labour-intensive and performed low on productivity until the industrial revolution influenced it in 19th century. This segment of the journey was named ‘traditional agriculture’ or Agriculture 1.0. With the industrial revolution, animal power was replaced with combustion engines (Zambon *et al.*, 2019) along with synthetic fertilizers and pesticides which triggered significant increase in agriculture production levels. This phase is popularly known as ‘Green Revolution’ or ‘Agriculture 2.0’ (CEMA, 2017). The third phase, ‘Agriculture 3.0’ or

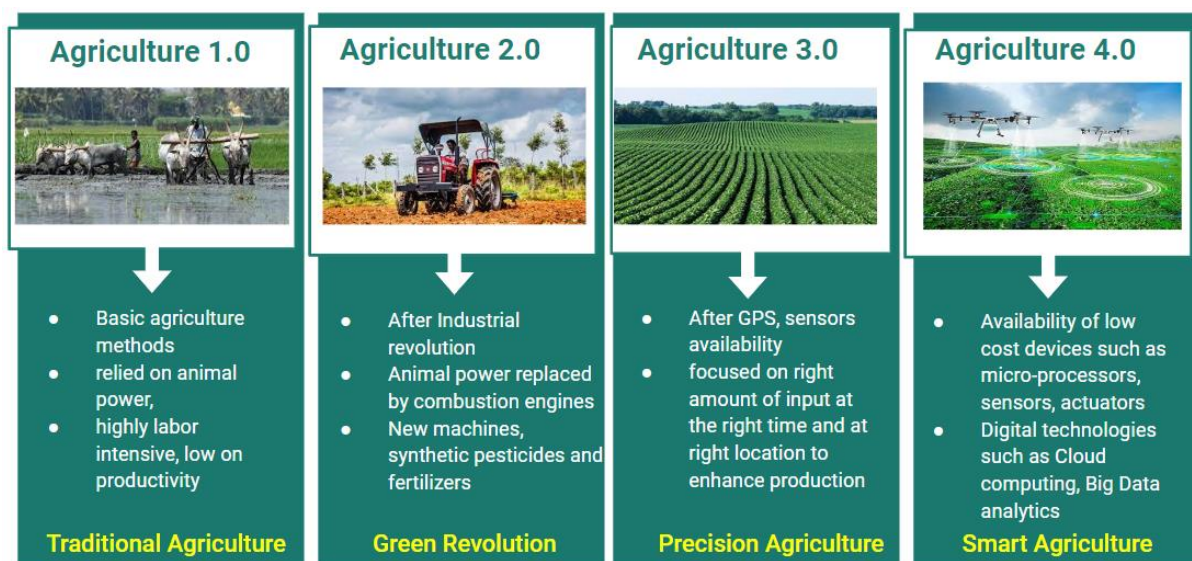


Figure 1.1: Journey of development in agriculture

‘Precision Agriculture’, made use of sensors, computer programs, GPS and other techniques to focus on right amount of input at the right time and at the right location to enhance productivity in fields.

After the development of several digital technologies, such as IoT, Big Data, AI, Cloud Computing *etc.* (Gacar *et al.*, 2017), and introduction of low cost devices such as micro-processors, sensors, actuators (Bronson & Knezevic, 2016), a new era of agriculture, namely “Agriculture 4.0” got triggered in 21st century (Zhai *et al.*, 2020). Agriculture 4.0, also known as "Smart Farming" or "Digital Agriculture," refers to the integration of digital technologies and data-driven approaches in agricultural production. It represents a transformative shift in the way farming is practiced, aiming to enhance productivity, efficiency, and sustainability. Here are some key digital technologies and their applications in agricultural production under Agriculture 4.0 (Gómez-Chabla *et al.*, 2018; Patrício & Rieder, 2018; Verdouw *et al.*, 2016; Wolfert *et al.*, 2017) :

1. **Internet of Things (IoT):** IoT enables the interconnectivity of various devices and sensors on the farm. These sensors collect data on soil moisture, temperature, humidity, and crop growth, providing real-time monitoring and insights for precision farming practices.
2. **Big Data and Analytics:** Advanced analytics techniques are employed to process large volumes of agricultural data, including weather patterns, soil conditions, and crop characteristics. Analysis of this data helps farmers make data-driven decisions, optimize resource allocation, and predict crop yields.
3. **Remote Sensing and Imaging:** Satellite imagery, drones, and aerial sensors capture high-resolution data, enabling farmers to monitor crop health, detect diseases, pests, and nutrient deficiencies. This facilitates targeted interventions, reducing the need for widespread application of agrochemicals.
4. **Precision Agriculture:** Precision agriculture involves applying inputs, such as fertilizers, water, and pesticides, precisely where and when they are needed. GPS technology, coupled with data from sensors and imaging, allows farmers to precisely map field variability and apply inputs accordingly, minimizing waste and improving efficiency.
5. **Robotics and Automation:** Robots and autonomous machinery are increasingly used in agricultural operations such as planting, seeding, harvesting, and weed control. These technologies reduce labor requirements, increase accuracy, and enable 24/7 operations.

6. **Blockchain Technology:** Blockchain provides a secure and transparent platform for recording and tracking agricultural transactions, ensuring traceability and improving supply chain management. It can help authenticate organic or fair-trade certifications, enable seamless transactions, and build trust between farmers and consumers.
7. **Farm Management Systems:** Integrated software platforms assist farmers in managing farm operations, crop rotation, inventory management, and financial analysis. These systems centralize data, facilitate decision-making, and streamline farm management tasks.

Digital technologies are shaping the world in a meaningful and productive way by touching and enriching our lives across all domains including healthcare, agriculture, energy, engineering, construction and transport (Aljawder & Al-Karaghoul, 2022; Gizelis *et al.*, 2022). The convergence of computer technologies and communication networks paved the way for digital technologies to reach the end user easily through small handheld computing devices such as smartphones, Personal Digital Assistants (PDAs), GPS devices *etc.* Digital technologies have the capability of transforming agricultural systems to be more productive through efficient use of available resources (Shang *et al.*, 2021). Digital Agricultural Technologies (DAT), Precision Agriculture Technologies (PAT), Smart Farming Technologies (SFT) are few examples to illustrate the digitization of agricultural processes and demonstrate the capabilities of information technology combined with communication networks through high production and easy operations (Klerkx *et al.*, 2019; R. Kumar, 2021). Although precision agriculture is one of the forms of digital agriculture (Carolan, 2018), some authors consider that Smart Farming is a broader concept as it includes digitalization of supply chains and food systems while Agriculture 4.0 is even larger domain as it may also include other technologies such as gene editing (Rose & Chilvers, 2018; Wolfert *et al.*, 2017).

Automation has replaced traditional methods of operation in farming and enabled the end user with real-time data analysis for accurate and faster decision making. Technologies such as computer vision (Patrício & Rieder, 2018), IoT (Gómez-Chabla *et al.*, 2018), Big Data (Wolfert *et al.*, 2017) and Machine Learning (Sharma *et al.*, 2020) have enabled agriculture sector with collection, storage, analysis and presentation of data in a highly effective manner with less manual efforts as illustrated in Figure 1.2. Additionally, artificial intelligence methods simplify the data analysis and empower the end user with enhanced decision making capability as compared to traditional systems of managing agricultural processes (Hildebrand *et al.*, 2020). Digital Agriculture comprising agri-technology and precision farming is an outcome of

application of data-driven technologies in agriculture leading to higher agricultural productivity and minimizing impact on the environment (Fishman *et al.*, 2020; Fuentes *et al.*, 2020; Liakos *et al.*, 2018). Smart Farming is a typical example that uses sensors, infrared cameras and Unmanned Aerial Vehicles (UAVs) replacing humans for data collection (Mukherjee *et al.*, 2019; D Pivoto *et al.*, 2018). Through machine learning algorithms, a better selection of crops, improved prediction on crop yield and disease, weather forecasting, minimum support price and smart irrigation have been made possible.

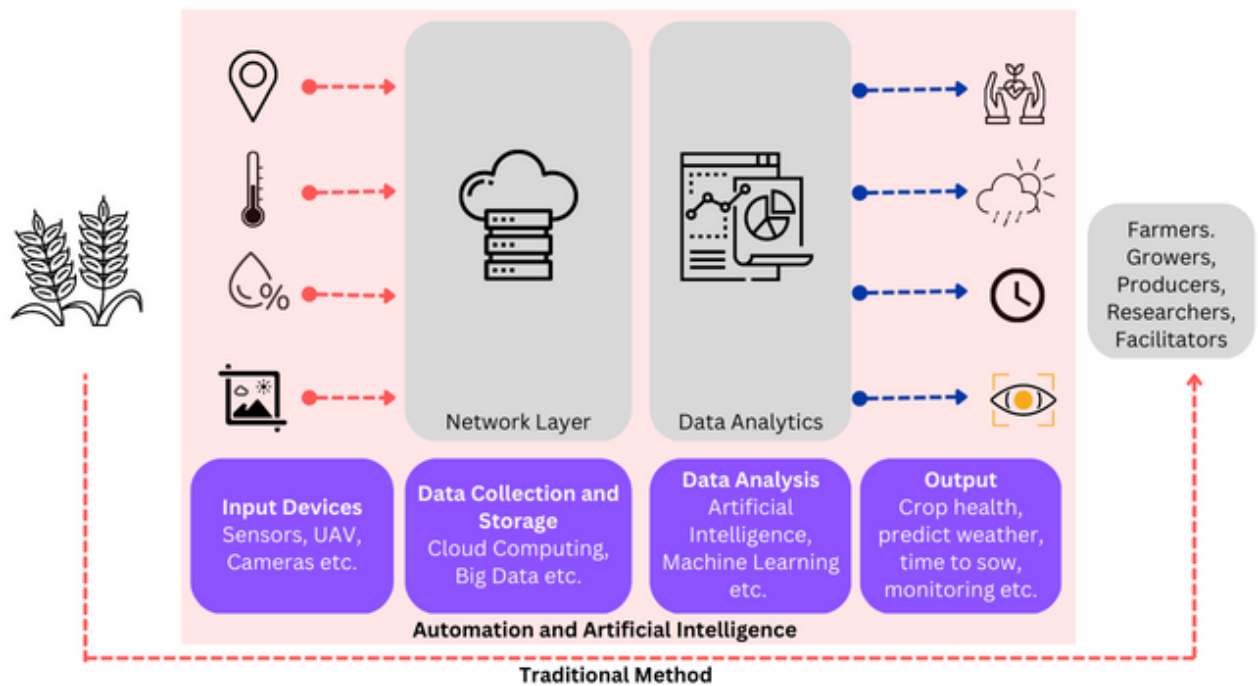


Figure 1.2: Data flow diagram for agricultural process

The adoption of these digital technologies in Agriculture 4.0 holds significant potential to optimize production, minimize environmental impact, improve resource efficiency, and enable sustainable farming practices. It empowers farmers with real-time data, actionable insights, and automation, ultimately enhancing productivity and contributing to the future of agriculture.

1.3 Artificial Intelligence in Agriculture

In agriculture, decision making is very critical aspect for good productivity and higher returns. At various stages such as selection of seed, identification of time for sowing, identification of crop disease, maintaining moisture level of crop, regulated irrigation *etc.*, farmers generally prefer to check physically and use their experience to make a decision (Sood *et al.*, 2021). With advancement in digital technologies, there are technical solutions and applications available to enable farmers with suitable inputs for making better decisions. These applications utilize big

data, machine learning and artificial intelligence to suggest suitable inputs for making decisions. AI combined with agriculture provides a vast domain of opportunities to explore and address the issues related to agricultural production efficiency in several ways (Klerkx *et al.*, 2019). As AI enables the end user with usable insights for faster and accurate decision making by analysing real-time data (Griva *et al.*, 2022), agricultural business units also prefer decision support systems based on artificial intelligence (Samantaray & Pant, 2017; Zhai *et al.*, 2020). AI helps with enriched insights for every stage in agriculture as shown in Figure 1.3 at a broad level for Crop and Livestock management. Beginning with pre-production, applications of AI enable farmers for selection of seed and suggest appropriate time for sowing based on weather conditions and analysis of historical information using Machine Learning. Similarly, in the production stage, activities like irrigation and crop health monitoring are enriched by AI to maintain moisture level and protect crops from diseases. Predicting economic value of future yield from satellite images, inventory control with predictive analysis of stock are few examples related to use of AI in supply chain management. With its high analytic capability, AI resides at the core of a solution being used under PAT, DAT and SFT.

Sector	Agriculture											
Domain	Crop										Livestock	
Stage	Pre-production		Production						Post-production		Operations Management	
Activity	Selection of seeds	Sowing	Irrigation		Crop Health Monitoring				Supply Chain		Monitoring	Productivity control
AI use cases	Predictive yield based insights	Time to sow predictions	Weather predictive irrigation	Moisture level controlled irrigation	Image analysis for disease identification	Early warning on pest/disease outbreak	Soil analysis	Real-time monitoring using drones	Stock tacking and predictions	Predicts economic value of future yield	Camera controlled health monitoring	Milk Production Tracking and predictive analysis

Figure 1.3: Different stages of agriculture and possible use of AI

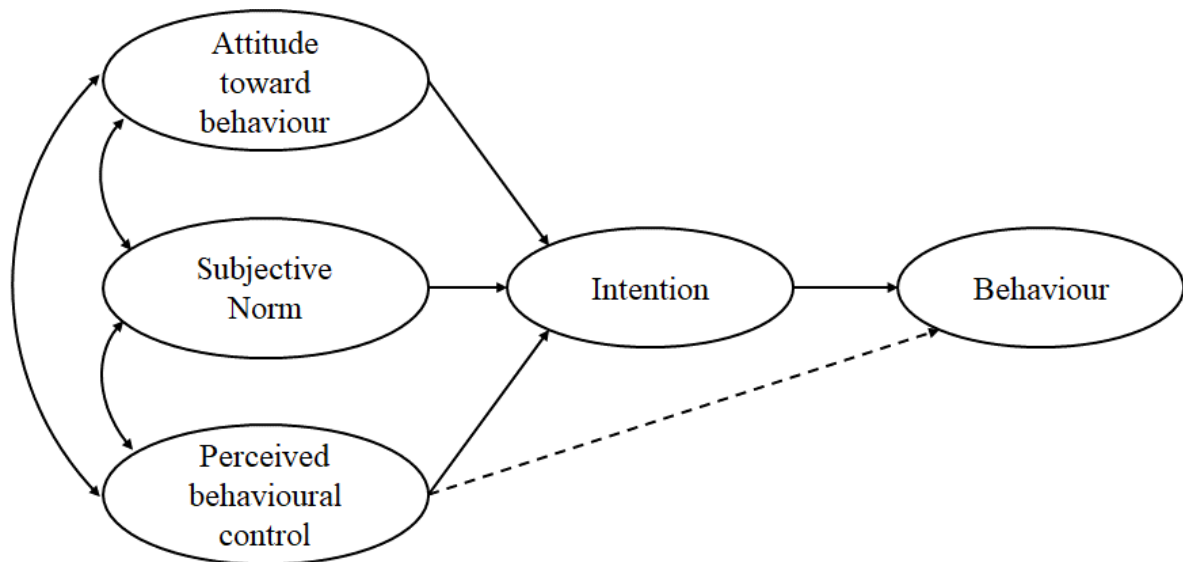


Figure 2.3: Theory of Planned Behaviour (TPB) (Ajzen, 1991)

Numerous studies (Monteleone *et al.*, 2020; Shang *et al.*, 2021) have supported the validity and applicability of TPB, highlighting its ability to predict and explain a wide range of behaviors. Researchers have utilized TPB to design interventions, identify key determinants of behavior change, and inform policy decisions in areas such as health promotion, environmental conservation, and marketing strategies. Overall, TPB's focus on attitudes, subjective norms, and perceived behavioral control makes it a valuable tool for understanding and predicting human behavior, contributing to the development of effective interventions and strategies aimed at behavior change.

2.2.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003) is a comprehensive framework that aims to explain user acceptance and adoption of technology. UTAUT integrates various theories, including the Theory of Reasoned Action, Technology Acceptance Model (TAM), and the Theory of Planned Behavior, to provide a holistic understanding of technology adoption. UTAUT incorporates various factors that influence technology adoption, including performance expectancy, effort expectancy, social influence, and facilitating conditions (Figure 2.4). It also considers the moderating effects of gender, age, and experience. UTAUT emphasizes that user intentions to adopt technology are determined by the combined influence of these factors. The model has been widely used to study technology acceptance and has demonstrated its effectiveness in predicting user behavior across different domains and technologies. UTAUT provides valuable insights for researchers, practitioners, and policymakers to understand and promote technology adoption and usage.

1.4 Overview of the research

This research is an attempt towards realization of technology benefits of AI-based solutions in agriculture. The think tank of Government of India, NITI Aayog has detailed plan of ‘Doubling Farmers’ Income’ to enhance wellbeing of farmers through holistic development of agricultural systems (*Report of the Committee on Doubling Farmers’ Income*, 2018). A strategy plan named ‘National Strategy for Artificial Intelligence’ has been released which aims to leverage use of AI technologies to revolutionize farming practices, enhance productivity, and ensure sustainable agricultural growth (A. Kumar, 2020). As AI can enable accurate crop prediction, soil health monitoring, pest detection, and efficient resource management, thus AI-powered solutions can empower farmers, improve yields, optimize resource utilization, and ultimately contribute to the economic upliftment of rural communities and the nation as a whole. With detailed study in this domain, this research contributes towards the technology initiative by government in agriculture.

1.5 Research Problem

Artificial intelligence has immense potential to increase the efficiency and productivity in agriculture. Despite the fact that the use of AI provides meaningful insights for enriched and timely decisions, still there are several challenges which act as deterrents to its adoption in agriculture (Khanna *et al.*, 2022; Sood *et al.*, 2021). However, the rate of adoption among farmers and producers is quite low globally. The low rate of adoption is delaying the achievement of sustainable development goal across many developed and developing countries. Although there have been several studies on adoption of technologies such as precision agriculture (Lambert *et al.*, 2015; Pathak *et al.*, 2019; Paustian & Theuvsen, 2017; Tamirat *et al.*, 2018; Tey & Brindal, 2022), smart farming (Balafoutis *et al.*, 2020; F Caffaro *et al.*, 2020; Giua, Materia, *et al.*, 2022), drones (M Michels *et al.*, 2021) and digital technology adoption (Groher, Heitkämper, & Umstätter, 2020), the studies on AI-based solution adoption and the drivers for such adoption in agriculture remain scarcely investigated, according to the extant relevant literature. As there is no study, especially in an Indian context, on adoption of AI-based solutions by farmers, producers and other stakeholders in agriculture value chain, it motivates to carry out research to investigate this area in detail and bring out useful insights for future use. With this background, we aim to answer the following broader Research Question (RQ) regarding adoption of AI-based solution: *what are the drivers of adoption of AI-based solutions in agriculture in India and what is their relative importance?* The research focuses

on identifying the factors influencing adoption by understanding the perspectives of end-users in a structured manner.

1.6 Research Objective

The primary objective of this research work is to identify the factors impacting intention to adopt Artificial Intelligence-Based solution in agriculture in Indian context with following sub-objectives:

- To identify and analyse the factors impacting intention to adopt Artificial Intelligence-Based solution in agriculture from extant literature
- To develop an integrated framework based on analysis of existing theoretical models
- To identify significant factors in Indian context through empirical evaluation of developed framework

1.7 Scope of the Research

The broader domain of this research focuses on the adoption of AI-based solutions in agriculture. In general, agriculture encompasses a broad range of activities related to crop cultivation, livestock rearing, and the development of value chains to meet the demand for food, fiber, and other agricultural products. To get comprehensive view of the subject, this study focuses on the adoption of AI-based solutions in all sub-domains of agriculture. The study is enriched with the insights from perspectives of (a) end users of the technology *i.e.* farmers; and (b) the enablers in the process of implementing new technology solutions *i.e.* facilitators which include agricultural universities, government offices, extensions, local contacts and co-operatives. For the purpose of study, data is collected from Northern states of India *i.e.*, Punjab and Haryana which are among the highest contributors towards the total agricultural production in the country.

1.8 Rationale for the study

India is one of such countries where agriculture is major contributor to its GDP and despite tremendous technology growth, the use of AI in agriculture is still at nascent stage. AI has numerous constructive use cases and agriculture has an established system for implementing new technology through farmers and facilitators , still several challenges act as deterrent to its adoption (Engås *et al.*, 2023; Scur *et al.*, 2023; Sood *et al.*, 2021; Thomas *et al.*, 2023). The low rate of adoption is causing delay in achieving sustainable development goal across many developing countries. Although government is keen to develop AI use cases for digital

agriculture in line with its AI strategy for the nation (A. Kumar, 2020) to reduce income disparity among farmers and improve productivity of value chain in agriculture sector, the rate of adoption is still very low which urges for a deeper understanding of the challenges leading to lower adoption rate and thus becomes a strong motivation towards the present study. The studies on adoption of AI-based solution remain scarcely investigated, particularly for farmers and facilitators, according to the extant relevant literature. With this background, we aim to answer the prime research question to shed more light on the perceptions of farmers and facilitators associated with AI-based solution adoption.

1.9 Organization of Thesis

The thesis of present research work is structured under different chapters. Chapter 2 reviews the literature available on the use of digital technologies in agriculture and provides insights of adoption of such technologies in agriculture. The outcome of literature review forms the basis of proposed integrated framework as explained in Chapter 3 which explains research methodology adopted in present study for farmers and facilitators. Chapter 4 presents analysis of the collected data using Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). It also presents the results of the study. Chapter 5 discusses the results for farmers and facilitators separately. It also highlights theoretical and practical implications of the study. Chapter 6 provides the conclusion from the study and directions to future work.

Chapter 2 Literature Review

2.1 Introduction

A literature review is important in research as it provides a comprehensive overview and analysis of existing knowledge and research on a specific topic. It helps researchers identify gaps, inconsistencies, and areas for further investigation. By reviewing relevant literature, researchers can build on existing knowledge, avoid duplication, and develop a strong theoretical framework for their study. It also enables researchers to understand the current state of research, identify methodologies, and conceptualize research questions.

In this chapter, systematic literature review of adopting AI-based solutions in agriculture, which is the foundation of this research, is presented. Beginning with well-known theoretical frameworks commonly employed in the literature of technology adoption, this chapter establishes the base for the review of literature. Section 2.2 presents different theories from Information Systems domain including Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovation (DoI) and Technology-Organization-Environment (TOE) framework. Section 2.3 explains the methodology adopted to explore literature on adoption of AI-based solutions in agriculture. It includes the selected databases, search keywords and query, inclusion and exclusion criteria for selecting articles for literature review. The literature review is carried out in multiple dimensions to comprehensively understand the domain of using AI-based solutions in agriculture. Section 2.4 presents gaps in the research from literature on adoption of AI-based solutions in agriculture. On the basis of literature review and identified gaps, an integrated framework for carrying out study is proposed in Section 2.5. Finally, Section 2.6 summarizes the overall literature review for the present study.

2.2 Theoretical Foundation

Several theories within the Information Systems field are put forth and applied to comprehend, forecast, and elucidate the elements that impact the adoption of technology, both at the individual and organizational levels. Majorly these theories include Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovation

(DoI) and Technology-Organization-Environment Framework (TOE Framework). These models share a common goal of studying human behaviour in relation to technology adoption and usage. They emphasize the importance of user attitudes, perceptions, social influences, and contextual factors in determining technology acceptance and adoption outcomes. Additionally, they consider factors such as perceived usefulness, ease of use, subjective norms, behavioural intentions, and the influence of the organizational and environmental context. These models provide frameworks for researchers and practitioners to better understand and predict user behaviours and decision-making processes regarding technology. They help inform the design, implementation, and successful integration of new technologies in various contexts, such as organizations, consumer markets, and societal settings.

2.2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a widely used theoretical framework for understanding users' acceptance and adoption of technology. TAM proposes that the intention to use technology is primarily influenced by two key factors: perceived usefulness and perceived ease of use. Perceived usefulness refers to the degree to which users believe that using the technology will enhance their performance, while perceived ease of use refers to the degree to which users perceive the technology as effortless to use (Davis, 1989). TAM has been widely applied in various research contexts and has demonstrated its validity and reliability in predicting user acceptance and adoption of technology (Lee *et al.*, 2003). Figure 2.1 illustrates TAM in framework. Numerous scholars have employed TAM to comprehend the adoption of IT across a range of research goals, themes, and information systems for its simplicity which makes it accessible to researchers across various disciplines and industries.

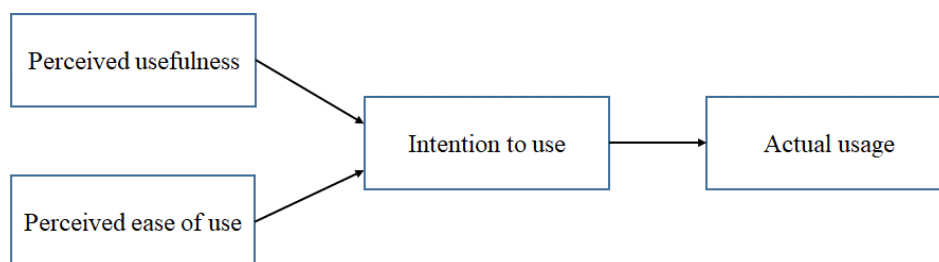


Figure 2.1: Technology Acceptance Model (Davis, 1989)

2.2.2 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) is a prominent theoretical framework used to understand and predict human behavior, including technology adoption. TRA posits that an individual's behavioral intentions are determined by their attitudes toward the behaviour and

subjective norms surrounding that behavior (Fishbein & Ajzen, 1975). Attitudes reflect an individual's positive or negative evaluations of the behavior, while subjective norms refer to the perceived social pressure to engage in or avoid the behavior. Several recent studies have applied TRA to investigate technology adoption. A study by Venkatesh *et al.* (2012) explored the adoption of mobile health applications using TRA as the theoretical foundation. The model's emphasis on attitudes and subjective norms provides valuable insights into the factors driving human decision-making and behavior. TRA model is depicted in Figure 2.2.

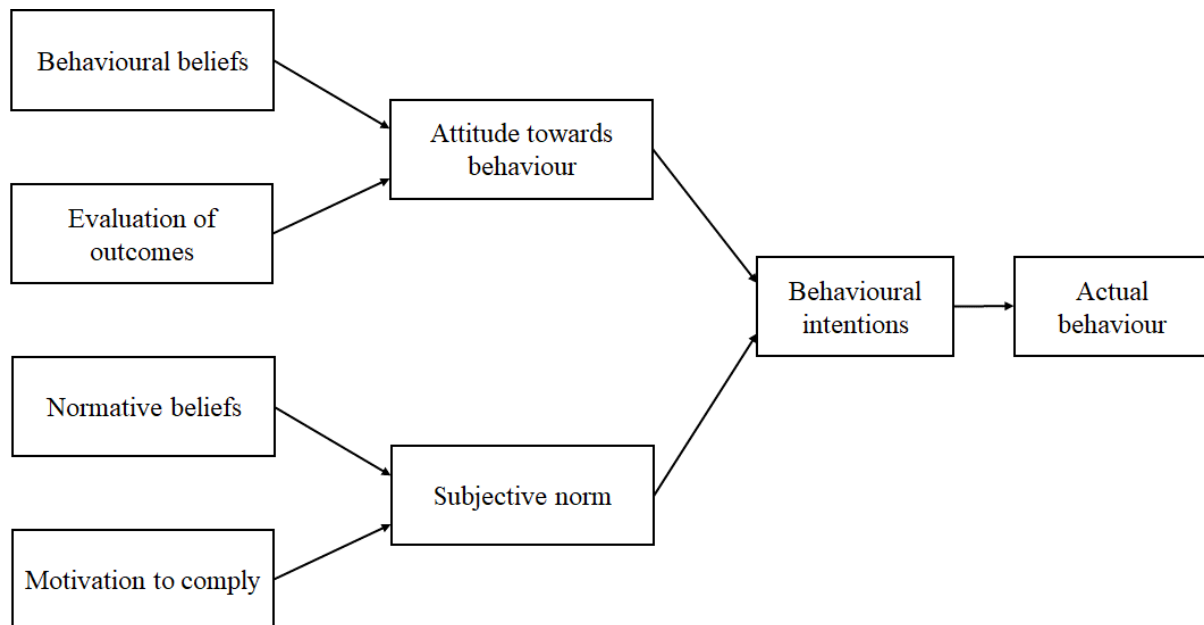


Figure 2.2: Theory of Reasoned Action (Fishbein & Ajzen, 1975)

2.2.3 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) proposed by Ajzen (1991) is a widely recognized and extensively used theoretical framework in social psychology for understanding and predicting human behavior. TPB posits that behavioral intentions are determined by three main factors: attitudes towards the behavior, subjective norms, and perceived behavioral control. Attitudes refer to an individual's positive or negative evaluations of the behavior, subjective norms involve the influence of social norms and the perceived expectations of others, and perceived behavioral control relates to the individual's perceived ability to perform the behaviour (Figure 2.3). TPB has been applied in various research contexts, including health-related behaviors, environmental sustainability, consumer decision-making, and organizational behavior. It provides a comprehensive understanding of the factors that shape human behavior by incorporating cognitive, social, and control factors.

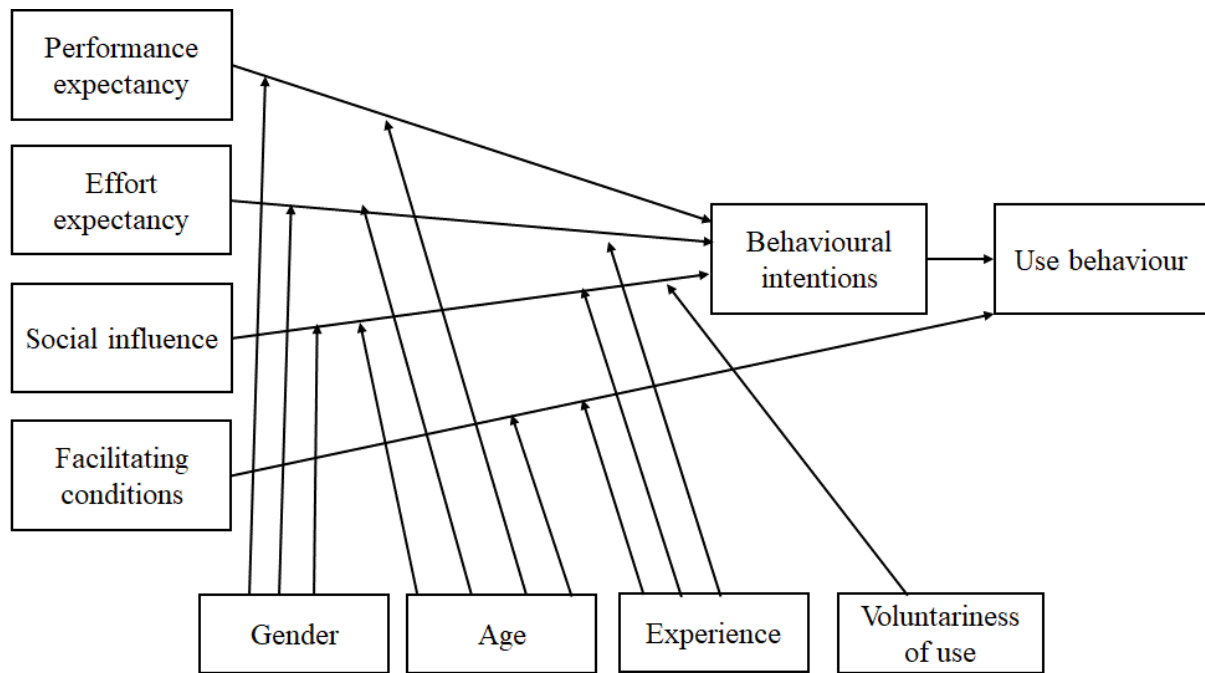


Figure 2.4: Unified Theory of Acceptance and Use of Technology (Venkatesh, 2003)

Researchers have applied UTAUT in different domains to examine technology acceptance. For instance, a study by Alalwan *et al.* (2018) utilized UTAUT to investigate the factors influencing users' acceptance of Internet banking while Liang *et al.* (2021) examine factors using UTAUT that influence managerial intention to adopt Blockchain technology in organizations. The versatility and robustness of UTAUT make it a valuable framework for understanding technology adoption across various fields. Its ability to incorporate multiple factors influencing adoption, such as performance expectancy, effort expectancy, and social influence, contributes to its relevance in predicting user behaviour and informing technology implementation strategies.

2.2.5 Diffusion of Innovation (DoI)

The Diffusion of Innovation (DoI) theory is a well-established framework that explores how innovations spread and are adopted within a social system. DoI is a widely used framework for understanding the adoption and diffusion of new ideas, products, or technologies within a social system. It focuses on the process by which innovations spread through various stages of adoption among individuals or groups. DoI theory identifies key factors that influence the rate and extent of adoption, such as the perceived relative advantage, compatibility, complexity, trialability, and observability of the innovation (Figure 2.5). It has been applied across diverse fields, including technology, healthcare, agriculture, and social sciences, to explain how

innovations are adopted and integrated into society, providing valuable insights into the dynamics of change and facilitating informed decision-making.

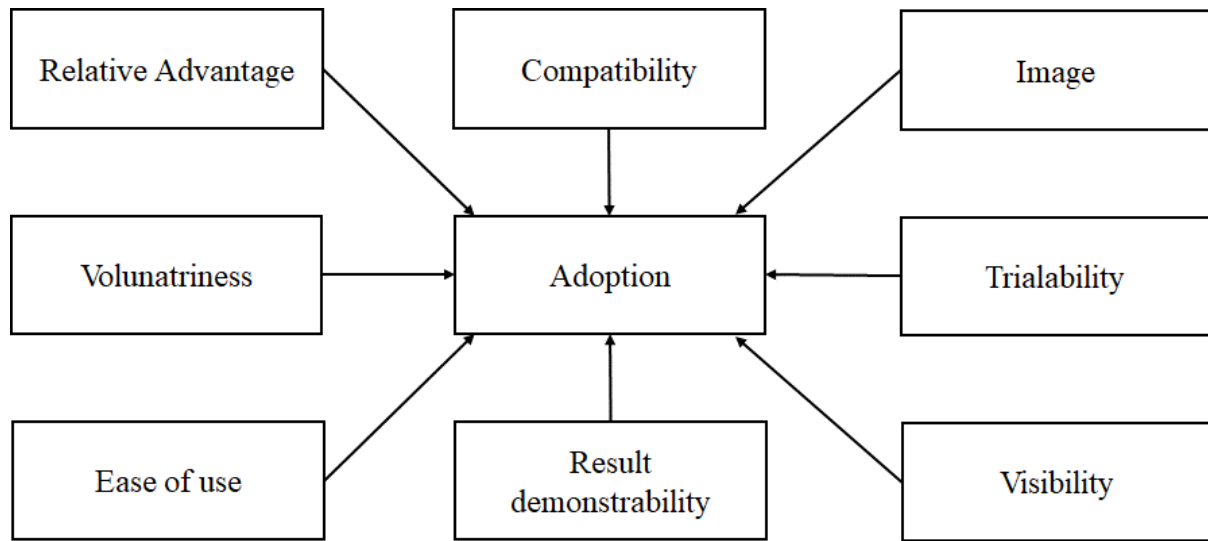


Figure 2.5: Diffusion of Innovation (Rogers, 2003)

Recent research (Balafoutis *et al.*, 2020; Bryant & Higgins, 2021; Giua, Materia, *et al.*, 2022; Shang *et al.*, 2021; Vecchio *et al.*, 2020) has applied DoI to analyze the factors influencing the adoption of new technologies in agriculture, including smart farming tools and precision agriculture systems. These studies have examined the relative advantage, compatibility, complexity, trialability, and observability of smart farming technologies, providing insights into the drivers and barriers of adoption. The application of DoI has helped researchers understand the diffusion process, assess the readiness of farmers to adopt new technologies, and identify strategies for improving technology adoption in the agricultural sector. These studies have contributed to advancing knowledge and guiding policy interventions for the successful implementation of smart farming technologies.

2.2.6 Technology-Organization-Environment Framework (TOE Framework)

The Technology-Organization-Environment (TOE) framework by Tornatzky *et al.* (1990) is a comprehensive model used to understand and analyze the factors influencing technology adoption and implementation within organizations. It recognizes that technology adoption is influenced not only by technological factors but also by organizational and environmental considerations. The TOE framework comprises three key dimensions: technology, organization, and environment (Figure 2.6). The technology dimension focuses on the characteristics of the technology itself, including its compatibility with existing systems,

complexity, and potential relative advantage over alternatives. The organization dimension considers internal factors such as the organization's structure, resources, capabilities, and culture. It explores how these factors can impact the organization's readiness and ability to adopt and implement new technologies. The environment dimension takes into account external factors such as market conditions, industry dynamics, regulatory frameworks, and competitive forces that can shape the adoption and implementation process.

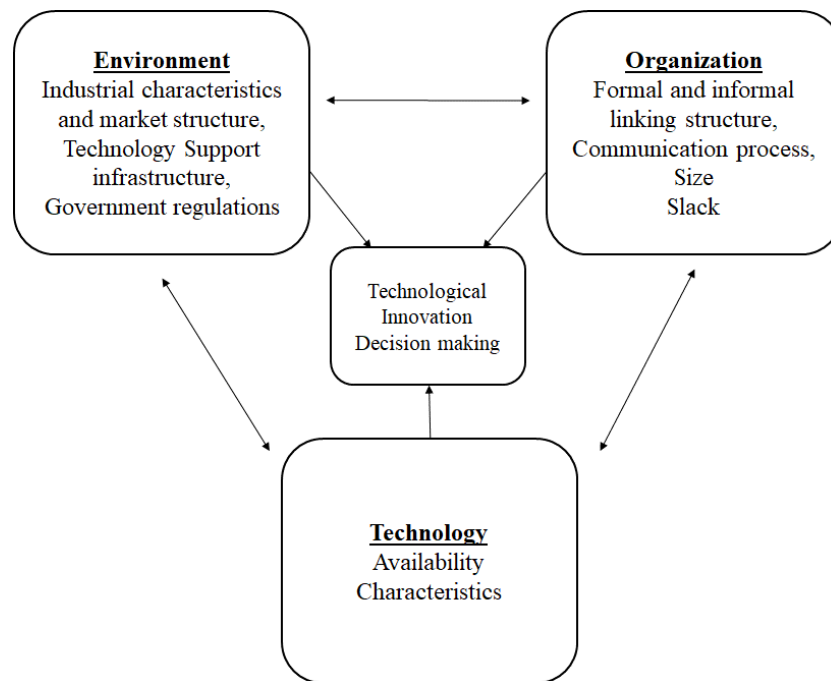


Figure 2.6: TOE Framework (Tornatzky et.al. 1990)

By examining the interplay between these dimensions, the TOE framework provides a holistic perspective on technology adoption. It acknowledges that successful adoption and implementation require alignment and interaction between technological, organizational, and environmental factors. The framework helps researchers and practitioners identify the critical determinants, barriers, and facilitators that influence technology adoption, diffusion, and assimilation within organizations. The TOE framework has been widely applied in various industries and contexts. It has been used to study the adoption of technologies such as e-commerce, cloud computing, enterprise systems, and renewable energy solutions (D. Kumar et al., 2017). By considering multiple dimensions, the TOE framework offers a comprehensive understanding of the complexities involved in technology adoption, supporting informed decision-making, effective implementation strategies, and the successful integration of new technologies within organizations.

The present study utilizes the combination of Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovation (DoI) and Technology-Organization-Environment (TOE) Framework as it offers a comprehensive and multi-dimensional approach. The combination of these models allows for a more comprehensive understanding of technology adoption by considering individual, social, organizational, and environmental factors. It provides a broader perspective that encompasses multiple dimensions and enables researchers and practitioners to identify the complex interactions and influences that shape technology adoption processes. Researchers, in this field of study, have widely used one theoretical framework to carry out analysis. In literature, combination of multiple theories has rarely been used. We adopted three different theories from the rich literature of Information Systems to enable this study to present a research model with high and effective prediction capability. Additionally, with this approach, we explore the topic using multiple perspectives of farmers and facilitators.

The Unified Theory of Acceptance and Use of Technology (UTAUT) is considered important and advantageous over other theories of adoption, such as TAM, TRA, and TPB, for several reasons. Firstly, UTAUT integrates and builds upon these earlier theories, combining the strengths and addressing the limitations of TAM, TRA, and TPB. It provides a more comprehensive and robust framework by incorporating additional factors such as social influence and facilitating conditions, alongside performance expectancy and effort expectancy. Secondly, UTAUT recognizes the moderating effects of various contextual factors, including gender, experience, and voluntariness of use. This allows for a more nuanced understanding of how these factors influence technology acceptance and use. Furthermore, UTAUT has been extensively tested and validated across diverse technological contexts and user populations. Its empirical foundation and broad applicability make it a reliable and widely accepted framework for studying technology adoption. Additionally, UTAUT's focus on user acceptance and actual technology use is valuable for organizations and researchers seeking to understand and promote technology adoption. By considering factors beyond individual beliefs and intentions, UTAUT offers a more comprehensive understanding of the complex dynamics involved in the acceptance and use of technology. Overall, UTAUT's integration of multiple theories, inclusion of contextual factors, and empirical validation make it a prominent and valuable framework for studying technology adoption, surpassing the individual limitations of TAM, TRA, and TPB.

DoI theory holds significance due to its comprehensive and holistic approach to technology adoption. It considers a broader range of factors, including the characteristics of innovations,

communication channels, social systems, and adopter categories. Unlike other theories that focus primarily on individual beliefs and intentions, DoI recognizes the social context and the dynamic nature of innovation diffusion. By studying the process of how innovations spread within a social system, DoI provides insights into the factors that facilitate or hinder adoption, making it valuable for understanding and influencing technology adoption at both individual and societal levels.

The Technology-Organization-Environment (TOE) Framework is important and valuable compared to other adoption models due to its comprehensive approach in understanding technology adoption in organizational settings. Unlike other models that primarily focus on individual-level factors, TOE considers a broader range of factors that influence technology adoption, including organizational characteristics and environmental factors. It recognizes that technology adoption is not solely influenced by individual beliefs but is also shaped by organizational context and external forces. By examining the interplay between technology, organization, and environment, TOE provides a holistic understanding of technology adoption, enabling organizations to identify and address barriers, leverage opportunities, and make informed decisions regarding technology implementation.

2.3 Review of Literature

This section explores the literature on adoption of AI in agriculture using systematic literature review approach. The main aim of the study is to synthesize the factors influencing adoption of AI in agriculture. The systematic literature review approach carries numerous advantages over traditional approach since it has the ability to combine the ideas from literature in a very clear, organised and reproducible way (Tranfield *et al.*, 2003). Through systematic literature review, the effect of bias and chance gets reduced and authenticity of data analysis gets enhanced (Reim *et al.*, 2015). Combined together, these advantages help improving the results and to draw conclusion from the analysis.

The main objective of literature review is to examine the available literature to identify constructs that significantly influence decision to adopt digital technologies including artificial intelligence, precision agriculture, digital agriculture *etc.* in agriculture. To ensure that the literature review presents a comprehensive view of adoption study, the factors responsible for AI adoption in non-agricultural sectors such as healthcare, finance, automobile and telecom are also reviewed (Cubric, 2020; Holzinger *et al.*, 2021).

The literature review sources the articles to study from a group of 3 different academic research databases comprising of SCOPUS, Web of Science and ACM. Following search string was executed in SCOPUS database: TITLE-ABS-KEY (("artificial intelligence" OR "machine learning" OR "decision support system" OR "neural networks" OR "deep learning" OR "cognitive" OR "automation" OR "robot*" OR "unmanned aerial vehicle*" OR "learning systems") AND (("digital" OR "precision" OR "smart") AND ("Adopt*" OR "Intent*" OR "Diffusion")) AND ("agricultur*" OR "farm*"))). Afterwards, a similar query was executed in Web of Science and ACM databases to get exhaustive list of articles relevant to the selected topic of study. The resulting dataset of 1824 articles from three databases was further enriched through addition of 27 articles from forward and backward search. It was observed that a large number of articles cover the use of different technologies in agriculture. In order to limit the focus towards study, the papers which studied the adoption of technology such as artificial intelligence, precision agriculture, digital agriculture, smart farming have been included in the present review. After removal of 212 duplicates, 1639 articles were screened based on title and abstract with which 1267 articles were excluded. In next step, the inclusion and exclusion criteria was applied on these articles which resulted in 65 articles. The process of article selection is explained in Figure 2.7.

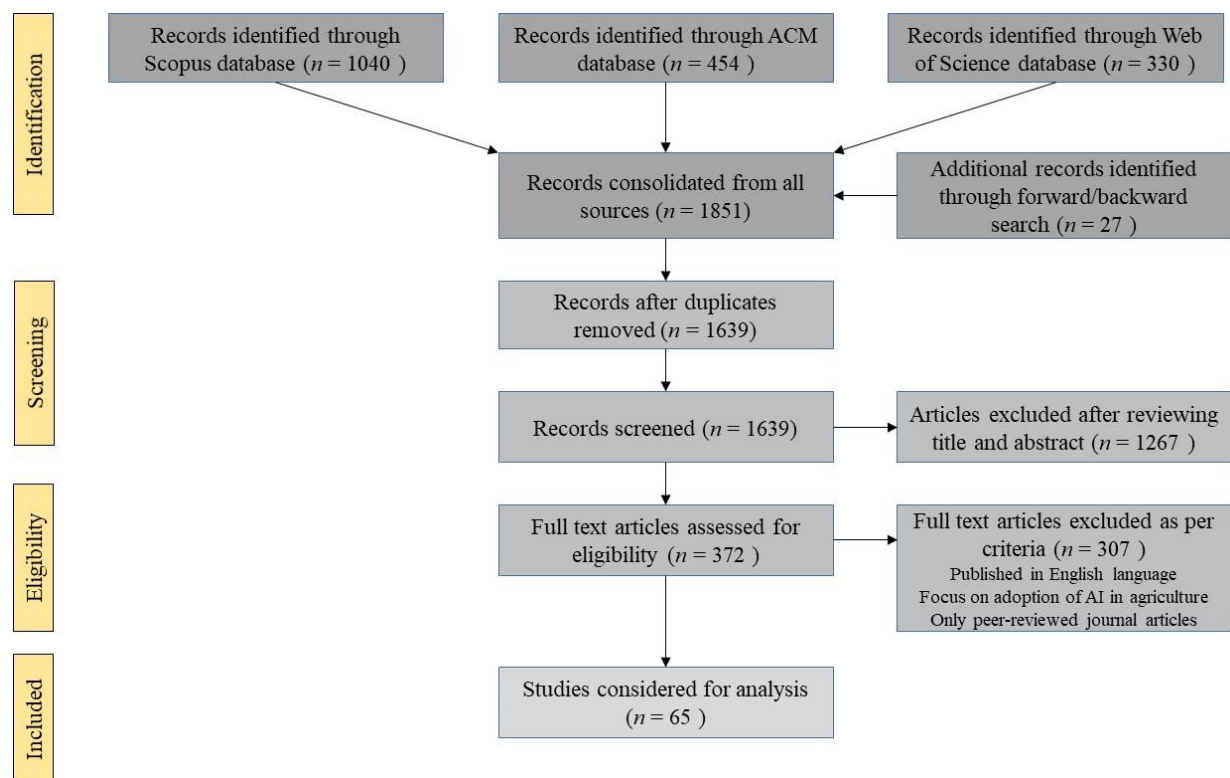


Figure 2.7: Article selection process

2.3.1 Overview of the selected studies

Based on the key characteristics from the set of selected 65 articles, a comprehensive summary is prepared as presented in Table 2-1. This table summarises the major highlights of the results from respective article along with its key characteristics including publication year, country of study, theoretical framework, research method and technology studied.

2.3.1.1 Publication Timeline

The articles selected in this systematic literature review were published between 2003 and 2022 (Figure 2.8). The fundamental issue examined in these studies is the adoption of AI in agriculture. Prior reviews include study of adoption of precision agriculture (Aubert *et al.*, 2012; Marvin T. Batte & Arnholt, 2003; Groher, Heitkämper, Walter, *et al.*, 2020; Lambert *et al.*, 2015; Monteleone *et al.*, 2020; Nowak, 2021; Pathak *et al.*, 2019; Paustian & Theuvsen, 2017; Tamirat *et al.*, 2018); digital agriculture (Cubric, 2020; Gabriel *et al.*, 2021; Groher, Heitkämper, & Umstätter, 2020; Ronaghi & Forouharfar, 2020; Shang *et al.*, 2021; Smidt, 2021); and smart farming (Bryant & Higgins, 2021; F Caffaro *et al.*, 2020; Federica Caffaro & Cavallo, 2019; Giua, Cristiana, *et al.*, 2022). Although there are several studies emphasising the benefits of AI in agriculture, its adoption has not been explicitly studied in the literature. The review indicates that selected articles have focused on widely varying set of technologies and further suggests to compile the factors influencing AI adoption in agriculture as the trend of research in this domain has started gaining focus over last 4 years.

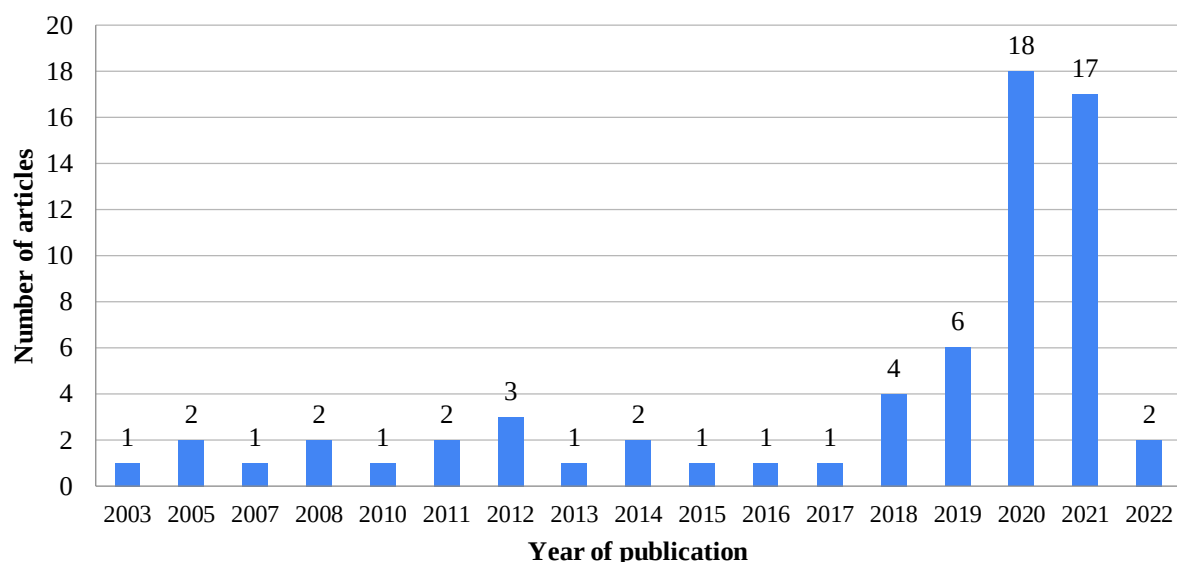


Figure 2.8: Yearly trend of publications

Table 2-1: Summary of included studies

S.No.	Author	Year	Country	Theoretical Framework	Method/Design	Technology studied	Results
P1	Adrian, A. M., Norwood, S. H., & Mask, P. L.	2005	USA	TAM	Survey (N=85)	Precision Agriculture Technologies	Intention to adopt precision agriculture directly influenced by perceived net benefit and confidence; indirectly by perceived usefulness
P2	Aubert, B. A., Schroeder, A., & Grimaudo, J.	2012	Canada	TAM, DoI	Survey (N=438)	Precision Agriculture Technologies	Perceived ease of use and perceived usefulness have positive influence on adoption while no effect of farm size and farmer's age was observed. Influence of resource availability, trialability, voluntariness and farmer's education level also seen.
P3	Balafoutis, A. T., van Evert, F. K., & Fountas, S.	2020	Multiple	DoI	Survey Data (N=1064)	Smart Farming Technology	Compatibility with existing machinery, information on advantages of new technology significantly affect adoption
P4	Balogh, P., Bai, A., Czibere, I., Kovach, I., Fodor, L., Bujdos, A., Sulyok, D., Gabnai, Z., & Birkner, Z.	2021	Hungary	-	Survey (N=594); Semi-structured interviews (N=30)	Precision Farming	Average farm size owners are highly willing to innovate; isolation of farmers using PAT is a barrier for spreading knowledge on innovation.
P5	Barnes, A. P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., van der Wal, T., & Gómez-Barbero, M.	2019	Multiple	-	Interview (N=971)	Precision Agriculture Technologies	Besides size and income differences, economic cost is barrier to adoption. Perceived economic return from technology influences adoption. Individual characteristics, such as innovative nature and information seeking behaviour; Financial support in terms of subsidy and taxation positively influenced adoption.
P6	Batte, M. T.	2005	USA	-	Survey Data (N=1001)	Computer use	Adoption of computer gets influenced by farm size and inversely by operator age.
P7	Batte, M. T., & Arnholt, M. W.	2003	USA	DoI	Case Studies (N=6)	Precision Farming	Farmers are highly motivated with high profit expected from PAT despite its high cost.
P8	Benyam, A. A., Soma, T., & Fraser, E.	2021	Multiple	Sustainability framework (Environmental, Economic, Social pillars)	Review (N=45)	Digital Agriculture Technologies	Major barriers for adoption - cost, accessibility, design complexities, limitations in embedding local ecological knowledge

P9	Bryant, M., & Higgins, V.	2021	Australia	DoI	Interviews (N=20)	Smart Farming Technology	Cultural scripts barrier to collaboration, useful for devising governance strategies
P10	Caffaro, F., & Cavallo, E.	2019	Italy	-	Survey (N=310)	Smart Farming Technology	Adoption of SFT positively influenced by farm size and negatively by lower education level and isolated working on farm. Highlighted need of specifically designed policies and training programs for encouraging its use.
P11	Caffaro, F., Micheletti Cremasco, M., Roccato, M., & Cavallo, E.	2020	Italy	TAM	Survey (N=314)	Smart Farming Technology	Formal and informal sources of information influence perceived usefulness which further affects adoption
P12	Caplan, S., Tilt, B., Hoheisel, G., & Baugher, T. A.	2014	USA	DOI	Interviews (N=24)	New technologies	Trust and knowledge of technology positively relate to its anticipated implementation; Solution designing lacks in considering operational needs of farmers
P13	Chaudhary, S., & Suri, P. K.	2021	India	-	Survey (N=441)	e-Trading Platform adoption	Top significant factors – easy to use, trust, infra availability, price, fast transaction cycle
P14	Cubric, M.	2020	Multiple	-	Survey (N=30)	Artificial Intelligence	Economic drivers of AI adoption (Cost, time, customer satisfaction, accuracy in decision making and predictions) weigh more as compared to social factors e.g. sustainability and well being)
P15	D'Antoni, J. M., Mishra, A. K., & Joo, H.	2012	USA	Utility maximization	Survey (N=469)	Precision Agriculture Technologies	Adoption highly influenced by perceived future importance of precision agriculture and input cost savings as compared to other attributes.
P16	Drewry, J. L., Shutske, J. M., Trechter, D., Luck, B. D., & Pitman, L.	2019	USA	-	Survey (N=1021)	Digital Technologies	Internet usage highly influenced by farm size, income, gender, and educational level; cost a concern for mobile and computer access.
P17	Gallardo, R. K., Grant, K., Brown, D. J., McFerson, J. R., Lewis, K. M., Einhorn, T., & Sazo, M. M.	2019	USA	-	Survey (N=119)	Precision Agriculture Technologies	Results of research projects and farmers' engagement encourage adoption; Barrier of economy of size can be reduced by making customer services available on purchase / rent.
P18	Gargiulo, J. I., Eastwood, C. R., Garcia, S. C., Lyons, N. A., Gargiulo I, J., Eastwood, C. R., Garcia, S. C., & Lyons, N. A.	2018	Australia	-	Survey (N=301)	Precision Dairy	Farmers with larger herd size adopted precision technology more. However, different perceptions regarding future of precision technologies were observed for herd size or farmers / service providers.

P19	Giua, C., Cristiana, V., & Camanzi, L.	2022	Italy	UTAUT	Survey (N=474)	Smart Farming Technology	Farm size positively influences adoption while age and education were not statistically significant.
P20	Groher, T., Heitkämper, K., & Umstätter, C.	2020	Switzerland	-	Survey (N=1497)	Digital Technologies	Higher use of sensors and measuring devices than data processing technologies in dairy farming for detecting diseases.
P21	Groher, T., Heitkämper, K., Walter, A., Liebisch, F., & Umstätter, C.	2020	Switzerland	-	Survey (N=827)	Precision Agriculture Technologies	Farmers involved in high value product as potential adopters with purpose of reducing physical workload through automation instead of evaluation of crop for supporting decisions.
P22	Haque, A., Islam, N., Samrat, N. H., Dey, S., & Ray, B.	2021	Bangladesh	-	-	AI and IoT	Comprehensive plan and economic resources including training and development for all stakeholders required for transformation to smart farming.
P23	Hayat, N., Al Mamun, A., Nasir, N. A. M., Selvachandran, G., Nawi, N. B. C., & Gai, Q. S.	2020	Pakistan	UTAUT	Survey (N=336)	Conservative Agriculture Practices	Adoption influenced by profit focus, environmental attitude and effort expectancy; Barriers: lower levels of trust on extension, performance expectancy and social influence
P24	Heldreth, C., Akrong, D., Holbrook, J., & Su, N. M.	2021	Multiple	-	-	Artificial Intelligence	Highlights need of farmer-centred approach for understanding perceptions of smallholder farmers about AI and providing suitable solution
P25	Holzinger, A., Weippl, E., Tjoa, A. M., & Kieseberg, P.	2021	Austria	-	-	Artificial Intelligence	Important role by AI in supporting SDGs and implementation should focus on reducing collateral damage
P26	Isgin, T., Bilgic, A., Forster, D. L., & Batte, M. T.	2008	USA	-	Survey (N=491)	Precision Farming	Significant factors: farm size, soil quality, demographic characteristics of farmers, urban influences, debt on farmer, farm location
P27	Jaafar, H., & Kharroubi, S. A.	2021	Lebanon	-	Survey (N=678)	Smart Irrigation Techniques	High majority of farmers know importance of better irrigation for improving economic production; Major predictors: socio-demographic characteristics (age, nationality, region); younger farmers highly willing to pay.
P28	Jelinski, M. D., Kelton, D. F., Luby, C., & Waldner, C.	2020	Canada	-	2016 Census of Agriculture (N=26935)	Multiple technologies (Computer/laptop, smartphone/tablet, auto-steering, auto-feeding, auto-environment, GPS, and GIS)	Significant factors: number of operators and farm size while gender and marginally relate to adoption

P29	Jellason, N. P., Robinson, E. J. Z., & Ogbaga, C. C.	2021	Africa	-	-	Agriculture 4.0	Barriers to adoption: knowledge, skills, infrastructure and finance
P30	Kutter, T., Tiemann, S., Siebert, R., & Fountas, S.	2011	Multiple	-	Interviews (N=49)	Precision Farming	Different communication strategies based on farm-size; expected major role of agricultural contractors for driving PF in upcoming years
P31	Lamb, D. W., Frazier, P., & Adams, P.	2008	Australia	DoI	-	Precision Agriculture Technologies	Highlights knowledge gap between developers and users, more focus required on development of protocols and realistic performance criteria to accelerate adoption.
P32	Lambert, D. M., Paudel, K. P., & Larson, J. A.	2015	USA	-	Survey (N=739)	Precision Agriculture Technologies	Growers having larger operating area with different information sources to learn precision farming likely to adopt technology bundles more.
P33	Larson, J. A.	2007	USA	-	Survey (N=941)	Remote Sensed Imagery	Younger, educated farmers with larger farm operations having tech-savvy nature were more likely adopters; important role of crop consultants for generating prescription map
P34	Lencsés, E., Takács, I., & Takács-György, K.	2014	Hungary	-	Interviews (N=72)	Precision Farming	High investment cost pose a barrier; farm size and age correlate significantly with adoption
P35	Liu, W., Shao, X.-F., Wu, C.-H., & Qiao, P.	2021	Multiple	-	Review (N=58)	ICT and Blockchain	ICT adoption is affected by application design factors while research in Blockchain technology focuses only on application design factors.
P36	Michels, M., Bonke, V., & Musshoff, O.	2020	Germany	UTAUT	Survey (N=207)	Smartphone adoption	Major constructs influencing adoption decision include performance expectancy, social norm, effort expectancy, and facilitating conditions
P37	Michels, M., Fecke, W., Feil, J.-H., Musshoff, O., Pigisch, J., & Krone, S.	2020	Germany	-	Survey (N=817)	Smartphone adoption	Major determinants of smartphone adoption: farmers' age, education, and farm size.
P38	Michels, M., von Hobe, C.-F., & Musshoff, O.	2020	Germany	Trans-theoretical model of behavioural change	Survey data (N=167)	Drones	Key factors affecting adoption: farmers' age, literacy on PAT and farm size
P39	Michels, M., von Hobe, C.-F., von Ahlefeld, P. J., & Musshoff, O.	2021	Germany	TAM	Survey data (N=167)	Drones	Key to higher adoption: increasing awareness and the confidence level of farmers to use drone
P40	Mitchell, S., Weersink, A., & Bannon, N.	2020	Canada	-	Survey (N=122)	Precision Agriculture Technologies	In general rate of adoption has increased; technology cost inversely influences; decisions provided consistent and demonstrative value
P41	Molina-Maturano, J., Verhulst, N., Tur-Cardona, J., Güereña, D. T., Gardeazábal-	2021	Mexico	UTAUT	Survey data (N=394)	Agricultural Apps	Significant predictors: performance expectancy, mastery-approach goal meaningful for youngsters only

	Monsalve, A., Govaerts, B., & Speelman, S.						
P42	Monteleone, S., de Moraes, E. A., de Faria, B. T., Aquino Junior, P. T., Maia, R. F., Neto, A. T., & Toscano, A.	2020	Brazil	TPB	Interviews (N=10), Case Study (N=4), Modeling and simulation	Precision Agriculture Technologies	Behavioural characteristics of farmers and operations management aspects influence adoption of PAT
P43	Nair, S., Wang, C., Eduardo, S., Belasco, E., Larson, J., Velandia, M., <i>et al.</i>	2011	USA	-	Survey (N=1692)	Precision Agriculture Technologies	Major factors: farm size, ownership and engagement in extension activities
P44	Nowak, B.	2021	Multiple	DoI	Review (N=17)	Precision Agriculture Technologies	Adoption of VRT depends on other technologies as well; Barriers: complexity and technical issues; Key motive for adoption may not be focus on efficiency and productivity.
P45	Pathak, H. S., Brown, P., & Best, T.	2019	Multiple	DOI	Review (N=34)	Precision Agriculture Technologies	In context of PAT, studies have missing constructs of DoI which have been otherwise used in context of other industries.
P46	Paustian, M., & Theuvsen, L.	2017	German	-	Survey (N=227)	Precision Agriculture Technologies	Significant influence by farming business focus, farm experience, farm size on adoption. Farm size below threshold of 100 ha negatively influenced adoption.
P47	Pfeiffer, J., Gabriel, A., & Gandorfer, M.	2021	German	Kollman's acceptance model	Survey (N=2012)	Digital Farming Technologies	Trust and positive attitude towards farming influence perception towards benefits. However, its benefits are unlikely to increase acceptance at large scale.
P48	Pierpaoli, E., Carli, G., Pignatti, E., & Canavari, M.	2013	Multiple	TAM	Review (N=20)	Precision Agriculture Technologies	Classified the factors under competitive-contingent, sociodemographic and financial factors; Highlighted that innovation that is disruptive in nature attracts farmers more than sustainable innovation.
P49	Pivoto, D., Barham, B., Waquil, P. D., Foguesatto, C. R., Dalla Corte, V. F., Zhang, D., & Talamini, E.	2019	Brazil	-	Survey (N=119)	Smart Farming Technology	Major barriers of adoption: Internet access in rural areas, reliable sources of information, low education level, training facility, required higher investment from companies Main drivers of adoption: enhanced productivity, better processes, lower costs and in-depth knowledge about cultivated areas; major influence by farm size
P50	Pivoto, D., Waquil, P. D., Talamini, E., Finocchio, C. P. S., Dalla Corte, V. F., & de Vargas Mores, G.	2018	Brazil	-	Interview (N=4), Bibliometric Analysis (N=179)	Smart Farming Technology	Major limiting factors: integration of available and new systems, education, skill set, operational knowledge of farmers

P51	Rasch, S., Shang, L., Heckeleei, T., Gerullis, M. K., & Jan, B.	2021	Multiple	DoI, TPB	Review (Farm Studies (N=32), Agent-based models (N=27))	Digital Farming Technologies	Studies focused more on characteristics of farm and operator than characteristics of technology, interaction, psychological and institutional factors.
P52	Rathod, P., & Dixit, S.	2020	India	-	-	Precision Dairy	Precision Dairy technology can be adopted with guidance from professional bodies in public or private domain at smaller scale to demonstrate higher yield and returns.
P53	Rodzalan, S. A., Yin, O. G., & Mohd Noor, N. N.	2020	Malaysia	-	Survey (N=150)	Artificial Intelligence	AI has potential to solve problems of pollution in environment and workforce shortage in agriculture.
P54	Ronaghi, M. H., & Forouharfar, A.	2020	Iran	UTAUT	Survey (N=392)	IoT	Major influencing factors: performance expectancy, social influence, effort expectancy, facilitating conditions, individual factors and behavioral intention.
P55	Rose, D. C., Sutherland, W. J., Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., Ffoulkes, C., Amano, T., & Dicks, L. V.	2016	UK	UTAUT	Interview (N=78), Survey (N=244)	Decision Support Tools	Highly influencing factors: usability of DSS, cost effectiveness, relevance to user expectations and anticipated performance levels.
P56	Salimi, M., Pourdarbani, R., & Nouri, B. A.	2020	Iran	TAM	Survey (N=378)	Agricultural Automation	Social and individual factors exhibit inverse relationship between social and individual characteristics with perceived usefulness, perceived ease of use.
P57	Skevas, T., & Kalaitzandonakes, N.	2020	USA	-	Survey (N=809)	UAV	Significant factors: potential gain (economic and environmental); socio-economic characteristics of farmers, farm characteristics, long-term commitment to farming; awareness
P58	Smidt, H. J.	2021	South Africa	Choice framework, Capabilities approach	Review (N=36)	Digital Technologies	Role of state is critical to support collaboration and engagement of stakeholders; focused framework required to facilitate adoption by small-scale farmers
P59	Spykman, O., Gabriel, A., Ptacek, M., & Gandorfer, M.	2021	Germany	-	Survey (N=174)	Field crop robots	Key factors: Farming system, Farm size, and occupational structure; while large farm owners showed interest in financial benefits, small-scale farmers focused on environmental benefits; organic farming had positive relation with intention to adopt.
P60	Takácsné György, K., Lámfalusi, I., Molnár, A., Sulyok, D., Gaál, M., Keményné Horváth, Z., Domán, C., Illés, I., Kiss,	2018	Hungary	-	Survey (N=425)	Precision Agriculture Technologies	Cost is major deterrent to adoption; suitable arrangement of financial support in form of subsidies may address this.

	A., Péter, K., & Kemény, G.						
P61	Tamirat, T. W., Pedersen, S. M., & Lind, K. M.	2018	Denmark and Germany	-	Survey (N=260)	Precision Agriculture Technologies	Age (young farmers), Farm size (midsize farms), awareness (participation in events) have high influence on adoption decision.
P62	Tey Y.S., Brindal, M. 2012	2012	Multiple	-	Review (N=10)	Precision Agriculture Technologies	To be comprehensive, future studies should include informational, behavioural and social perspectives of adoption decision.
P63	Tey Y.S., Brindal, M. 2022	2022	Multiple	-	Review (N=23)	Precision Agriculture Technologies	Main factors: perceived profitability, use of computer, involvement of consultants
P64	Vecchio, Y., Agnusdei, G. P., Miglietta, P. P., & Capitanio, F.	2020	Italy	DOI	Survey (N=200)	Precision Farming	Information policy ensuring information availability and reducing complexity is critical for increasing rate of adoption.
P65	Walton, J. C., Larson, J. A., Roberts, R. K., Lambert, D. M., English, B. C., Larkin, S. L., <i>et al.</i>	2010	USA	Random utility model	Survey (N=765)	PDA/Handheld GPS devices	Age (younger farmers) is important in combination with higher yield variability for adoption

2.3.1.2 Theories

The selected 65 articles have utilized numerous theoretical frameworks for examining different factors for adoption of precision agriculture, digital agriculture and smart farming in agriculture (see Table 2-2). The most adopted theoretical frameworks were DOI, TAM and UTAUT which signifies that these frameworks are highly relevant for the studying adoption of technology.

Table 2-2: Theoretical frameworks utilised in studies

Theoretical Frameworks	Total Number
DoI	8
UTAUT	6
TAM	5
Choice framework, Capabilities approach	1
TPB	1
TAM, DoI	1
DoI, TPB	1
Trans-theoretical model of behavioural change	1
Kollman's acceptance model	1
Utility maximization	1
Random utility model	1
Sustainability framework (Environmental, Economic, Social pillars)	1
No theory utilised	37
Grand Total	65

2.3.1.3 Research methods

The set of articles in the present review suggests that several research methods have been employed for examining the relationship among independent factors and dependent variable. The selected articles were classified under three categories (McLeod *et al.*, 2016) as: (a) qualitative, if it highlighted the explanation and development of understanding about the context; (b) quantitative, if it emphasised the association between factors by means of data collection and statistical analysis (Hoehle *et al.*, 2012); (c) mixed, if the articles uses both qualitative and quantitative methods in the study. Out of the total 65 articles selected in the present review, 42 articles utilized quantitative research method, while 21 employed qualitative approach and 2 studies made use of mixed approach in the analysis as shown in Figure 2.9.

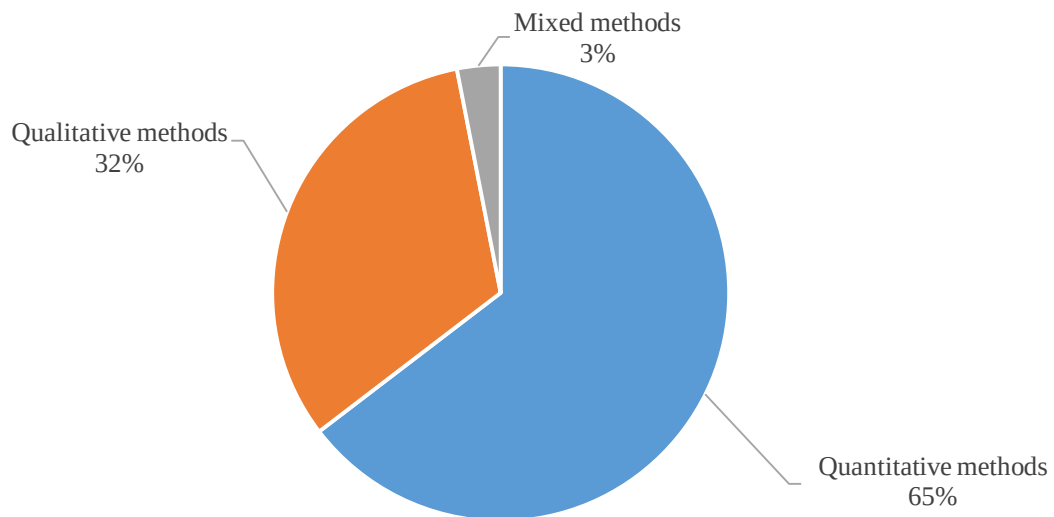


Figure 2.9: Distribution of methods used in the selected studies

2.3.1.4 Geographic scope

The selected 65 articles in the present study were geographically distributed across countries as depicted in Figure 2.10. A number of studies which were carried out in more than one country have been recorded under the ‘Multiple’ category. Most of the studies were focused on developed countries such as USA (n=13) and the Germany (n=5). As the emerging countries have a limited research in this domain, there is tremendous scope of exploring this topic to increase penetration of new technology for achieving better productivity.

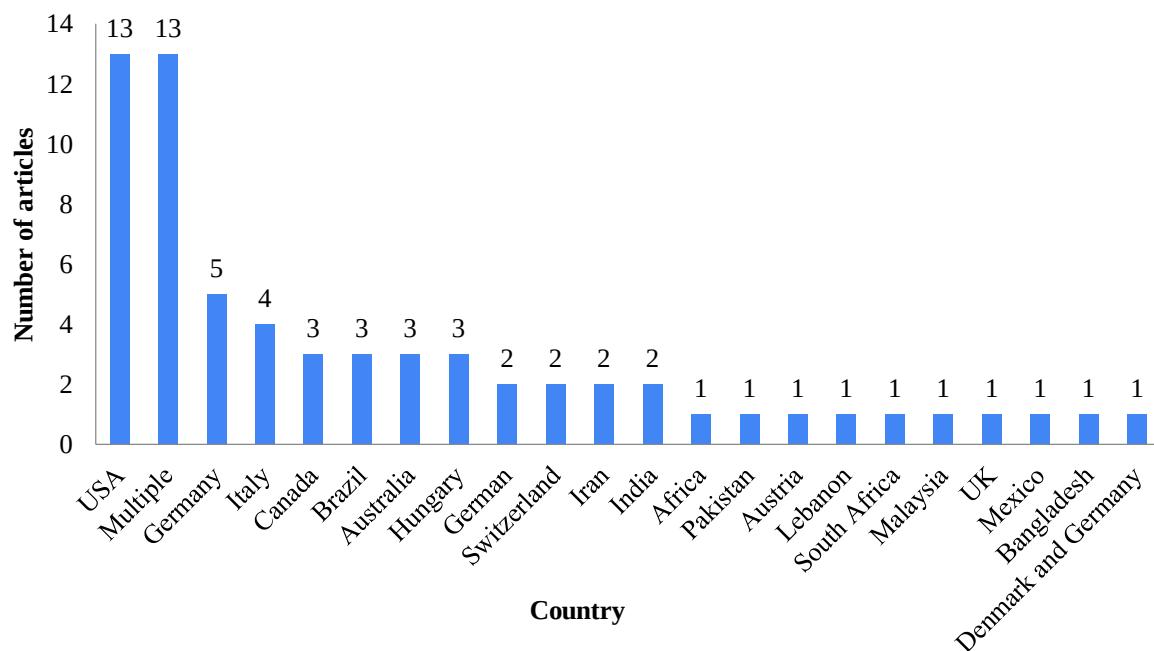


Figure 2.10: Geographic distribution of selected studies

2.3.1.5 Technologies studied

Selected 65 articles represent study of adopting several technologies in agricultural domain. Most commonly studied technology is Precision Agriculture (n=25) followed by Smart Farming technology (n=8) and Digital Agriculture Technologies (n=6) as presented in Table 2-3. With technological enhancements in computing and and data analytic domain, several new technologies including AI, IoT, Blockchain, UAV etc. have been of great interest to researchers.

Table 2-3: Technologies studied in the selected articles

Technology	Number of Papers
Precision Agriculture Technologies	25
Smart Farming Technology	8
Digital Agriculture Technologies	6
Artificial Intelligence	4
Precision Dairy	2
Smartphone adoption	2
Drones	2
Multiple technologies (Computer/laptop, smartphone/tablet, auto-steering, auto-feeding, auto-environment, GPS, and GIS)	1
Conservative Agriculture Practices	1
PDA/Handheld GPS devices	1
Agriculture 4.0	1
Decision Support Tools	1
AI and IoT	1
New technologies	1
Agricultural Automation	1
Computer use	1
Agricultural Apps	1
Remote Sensed Imagery	1
ICT and Blockchain	1
IoT	1
UAV	1
e-Trading Platform adoption	1
Field crop robots	1
Grand Total	65

2.3.2 Analysis of selected studies

For examination of the quality of selected articles in a subjective manner, Quality Evaluation (QE) sets a base for the comparison of the selected studies. QE criteria helps researchers to

ensure that only high-quality, relevant, and reliable studies are included in the literature review. These criteria help filter out studies that do not meet specific standards, such as rigorous research methods, appropriate data analysis techniques, and relevance to the research topic. Based on the QE criteria suggested by scholars (Behera *et al.*, 2019) and given in Appendix-1, the shortlisted articles have been evaluated and assigned a score for each of the criteria item which was summed up and final values have been presented in Table 2-4. With average QE score of 6.3 combined for all four criteria, the selected articles represent a relevant set suitable for further study and analysis.

To conduct a comprehensive view of the literature available for adoption of digital technologies in agriculture, the selected 65 studies were reviewed, and the different perspectives of available literature were examined by slicing the data across four dimensions. The four dimensions include – stakeholder involvement (farmer or facilitator), research area (crop, livestock, agricultural value chain, or general), research design (qualitative or quantitative) and economic status of the country (emerging or developed). The purpose of this classification in literature analysis across four dimensions is to gain insight of available literature through its cross-sectional view across different constructs used in study. These dimensions provided a cross-sectional view for getting detailed insight of literature by addressing following questions: (1) *Who has been studied in literature?* – Literature shows that authors have used farmers and facilitators in their studies. This dimension has been captured as stakeholder involvement (farmer, facilitator or both) in Table 2-5; (2) *Which domain of the agriculture has been studied in literature?* – This dimension indicates the domain of agriculture (crops, livestock, agricultural value chain, or general) which has been studied in the literature for adoption of digital technologies; (3) *Where have the studies been conducted?* – The segmentation of country, in terms of ‘emerging’ or ‘developed’, where the respective studies were conducted, indicates effect of economic development taken into account by the authors while selecting the country to study the factors influencing adoption of digital technologies; (4) *How the studies were analysed in literature?* – The methodology used in analysis (quantitative or qualitative or mixed) by various authors gives an insight of the type of analysis in the respective studies. Table 2-5 presents the summary of the analysis carried out.

Table 2-4: Journal, Country, H Index, Citation and Quality evaluation scores (May 2022)

Study	Journals	Country	H-Index	Citations	QE1	QE2	QE3	QE4	Total (QE1 + QE2 + QE3 + QE4)
P1	Computers and Electronics in Agriculture	Netherlands	133	397	1.5	2	2	2	7.5
P2	Decision Support Systems	Netherlands	161	151	1.5	2	2	2	7.5
P3	Agronomy	Switzerland	50	27	1.5	2	2	1.5	7
P4	Agronomy	Switzerland	50	5	3.5	2	2	1.5	9
P5	Land Use Policy	UK	125	165	1.5	1	2	2	6.5
P6	Computers and Electronics in Agriculture	Netherlands	133	142	1.5	1	2	2	6.5
P7	Computers and Electronics in Agriculture	Netherlands	133	183	2	2	2	2	8
P8	Journal of Cleaner Production	UK	232	4	2	1	1	2	6
P9	Journal of Rural Studies	UK	114	7	2	2	2	2	8
P10	Agriculture	Switzerland	43	31	1.5	2	2	1.5	7
P11	Journal of Rural Studies	UK	114	41	1.5	2	2	2	7.5
P12	HortTechnology	USA	59	21	2	1	1	1.5	5.5
P13	International Journal of Information Technology	Singapore	16	0	1.5	1	1	1	4.5
P14	Technology in Society	UK	58	54	2	2	1	2	7
P15	Computers and Electronics in Agriculture	Netherlands	133	95	1.5	1	2	2	6.5
P16	Computers and Electronics in Agriculture	Netherlands	133	25	1.5	1	2	2	6.5
P17	HortTechnology	USA	59	25	1.5	1	2	1.5	6
P18	Journal of Dairy Science	US	204	103	1.5	1	1	2	5.5
P19	Technology in Society	UK	58	0	1.5	2	2	1.5	7
P20	Animal	UK	83	32	1.5	2	2	2	7.5
P21	Precision Agriculture	Netherlands	70	29	1.5	2	2	1.5	7
P22	Sustainability	Switzerland	109	2	2	1	0	2	5
P23	Land	Switzerland	23	4	1.5	2	2	1	6.5
P24	Interactions	US	48	2	2	1	1	1.5	5.5
P25	Lecture Notes in Computer Science	Germany	415	16	2	1	1	2	6
P26	Computers and Electronics in Agriculture	Netherlands	133	142	1.5	1	2	2	6.5
P27	Agricultural Water Management	Netherlands	139	2	1.5	1	2	2	6.5
P28	Canadian Veterinary Journal	Canada	62	1	1.5	0	1	1.5	4

P29	Applied Sciences	Switzerland	75	4	1.5	2	1	1.5	6
P30	Precision Agriculture	Netherlands	70	211	2	0	2	2	6
P31	Computers and Electronics in Agriculture	Netherlands	133	105	2	1	1	2	6
P32	Journal of Agricultural and Resource Economics	USA	51	77	1.5	2	2	2	7.5
P33	Southern Agricultural Economics Association Annual Meetings			3	1.5	0	2	1	4.5
P34	Sustainability	Switzerland	109	43	2	1	1	2	6
P35	Journal of Cleaner Production	UK	232	30	2	1	1	2	6
P36	Precision Agriculture	Netherlands	70	25	1.5	1	2	1.5	6
P37	Precision Agriculture	Netherlands	70	71	1.5	0	2	2	5.5
P38	Journal of Rural Studies	UK	114'	27	1.5	1	2	2	6.5
P39	Precision Agriculture	Netherlands	70	4	1.5	2	2	1.5	7
P40	Canadian Journal of Plant Science	Canada	63	2	1.5	1	1	1.5	5
P41	Agronomy	Switzerland	50	7	1.5	2	2	1.5	7
P42	Sensors	Switzerland	196	9	2	2	1	2	7
P43	Journal of Agribusiness	USA	43	5	1.5	1	2	1	5.5
P44	Agricultural Research	Switzerland	28	4	2	2	1	1	6
P45	Precision Agriculture	Netherlands	70	81	2	2	2	2	8
P46	Precision Agriculture	Netherlands	70	210	1.5	2	2	2	7.5
P47	Agriculture and Human Values	Netherlands	80	33	1.5	1	1	2	5.5
P48	Procedia Technology	-	-	351	2	1	2	2	7
P49	International Food and Agribusiness Management Review	US	40	36	2	1	2	1.5	6.5
P50	Information Processing in Agriculture	China	35	215	1.5	1	1	2	5.5
P51	Agricultural Systems	UK	118	21	1.5	2	2	2	7.5
P52	Indian Journal of Animal Sciences	India	23	3	2	1	0	1	4
P53	International Journal of Advanced Science and Technology	Australia	17	5	1.5	0	1	1	3.5
P54	Technology in Society	UK	58	34	1.5	2	1	1.5	6
P55	Agricultural Systems	UK	118	342	3.5	1	1	2	7.5
P56	Acta Technologica Agriculturae	Poland	10	17	1.5	0	2	1	4.5
P57	International Food and Agribusiness Management Review	US	40	7	1.5	1	1	1	4.5

P58	Information Technology for Development	UK	41	3	2	2	1	1	6
P59	Computers and Electronics in Agriculture	Netherlands	133	9	1.5	2	2	2	7.5
P60	Studies in Agricultural Economics	Hungary	15	15	1.5	1	2	1	5.5
P61	Acta Agriculturae Scandinavica Section B	UK	39	53	1.5	2	2	1.5	7
P62	Precision Agriculture	Netherlands	70	361	2	2	2	2	8
P63	Precision Agriculture	Netherlands	70	0	2	2	2	1.5	7.5
P64	International Journal of Environmental Research and Public Health	Switzerland	138	53	1.5	0	1	2	4.5
P65	Journal of Agricultural and Applied Economics	-	-	40	1.5	1	2	1	5.5

Table 2-5: Summary of self-reported independent variables (arranged in ascending order)

S.N o.	Construct 65 (100%)	Stakeholder Involvement (SI)					Research Area (RA)						Research Design (RD)				Country Status			
		Farmers SI ₁ (n=44)	Facilitators SI ₂ (n=4)	Both SI ₃ (n=10)	General SI ₄ (n=7)	%	Crop RA ₁ (n=37)	Live stock RA ₂ (n=3)	General RA ₃ (n=23)	AVC RA ₄ (n=1)	Multiple RA ₅ (n=1)	%	Qualitative RD ₁ (n=25)	Quantitative RD ₂ (n=38)	Mixed RD ₃ (n=2)	%	Developed CS ₁ (n=39)	Emerging CS ₂ (n=17)	Mixed CS ₃ (n=9)	%
1	Farm size 37 (57)	P1, P2, P5, P6, P7, P10, P15, P16, P17, P19, P20, P21, P26, P27, P32, P33, P34, P37, P38, P39, P43, P46, P59, P61, P62, P64, P65	P42	P4, P29, P30, P48, P63	P35, P44, P51, P52,	SI ₁ (73) SI ₂ (3) SI ₃ (13) SI ₄ (11)	P1, P2, P5, P10, P15, P17, P19, P26, P27, P30, P32, P33, P34, P35, P38, P39, P42, P43, P44, P46, P59, P61, P64, P65	P20, P52	P4, P6, P7, P21, P29, P37, P48, P51, P62, P63,	-	P16	RA ₁ (65) RA ₂ (6) RA ₃ (26) RA ₄ (0) RA ₅ (3)	P7, P29, P30, P34, P35, P42, P44, P48, P51, P52, P62, P63	P1, P2, P5, P6, P10, P15, P16, P17, P19, P20, P21, P26, P27, P32, P33, P37, P38, P39, P43, P46, P59, P61, P64, P65	P4	RD ₁ (32) RD ₂ (65) RD ₃ (3)	P1, P2, P4, P5, P6, P7, P10, P15, P16, P17, P19, P20, P21, P26, P30, P32, P33, P37, P38, P39, P43, P46, P59, P61, P62, P64, P65	P27, P29, P34, P42, P52,	P35, P44, P48, P51, P63,	CS ₁ (74) CS ₂ (13) CS ₃ (13)
2	Facilitating conditions 36 (55)	P2, P5, P12, P13, P15, P16, P17, P19, P23, P26, P33, P36, P41, P43, P46, P47, P53, P54, P57, P58, P59, P60, P62, P65	P50	P4, P29, P45, P48, P55, P63	P14, P35, P44, P51, P52,	SI ₁ (67) SI ₂ (3) SI ₃ (17) SI ₄ (13)	P2, P5, P12, P13, P15, P17, P19, P23, P26, P33, P35, P36, P41, P43, P44, P46, P47, P54, P59, P65	P52	P4, P14, P29, P45, P48, P50, P51, P53, P55, P57, P60, P62, P63	P58	P16	RA ₁ (55) RA ₂ (3) RA ₃ (36) RA ₄ (3) RA ₅ (3)	P12, P14, P29, P35, P44, P45, P48, P50, P51, P52, P58, P62, P63	P2, P5, P13, P15, P16, P17, P19, P23, P26, P33, P36, P41, P43, P46, P47, P53, P54, P57, P59, P60, P65	P4, P55	RD ₁ (36) RD ₂ (58) RD ₃ (6)	P2, P4, P5, P12, P15, P16, P17, P19, P26, P33, P36, P43, P46, P47, P55, P57, P59, P62, P65	P13, P23, P29, P41, P50, P52, P53, P54, P58, P60,	P14, P35, P44, P45, P48, P51, P63,	CS ₁ (53) CS ₂ (28) CS ₃ (19)
3	Age 33 (51)	P2, P5, P6, P7, P15, P16, P19, P23, P26, P27, P32, P33, P34, P37, P38, P39, P43, P47, P57, P59, P61, P62, P64, P65	P50	P4, P29, P30, P48, P55, P63,	P35, P51	SI ₁ (73) SI ₂ (3) SI ₃ (18) SI ₄ (6)	P2, P5, P15, P19, P23, P26, P27, P30, P32, P33, P34, P35, P38, P39, P43, P47, P59, P61, P64, P65	-	P4, P6, P7, P29, P37, P48, P50, P51, P55, P57, P62, P63	-	P16	RA ₁ (61) RA ₂ (0) RA ₃ (36) RA ₄ (0) RA ₅ (3)	P7, P29, P30, P34, P35, P48, P50, P51, P62, P63,	P2, P5, P6, P15, P16, P19, P23, P26, P27, P32, P33, P37, P38, P39, P43, P47, P57, P59, P61, P64, P65	P4, P55	RD ₁ (30) RD ₂ (64) RD ₃ (6)	P2, P4, P5, P6, P7, P15, P16, P19, P26, P30, P32, P33, P37, P38, P39, P43, P47, P55, P57, P59, P61, P62, P64, P65	P23, P27, P29, P34, P50,	P35, P48, P51, P63,	CS ₁ (73) CS ₂ (15) CS ₃ (12)
4	Education 31 (48)	P1, P2, P5, P8, P10, P15, P16, P19, P26, P32, P33, P34, P37, P38, P43, P57,	P49, P50	P4, P18, P29, P30, P48, P63,	P14, P51	SI ₁ (68) SI ₂ (6) SI ₃ (20) SI ₄ (6)	P1, P2, P5, P8, P10, P15, P19, P26, P30, P32, P33, P34,	P18	P4, P14, P29, P37, P48, P49, P50, P51,		P16	RA ₁ (58) RA ₂ (3) RA ₃ (36) RA ₄ (0) RA ₅ (3)	P8, P14, P29, P30, P34,	P1, P2, P5, P10, P15, P16, P18, P19, P26, P32, P33, P37,	P4	RD ₁ (35) RD ₂ (62) RD ₃ (3)	P1, P2, P4, P5, P10, P15, P16, P18, P19, P26, P30, P32,	P29, P34, P49, P50,	P8, P14, P48, P51, P63,	CS ₁ (71) CS ₂ (13) CS ₃ (16)

S.N o.	Construct 65 (100%)	Stakeholder Involvement (SI)					Research Area (RA)						Research Design (RD)				Country Status			
		Farmers SI ₁ (n=44)	Facilitators SI ₂ (n=4)	Both SI ₃ (n=10)	General SI ₄ (n=7)	%	Crop RA ₁ (n=37)	Live stock RA ₂ (n=3)	General RA ₃ (n=23)	AVC RA ₄ (n=1)	Multiple RA ₅ (n=1)	%	Qualitative RD ₁ (n=25)	Quantitative RD ₂ (n=38)	Mixed RD ₃ (n=2)	%	Developed CS ₁ (n=39)	Emerging CS ₂ (n=17)	Mixed CS ₃ (n=9)	%
		P59, P61, P62, P64, P65,					P38, P43, P59, P61, P64, P65,		P57, P62, P63,				P48, P49, P50, P51, P62, P63,	P38, P43, P57, P59, P61, P64, P65,			P33, P37, P38, P43, P57, P59, P61, P62, P64, P65,			
5	Performance Expectancy 27 (42)	P1, P2, P3, P7, P11, P12, P17, P19, P23, P24, P27, P36, P39, P41, P54, P58, P60, P61, P62,	-	P31, P45, P48, P55, P56, P63,	P14, P51	SI ₁ (70) SI ₂ (0) SI ₃ (22) SI ₄ (8)	P1, P2, P11, P12, P17, P19, P23, P24, P27, P31, P36, P39, P41, P54, P61,		P3, P7, P14, P45, P48, P51, P55, P56, P60, P62, P63	P58	-	RA ₁ (56) RA ₂ (0) RA ₃ (41) RA ₄ (3) RA ₅ (0)	P3, P7, P12, P14, P24, P31, P45, P48, P51, P58, P62, P63	P1, P2, P11, P17, P19, P23, P27, P36, P39, P41, P54, P56, P60, P61,	P55	RD ₁ (44) RD ₂ (52) RD ₃ (4)	P1, P2, P7, P11, P12, P17, P19, P31, P36, P39, P55, P61, P62,	P23, P24, P27, P41, P54, P56, P58, P60,	P3, P14, P45, P48, P51, P63,	CS ₁ (48) CS ₂ (30) CS ₃ (22)
6	Risk aversion 25 (38)	P1, P2, P5, P9, P12, P13, P16, P23, P24, P37, P38, P39, P41, P60, P62,	P40	P4, P30, P45, P48, P55, P56,	P14, P35, P51,	SI ₁ (60) SI ₂ (4) SI ₃ (24) SI ₄ (12)	P1, P2, P5, P9, P12, P13, P23, P24, P30, P35, P38, P39, P40, P41,	-	P4, P14, P37, P45, P48, P51, P55, P56, P60, P62	-	P16	RA ₁ (56) RA ₂ (0) RA ₃ (40) RA ₄ (0) RA ₅ (4)	P9, P12, P14, P24, P30, P35, P45, P48, P51, P62	P1, P2, P5, P13, P16, P23, P37, P38, P39, P40, P41, P56, P60,	P4, P55	RD ₁ (40) RD ₂ (52) RD ₃ (8)	P1, P2, P4, P5, P9, P12, P16, P30, P37, P38, P39, P40, P55, P62,	P13, P23, P24, P41, P56, P60,	P14, P35, P45, P48, P51,	CS ₁ (56) CS ₂ (24) CS ₃ (20)
7	Financial Conditions 24 (37)	P5, P8, P9, P12, P13, P15, P16, P17, P32, P33, P57, P60, P62, P65,	P40	P4, P18, P48, P55, P63,	P14, P35, P51, P52,	SI ₁ (58) SI ₂ (8) SI ₃ (21) SI ₄ (17)	P5, P8, P9, P12, P13, P15, P17, P32, P33, P35, P40, P65,	P18, P52	P4, P14, P48, P51, P55, P57, P60, P62, P63,		P16	RA ₁ (50) RA ₂ (8) RA ₃ (38) RA ₄ (0) RA ₅ (4)	P8, P9, P12, P14, P35, P48, P51, P52, P62, P63	P5, P13, P15, P16, P17, P18, P32, P33, P40, P57, P60, P65,	P4, P55	RD ₁ (42) RD ₂ (50) RD ₃ (8)	P4, P5, P9, P12, P15, P16, P17, P18, P32, P33, P40, P55, P57, P62, P65,	P13, P52, P60,	P8, P14, P35, P48, P51, P63,	CS ₁ (63) CS ₂ (12) CS ₃ (25)

S.N a.	Construct 65 (100%)	Stakeholder Involvement (SI)					Research Area (RA)						Research Design (RD)				Country Status			
		Farmers SI ₁ (n=44)	Facilitators SI ₂ (n=4)	Both SI ₃ (n=10)	General SI ₄ (n=7)	%	Crop RA ₁ (n=37)	Live stock RA ₂ (n=3)	General RA ₃ (n=23)	AVC RA ₄ (n=1)	Multiple RA ₅ (n=1)	%	Qualitative RD ₁ (n=25)	Quantitative RD ₂ (n=38)	Mixed RD ₃ (n=2)	%	Developed CS ₁ (n=39)	Emerging CS ₂ (n=17)	Mixed CS ₃ (n=9)	%
8	Effort Expectancy 22 (34)	P1, P2, P11, P12, P13, P19, P21, P23, P32, P36, P39, P41, P54, P57, P64,	-	P45, P48, P55, P56,	P35, P44, P51,	SI ₁ (68) SI ₂ (0) SI ₃ (18) SI ₄ (14)	P1, P2, P11, P12, P13, P19, P23, P32, P35, P36, P39, P41, P44, P54, P64	-	P21, P45, P48, P51, P55, P56, P57,	-	-	RA ₁ (68) RA ₂ (0) RA ₃ (32) RA ₄ (0) RA ₅ (0)	P12, P35, P44, P45, P48, P51	P1, P2, P11, P13, P19, P21, P23, P32, P36, P39, P41, P54, P56, P57, P64	P55	RD ₁ (27) RD ₂ (68) RD ₃ (5)	P1, P2, P11, P12, P19, P21, P32, P36, P39, P55, P57, P64	P13, P23, P41, P54, P56,	P35, P44, P45, P48, P51,	CS ₁ (54) CS ₂ (23) CS ₃ (23)
9	Farming Business Focus 14 (22)	P6, P7, P9, P16, P20, P21, P23, P27, P28, P38, P39, P47,	-	-	P35, P51	SI ₁ (86) SI ₂ (0) SI ₃ (0) SI ₄ (14)	P9, P23, P27, P35, P38, P39, P47,	P20	P6, P7, P21, P28, P51,	-	P16	RA ₁ (50) RA ₂ (7) RA ₃ (36) RA ₄ (0) RA ₅ (7)	P7, P9, P35, P51	P6, P16, P20, P21, P23, P27, P28, P38, P39, P47	-	RD ₁ (29) RD ₂ (71) RD ₃ (0)	P6, P7, P9, P16, P20, P21, P28, P38, P39, P47	P23, P27	P35, P51	CS ₁ (72) CS ₂ (14) CS ₃ (14)
10	Farming experience 11 (17)	P16, P20, P26, P28, P38, P46, P47, P62,	-	P30, P48, P63,	-	SI ₁ (73) SI ₂ (0) SI ₃ (27) SI ₄ (0)	P26, P30, P38, P46, P47,	P20	P28, P48, P62, P63,	-	-	RA ₁ (45) RA ₂ (9) RA ₃ (37) RA ₄ (0) RA ₅ (9)	P30, P48, P62, P63	P16, P20, P26, P28, P38, P46, P47	-	RD ₁ (36) RD ₂ (64) RD ₃ (0)	P16, P20, P26, P28, P30, P38, P46, P47, P62,	-	P48 P63	CS ₁ (82) CS ₂ (0) CS ₃ (18)
11	Social influence 10 (15)	P13, P19, P23, P24, P36, P41, P54,	-	P48, P56	P51	SI ₁ (70) SI ₂ (0) SI ₃ (20) SI ₄ (10)	P13, P19, P23, P24, P36, P41, P54,	-	P48, P51, P56	-	-	RA ₁ (70) RA ₂ (0) RA ₃ (30) RA ₄ (0) RA ₅ (0)	P24, P48, P51	P13, P19, P23, P36, P41, P54, P56	-	RD ₁ (30) RD ₂ (70) RD ₃ (0)	P19, P36	P13, P23, P24, P41, P54, P56,	P48, P51	CS ₁ (20) CS ₂ (60) CS ₃ (20)
12	Compatibility 9 (14)	P2, P3, P9, P12, P16, P60,	-	P30, P45	P51	SI ₁ (67) SI ₂ (0) SI ₃ (22) SI ₄ (11)	P2 P9 P12 P30	-	P3, P45, P51, P60,	-	P16	RA ₁ (44) RA ₂ (0) RA ₃ (44) RA ₄ (0) RA ₅ (12)	P3, P9, P12, P30, P45, P51	P2, P16, P60,	-	RD ₁ (67) RD ₂ (33) RD ₃ (0)	P2, P9, P12, P16, P30,	P60	P3, P45, P51,	CS ₁ (56) CS ₂ (11) CS ₃ (33)
13	Formal / Informal Links 7 (11)	P5, P12, P19, P57,	P4	-	P35, P51	SI ₁ (57) SI ₂ (14) SI ₃ (0) SI ₄ (29)	P5, P12, P19, P35,	-	P4, P51, P57,	-	-	RA ₁ (57) RA ₂ (0) RA ₃ (43) RA ₄ (0) RA ₅ (0)	P12, P35, P51,	P5, P19, P57,	P4	RD ₁ (43) RD ₂ (43) RD ₃ (14)	P4, P5, P12, P19, P57,	-	P35, P51	CS ₁ (71) CS ₂ (0) CS ₃ (29)
14	Region 6 (9)	P32, P33, P37, P43, P47, P62,	-	-	-	SI ₁ (100) SI ₂ (0) SI ₃ (0) SI ₄ (0)	P32, P33, P43, P47,	-	P37, P62	-	-	RA ₁ (67) RA ₂ (0) RA ₃ (33) RA ₄ (0) RA ₅ (0)	P62	P32, P33, P37, P43, P47,	-	RD ₁ (17) RD ₂ (83) RD ₃ (0)	P32, P33, P37, P43, P47, P62,	-	-	CS ₁ (100) CS ₂ (0) CS ₃ (0)
15	Cultural Tradition 5 (8)	P20, P21, P27	P42	-	P44	SI ₁ (60) SI ₂ (20) SI ₃ (0) SI ₄ (20)	P27, P42, P44	P20	P21	-	-	RA ₁ (60) RA ₂ (20) RA ₃ (20) RA ₄ (0) RA ₅ (0)	P42, P44	P20, P21, P27	-	RD ₁ (40) RD ₂ (60) RD ₃ (0)	P20, P21	P27, P42	P44	CS ₁ (40) CS ₂ (40) CS ₃ (20)
16	Trialability 5 (8)	P2, P12	-	P45, P48	P51	SI ₁ (40) SI ₂ (0) SI ₃ (40) SI ₄ (20)	P2, P12	-	P45, P48, P51	-	-	RA ₁ (40) RA ₂ (0) RA ₃ (60) RA ₄ (0) RA ₅ (0)	P12, P45, P48, P51	P2	-	RD ₁ (80) RD ₂ (20) RD ₃ (0)	P2, P12	-	P45, P48, P51	CS ₁ (40) CS ₂ (0) CS ₃ (60)

2.4 Research Gap

The combination of agriculture with artificial intelligence has proven to be a promising opportunity area as it has potential to solve the problems of agricultural production efficiency in numerous ways. The relevance of this subject has motivated the researchers globally to study and identify use cases in this area over the last few years. Zhai *et al.* (2020) surveyed and evaluated thirteen decision support systems using a standard criteria for its accessibility, scalability, interoperability and other aspects and identified requirements for improvement majorly in graphical user interface and functionalities of systems. El-Gayar *et al.* (2019) devised a framework to include key aspects of agricultural processes, involved stakeholders and supply chain and focused on socio-technical and socio-economic drivers and challenges of big data and artificial intelligence which they viewed in two contexts – developed countries with severe shortage of labour and developing countries with nascent technology infrastructure. The possibility of automatic recognition and interpretation of images from earth observation satellites using big data analysis and artificial intelligence is explored in Huang *et al.* (2018). Jha *et al.* (2019) reviewed the current implementation of automation and applications of artificial neural network, machine learning and IoT in agriculture. They also proposed an idea of IoT based solution for flower and leaf identification using machine learning.

M Cubric (2020) studied the drivers and barriers for adoption of AI across various business sectors including healthcare, information technology, energy, agriculture, apparel industry, engineering, smart city, tourism and transport. In another study, Holzinger *et al.*, (2021) emphasised on the security, safety and privacy perspectives on AI for agriculture and healthcare in view of Sustainable Development Goals (SDGs) through digital transformation. IoT and AI have been identified as critical prerequisites to smart farming as these are highly interoperable and use cutting-edge technologies (Haque *et al.*, 2021). Further, the role of responsible leadership was stressed for strengthening outcomes towards sustainable agriculture. (Heldreth *et al.*, 2021) indicated scarcity of research and resources available to organizations for building farm-centred AI systems. The authors highlighted unique considerations for researching farmer-centred AI which included common hardware and data constraints, challenge of digital literacy and language barrier, need to build trust with farmers through transparency and co-designing applications with farmers and intermediaries. The study by Rodzalan *et al.*, (2020) focused on adoption related issues and drivers of AI in agriculture in Malaysia through quantitative analysis of 150 farmers using impact-uncertainty analysis. Although the study focused on the AI adoption particularly in agriculture but lacked in comprehensive literature review and theoretical framework. These findings motivated us to

carry out detailed study on identification of factors that influence adopting AI in agriculture. Following this, we analysed all major constructs in the literature and proposed a framework for adoption of AI in agriculture.

In the past, a few review studies were conducted on the use of digital technologies enabling agriculture sector with enhanced decision making for better productivity. Gómez-Chabla *et al.* (2019) reviewed the use of IoT in agriculture focusing on 60 articles with three perspectives (a) IoT applications in agriculture such as intelligent greenhouse; (b) use of IoT devices like drones; and (c) IoT-based software applications using artificial intelligence. With strong focus on disease detection, grain quality and phenotyping using computer vision, Patrício *et al.* (2018) reviewed 25 articles selected from dataset for 5-year period and highlighted its benefits to enable researchers with adequate data for objective analysis of samples and automating laborious tasks. A systematic literature review by Sharma *et al.* (2020) on the use of Machine Learning in improving Agriculture Supply Chain (ASC) performance based on study of 93 articles highlights benefits of ML in decision making in ASC. Although these studies have provided a systematic literature review of using IoT, computer vision and ML in agriculture, these further encourage researchers to study the broader topic of Artificial Intelligence with a wider timespan and large number of articles to understand depth and breadth of the subject.

In contrast to the views presented earlier, this study presents a comprehensive review of research work on using artificial intelligence in the field of agriculture. A number of papers are discussed that capture the implementation of machine learning, decision support systems, deep learning, neural networks and various other techniques for improving ways of working in agricultural field and business processes. This study aims to summarize different challenges of using artificial intelligence based agricultural applications and automation processes that replace humans to reduce efforts and provide improved efficiency. In addition, this review intends to identify opportunities in agricultural systems and business to be an updated reference for future work.

2.5 Development of framework for present study

This section presents the analytical method used to identify constructs from literature review for utilizing those in the proposed framework for carrying out further study (Sood *et al.*, 2022). Various theories have been utilised in literature to understand, predict and explain factors influencing adoption of technology which include TAM (Davis, 1989), DoI (Rogers, 2003), UTAUT (Venkatesh *et al.*, 2003) and TOE Framework (Tornatzky *et al.*, 1990). A partial literature refers to TPB (Ajzen, 1991) and utility maximization theory for understanding the end user behavior and action to adopt new technology. In this research work, the key constructs

have been identified using three independent theoretical frameworks – DoI, UTAUT and TOE. While DoI provides fundamental basis for diffusion of a new innovation, UTAUT is a comprehensive framework for study of technology adoption based on several other models from IS literature such as Theory of Planned Behavior (TPB), Theory of Reasoned Action (TRA) *etc.* Additionally, TOE helps to relate and classify the constructs to the relevant context of technology, organization and environment. In combination, these frameworks were useful in grouping and organizing the key factors from the selected studies.

The articles selected for present study have been reviewed critically for determining the different constructs influencing the adoption of AI in agriculture. All the identified constructs were recorded in tabular form for every selected article while depicting their importance in terms of significant or non-significant in the study as illustrated in Figure 2.11. The frequency *i.e.* number of times a construct is recognized as significant is also captured in the analysis. Following this, we devised an algorithmic approach to identify highly significant factors from these studies using criteria as presented in Algorithm-1 below.

Algorithm 1 Significant Factor Selection Approach

Input: Selected adoption studies from literature

Output: Significant factor selected for AI adoption study

Begin:

- 1: For articles 1 to 65 selected articles
 - (a) Compile list of factors used in each article.
 - (b) Classify the factors as significant or non-significant based on results.
- 2: Calculate total number of times (N) every factor is used in all 65 studies.
- 3: Calculate total number of times (S) significant factor is used in all 65 studies.
- 4: Calculate percentage of times a factor is identified as significant ($P = (S/N) * 100$)
- 5: Select factor for AI adoption study if $P \geq 50\%$ (at least 50% of studies indicate that particular factor is significant) and $N \geq 5$ (at least five studies have included the particular factor)

End

The approach yielded 30 factors which represented that at least 50% of studies identified these as significant and at least five studies have included the particular factor. Using the lens of three selected theories, these factors are grouped as indicated in bold in Figure 2.11. For example, *perceived usefulness* from TAM, *relative advantage* from DOI and *high profits / yield* have been mapped to the *performance expectancy* from UTAUT in proposed research framework. Similarly, *perceived ease of use* from TAM and *complexity* in DOI are mapped to *effort expectancy* from UTAUT in proposed research model. The aspect of security and privacy in agriculture, though important, has been studied less commonly in literature. This has been included to understand its influence on adoption decisions for its growing importance (Castle *et al.*, 2016; Heldreth *et al.*, 2021; Shutske *et al.*, 2018) .

Further, to organize the above listed factors, these are classified into five categories – individual characteristics (performance expectancy, effort expectancy, risk aversion), environmental factors (facilitating conditions, social influence, information availability, financial conditions), structural factors (farm size, formal and informal links, farming business focus), technology factors (compatibility, security and privacy), and demographic factors (age, education, farming experience). The factors identified using systematic literature review are organised to form basis of proposed model as presented in Figure 2.12 for study in present research work (Sood *et al.*, 2022). The framework developed using these factors explores the relationship of different components with dependent variable of intention to adopt AI.

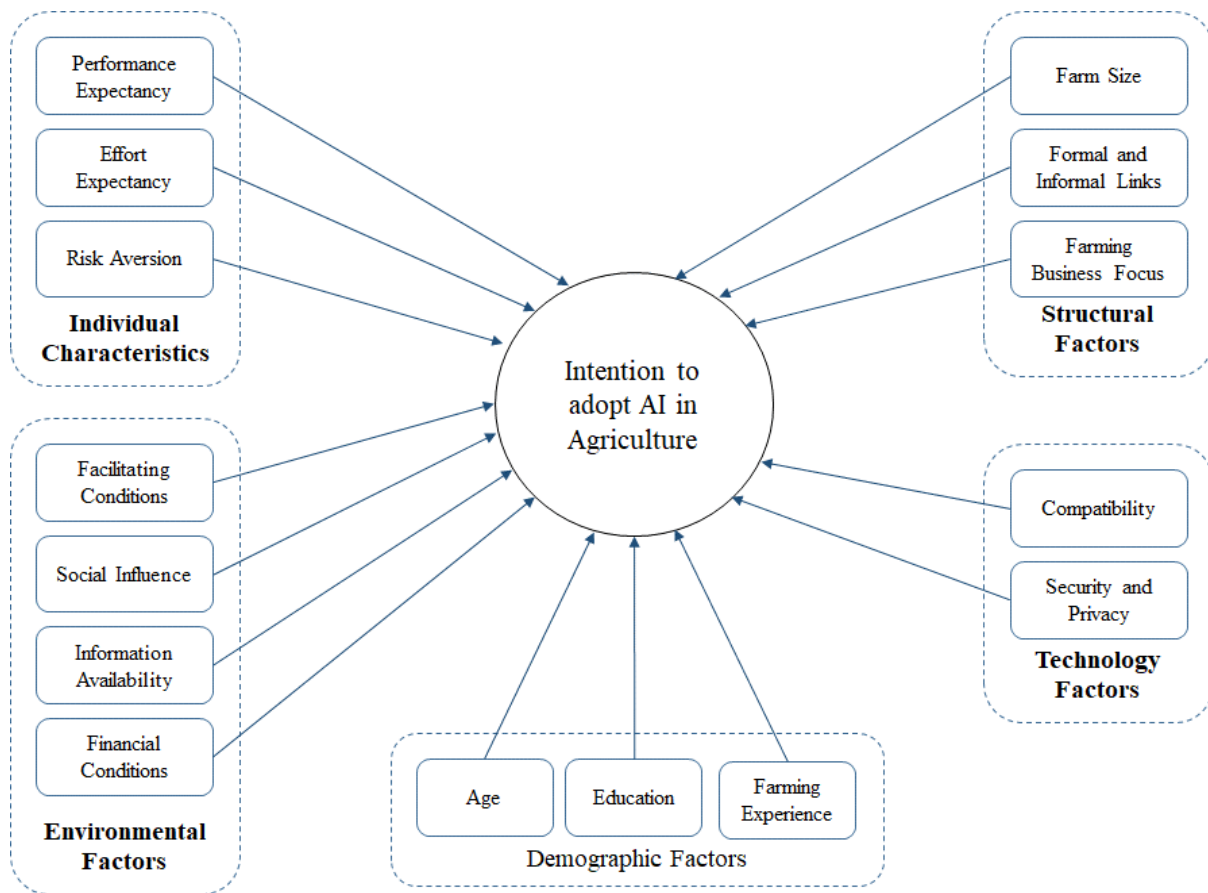


Figure 2.12: Integrated framework based on literature for present study

Based on the classification, the description of each variable used in present study is given below:

2.5.1 Individual characteristics

2.5.1.1 Performance expectancy

Performance expectancy is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance (Venkatesh *et al.*, 2003). Expectations associated with performance of digital technologies in agriculture have been

studied in various articles in the form of different constructs e.g. relative advantage (Balafoutis *et al.*, 2020), (Pathak *et al.*, 2019), (Aubert *et al.*, 2012)) from DoI or perceived usefulness from TAM (F Caffaro *et al.*, 2020; Cubric, 2020; M Michels *et al.*, 2021; Pierpaoli *et al.*, 2013). It stands as a primary determinant of adoption, offering insight into how user attitudes and intentions to use are influenced. A positive perception about the innovative solution increases the intention of decision makers to adopt the new solution.

2.5.1.2 Effort expectancy

Effort expectancy is defined as the degree of ease associated with the use of the system. In several studies this attribute has been investigated as ‘perceived ease of use’ from TAM (Chaudhary & Suri, 2021; Nowak, 2021; Salimi *et al.*, 2020) which positively influences the intention to adopt and as ‘complexity’ from DOI (Pathak *et al.*, 2019; Shang *et al.*, 2021; Vecchio *et al.*, 2020) which negatively influences the adopting intention.

2.5.1.3 Risk aversion

Tendency to avoid activities involving risk influences intention and decision to adopt a new technology solution. Risk-averse nature slows down the adoption process (Daberkow & McBride, 2003) and is generally caused by distrust in the new solution (Heldreth *et al.*, 2021). In contrast, confidence building in technology leads to adoption if it keeps its promise to be profitable. In literature, authors have studied this aspect in form of trust, confidence, motivation, interest and willingness (Barnes *et al.*, 2019; Bryant & Higgins, 2021; Pathak *et al.*, 2019; Salimi *et al.*, 2020; Shang *et al.*, 2021; Tey & Brindal, 2012).

2.5.2 Environmental factors

2.5.2.1 Facilitating conditions

As per an individual’s belief, the existence of organizational and technical infrastructure to support use of the new system is referred to as facilitating conditions (Venkatesh *et al.*, 2003). For promoting use of new technology in field, government tends to make changes in policies and plans which increases adoption by end users (B. Li *et al.*, 2021). In the context of agriculture, this construct has been studied by several researchers using UTAUT framework and is observed as significant factor (Giua, Materia, *et al.*, 2022; Marius Michels *et al.*, 2020; Molina-Maturano *et al.*, 2021; Ronaghi & Forouharfar, 2020). In addition to this, it has also been studied as technological readiness (Barnes *et al.*, 2019; Chaudhary & Suri, 2021; Jellason *et al.*, 2021; Rathod & Dixit, 2020; Smidt, 2021), technical support availability (Aubert *et al.*, 2012; Cubric, 2020; Gallardo *et al.*, 2019; Pathak *et al.*, 2019). In the present study, use

facilitating conditions as representative of technological readiness and technical support availability of agricultural set-up for users intending to adopt AI-based solutions.

2.5.2.2 Social influence

Venkatesh *et al.* (2003) defines the social influence as “the degree to which an individual perceives that how important others believe he or she should use the new system”. The present study reflects this perspective by referring to the extent to which the farmer comprehends the relevance of why others believe they should use the AI-based solution in their fields. This includes the effect of pressure from society and peers on adoption of this innovation. This factor has been included in several studies (B. Li *et al.*, 2021; Tey & Brindal, 2012).

2.5.2.3 Information availability

The degree of ease of availability of information to farmers has been strong factor in adoption of new technology solution as studied by users (Lambert *et al.*, 2015; B. Li *et al.*, 2021). Realising the fact that information flow from extension agency to individual farmer plays a critical role in deciding whether farmer is laggard or innovator (Bryant & Higgins, 2021), several initiatives in financial, technological and social domains are taken up by government and private organizations for information and knowledge dissemination about the new technology. The relevant information regarding new technology, enable farmers to make conscious decisions towards adoption.

2.5.2.4 Financial conditions

The factors representing financial state of the end users are very critical in explaining their intention to adopt the new technology. Affordable solutions are highly preferred by the users along with other conditions (Benyam *et al.*, 2021). Further, the availability of financial resources in form of loan or subsidy to farmers helps to promote the adoption of new technology (Carrer *et al.*, 2017). Many studies found this factor significant (Bryant & Higgins, 2021; Caplan *et al.*, 2014; Chaudhary & Suri, 2021; Cubric, 2020; Drewry *et al.*, 2019; Gallardo *et al.*, 2019; Mitchell *et al.*, 2021; Pierpaoli *et al.*, 2013; Rathod & Dixit, 2020; Skevas & Kalaitzandonakes, 2020; Takácsné György *et al.*, 2018).

2.5.3 Structural factors

2.5.3.1 Farm size

Farm size is defined as the work area of a farmer or the scale at which the technology will be applied by farmers or end-user. A relationship between willingness of farmers to innovate using a new technology with their farm size has been observed in literature (M T Batte, 2005; D Pivoto *et al.*, 2018).

2.5.3.2 Formal and informal links

The links of farmers through formal and informal channels, help for dissemination of which increases awareness among farmers about new technology (Barnes *et al.*, 2019; Liu *et al.*, 2021; Skevas & Kalaitzandonakes, 2020) and hence leads to high perceived usefulness and intention to adopt. (F Caffaro *et al.*, 2020). On the other hand, study shows that isolation of precision farmers acts as deterrent to spread knowledge on the innovation (Balogh *et al.*, 2021). Thus, formal and informal links of farmers represent a social connect which will lead to adoption of new technology.

2.5.3.3 Farming Business Focus

Focus on farming business leads to the intention of farmers to select new technology (Vecchio *et al.*, 2020). This construct has been studied in literature in several forms such as farm's ownership status (sole or joint ownership), number of hours spent on farms, the ratio of farm income to total income of farmer, production specialization *etc.* (M T Batte, 2005; Bryant & Higgins, 2021; Hayat *et al.*, 2020; Jaafar & Kharroubi, 2021; Liu *et al.*, 2021; M Michels, von Hobe, *et al.*, 2020; Shutske *et al.*, 2018).

2.5.4 Technology factors

2.5.4.1 Compatibility

By its definition, compatibility pertains to "the degree to which the innovation is perceived as consistent with potential adopter's existing values, past experiences and current needs" (Rogers, 2003). Agricultural work involves numerous routine activities which need to be supported by new technology solution without any major change in the existing set-up and adding productive value to these activities (Aubert *et al.*, 2012; Balafoutis *et al.*, 2020). The level of compatibility brought up by Smart Farming solutions tends to increase its adoption intention among farmers and facilitators.

2.5.4.2 Security and Privacy

The aspect of security and privacy has been studied less commonly in literature, but it still carries high significance in adoption decisions. Security pertains to the safeguarding of user data and information, whereas privacy encompasses the ownership of farm data. (Castle *et al.*, 2016). Since farm data can be shared without inhibiting its use by original user, it is important to understand the concern related to security and privacy. A study of livestock and crop producers by Shutske *et al.* (2018) indicated that security and privacy was highlighted as major concern by agricultural cooperative IT experts. Heldreth *et al.* (2021b) underlined the need of assurance to farmers on privacy and security of data. The government and other organizations

ensure transparency by taking informed consent before collecting farm related data. Such initiatives foster trust among farmer community and tends to increase adoption of new technology.

2.5.5 Demographic factors

2.5.5.1 Age

Age of farmer in years is an important parameter to make decision to adopt a new technology. This construct has been studied in literature as positive predictor towards adoption (Daberkow & McBride, 2003; Isgin *et al.*, 2008) and has shown negative effects also on adoption of new technology in several studies (D'Antoni *et al.*, 2012; Lambert *et al.*, 2015). With age, farmers get longer planning horizons and gain better perspectives to understand the importance and role of using a new technology.

2.5.5.2 Education

Education level of farmers has a vital role towards adoption of new technology. Literature shows that the level of education in early-adopters of a new technology is higher as compared to that in late-adopters (Rogers, 2003). Additionally, a good level of education helps an individual to learn new technology and its operations. Several studies have found *education* positively influencing the adoption of new technology (Lambert *et al.*, 2015; Pivoto *et al.*, 2019; Walton *et al.*, 2010).

2.5.5.3 Farming Experience

Experience in farming help farmers to understand their business and practices better, which in turn enable them to make better decisions. The literature indicates a mixed perspective that younger farmers would prefer to be assisted by new technology as they lack experience (Aubert *et al.*, 2012; M Michels, Fecke, *et al.*, 2020), and older farmers with higher experience would not need any additional input (Isgin *et al.*, 2008). In one of the recent studies, (Tey & Brindal, 2022) observed that farming experience had a varying effect ranging from positive to negative with lower statistical power.

The integrated framework includes different dimensions for evaluating factors influencing adoption of AI-based solutions in agriculture and this framework is employed in present study using research methodology as explained in next chapter.

2.6 Summary of Literature Review

The combination of agriculture and artificial intelligence (AI) has great potential to improve agricultural production efficiency. Researchers have been studying and identifying use cases

in this area. Several studies have evaluated decision support systems and identified areas for improvement, such as graphical user interfaces and functionalities. The use of AI in agriculture has been explored in various contexts, including developed and developing countries. Adoption of AI in agriculture faces challenges related to factors like accessibility, scalability, interoperability, and security. Studies have reviewed the use of IoT, computer vision, and machine learning in agriculture, but more comprehensive research is needed.

A number of theories are used in the Information Systems domain to understand and predict the factors influencing the adoption of technology at individual and organizational levels. These theories include the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovation (DoI) and Technology-Organization-Environment Framework (TOE Framework). In overall, these theories highlight the importance of user attitudes, perceptions, social influences, and contextual factors in determining technology adoption outcomes. They provide frameworks for researchers and practitioners to understand user behaviors and decision-making processes related to technology adoption, informing the design and implementation of new technologies in various contexts. The combination of the DoI, UTAUT, and TOE Framework offers a comprehensive and multi-dimensional approach to studying technology adoption, considering individual, social, organizational, and environmental factors.

The systematic literature review analyzed a set of articles published between 2003 and 2022, focusing on the adoption of artificial intelligence (AI) in agriculture. Previous reviews had examined related topics such as precision agriculture, digital agriculture, and smart farming. The review identified various theoretical frameworks utilized in the selected articles, with the most common ones being DOI, TAM, and UTAUT. In terms of research methods, the articles employed qualitative, quantitative, or mixed approaches. Geographically, most studies were conducted in developed countries like the USA and Germany. The technologies studied included precision agriculture, smart farming, digital agriculture, and others. The selected articles were evaluated using quality evaluation criteria, and their scores indicated a relevant set suitable for further study. The analysis categorized the literature based on stakeholder involvement, research area, research design, and economic status of the country. A framework has been developed to understand the factors influencing the adoption of AI in agriculture, categorized into individual characteristics, environmental factors, structural factors, technology factors, and demographic factors. The framework aims to provide a comprehensive reference for the analysis presented in next chapter.

Chapter 3 Research Methodology

Based on the review of literature, an integrated framework for present study is proposed in previous chapter. This chapter presents the research methodology adopted in the present research work. Research methodology provides a systematic and structured approach to investigate, analyze, and interpret data. It ensures rigorous data collection, validity, and reliability of the results. A clear research design and ethical considerations are integral parts of methodology, contributing to the overall quality and credibility of the study. Methodology also allows for replication and generalizability of findings, promoting the advancement of knowledge. By guiding researchers in data collection and analysis, it ensures consistency, control, and adaptability, leading to sound conclusions and meaningful contributions to the field of study.

Given the scarcity of research on the adoption of AI-based solutions in agriculture, particularly within the context of India, an exploratory study is deemed the most suitable approach. The primary goal of explorative study is to gain insights, generate hypotheses, and identify potential research questions. Further, a positivist research approach is considered appropriate, aligning with the goal of this study, which aims to contribute to the expanding body of knowledge on the adoption of digital technology solutions like AI-based solutions in agriculture. Such an approach emphasizes objectivity, empirical observation, and involves formulation and quantitative testing of framework. In the realm of researching innovation diffusion and adoption, quantitative methods grounded in surveys conducted through questionnaires have gained substantial prevalence. Hence, this study adopts a quantitative, cross-sectional research methodology centered around questionnaire surveys.

This chapter presents the research methodology adopted to understand the adoption intent for AI-based solutions in agriculture in Indian context. Section 3.1 describes the methodological process adopted in present study which includes several stages such as literature review, development of research framework, development of research instrument *etc.* While Section 3.2 to Section 3.4 highlight the unit of analysis, population, respondents and sample size, the Section 3.5 depicts sampling and data collection methodology utilised in the present study. Section 3.6 and Section 3.7 present details of research instrument for measurement of adoption intent and checking its reliability, respectively. Section 3.8 explains data analysis methods employed in present study. Finally, Section 3.9 summarizes the overall research methodology adopted in this study.

3.1 Research Methodology

The research methodology adopted in the present study attempts to fulfil the research objectives and scope defined for the study. Research Objective 1 focuses on identifying and analyzing the factors that influence the intention to adopt AI-based solutions in agriculture, drawing insights from existing literature. This objective is addressed through systematic literature review which identifies the factors influencing adoption intent for AI-based solutions in agriculture. By identifying the significant factors from the previous studies, the systematic literature review also attributes toward development of framework as per Research Objective 2 of this study. The literature review enables the study to build on existing knowledge and theories, combining the UTAUT, TOE, and DOI models into a single integrated framework. By drawing from established theoretical perspectives, the study ensures a comprehensive approach to understanding the factors influencing adoption intent. The last objective of the study *i.e.* Research Objective 3 is fulfilled by empirical evaluation of the proposed model using structural equation modelling. The objectives of research and methodology adopted is elucidated as follows:

Research Objective-1: To identify and analyse the factors impacting intention to adopt Artificial Intelligence-Based solution in agriculture from extant literature

Methodology: A thorough literature review in Chapter 2 examines articles from different academic research databases and identifies the factors influencing intention to adopt digital technology solutions in agriculture using a lens of combination of three theoretical well-known models of technology adoption. The review includes studies from various countries and regions to ensure a diverse representation of factors influencing adoption intent.

Research Objective-2: To develop an integrated framework based on analysis of existing theoretical models

Methodology: The factors identified from literature review using combined set of three theories constitute a framework which is used to study the adoption of AI-based solutions in agriculture. The integrated framework proposed in Chapter 2 represents inter-relationship of independent factors from literature with dependent factor as intention to adopt the digital solutions.

Research Objective-3: To identify significant factors in Indian context through empirical evaluation of developed framework

Methodology: As this kind of combination of theoretical models has rarely been used in literature for studying adoption of digital technology in agriculture, there is no reliable

instrument available to measure intention to adopt AI-based solution in agriculture which further demands a new scale for evaluation. Literature review facilitates to identify and generate suitable items for questionnaire for further study. As presented in Chapter 4, data is collected using the questionnaire, and its reliability is tested using Cronbach's alpha, and need-based improvement is carried out for assessing scale validity. Thereafter, hypotheses are generated taking into account new factors using Exploratory Factor Analysis (EFA). Confirmatory Factor Analysis (CFA) is utilized for assessing the convergent validity, discriminant validity and composite reliability of measurement model. Structural Equation Modeling (SEM) is used to understand the impact on adoption intent for AI-based solutions in agriculture.

3.1.1 The Methodological Process

The complete study is carried out under different stages which are depicted using a flowchart in Figure 3.1. The methodological process of the research starts with comprehensive literature review as presented in Chapter 2. It provides clarity on the journey of digital technology adoption in agriculture over time and the theoretical perspective for acquiring research insights into the factors influencing adoption intent for digital solution. A thorough literature review enables to develop framework for further research. The systematic literature review lays the foundation for the subsequent stages of the research, guiding the development of the research instrument and providing a robust theoretical framework for the empirical evaluation of the adoption of AI-based solutions in agriculture. This subsequently results in the formulation of a research design to tackle each research objective in Chapter 3 followed by the development of research instrument for data collection. In the next stages, analysis of the collected data is carried out using analytical techniques such as EFA, CFA and SEM. Research hypotheses are generated, considering new factors identified through EFA. The convergent validity, discriminant validity, and composite reliability of the measurement model is assessed using CFA. SEM is then utilized to understand the impact of these factors on the intention to adopt AI-based solutions in agriculture. Finally, the results of analysis for inter-relationship of factors are discussed in Chapters 5 and conclusion and directions to future work is presented in Chapter 6.

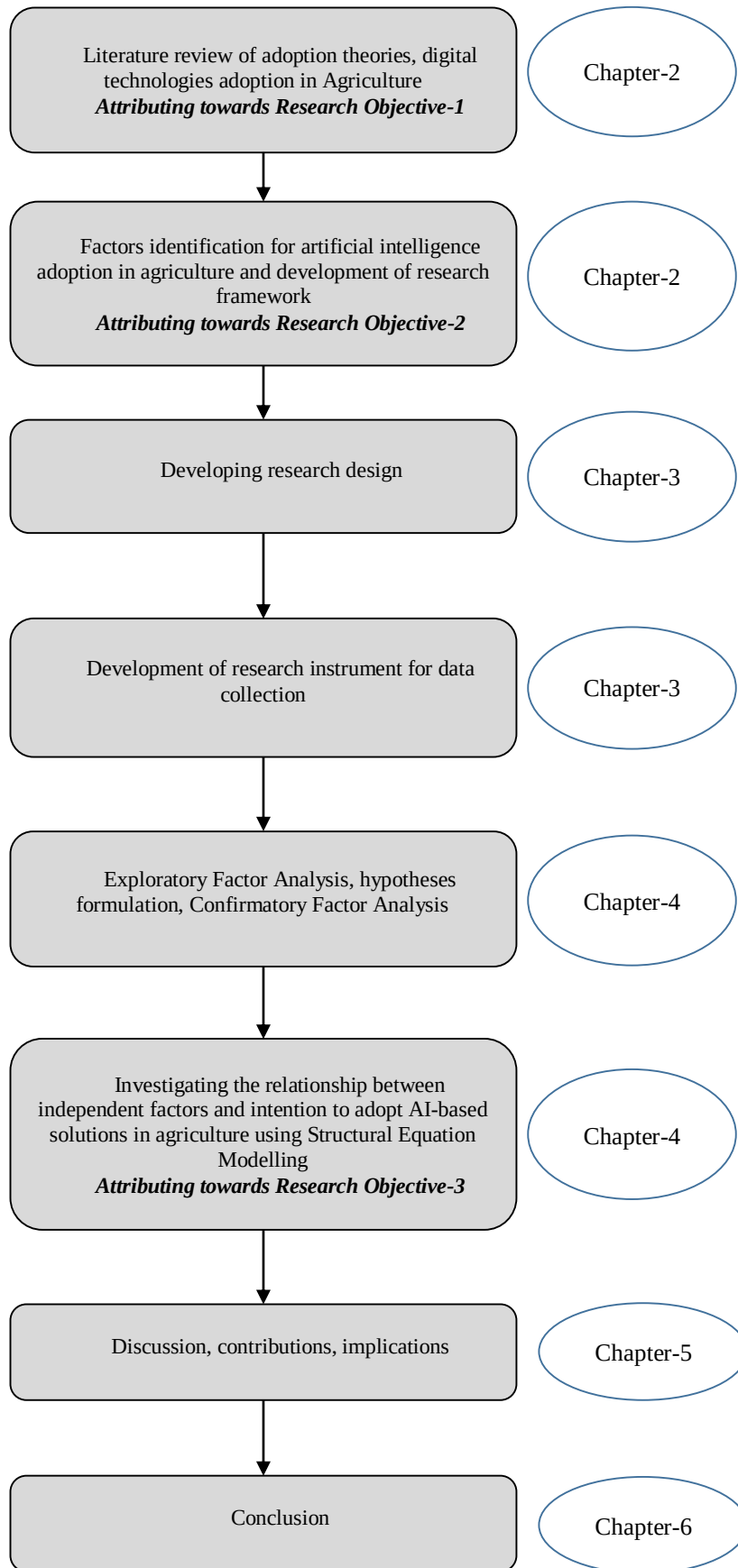


Figure 3.1: Methodological process

3.2 Unit of analysis

The unit of analysis refers to the specific entity or level of observation on which a researcher focuses the analysis. It is crucial because it determines the scope and validity of research findings, allowing researchers to draw accurate conclusions about the phenomena under investigation (S. Kumar, 2018). The choice of unit of analysis impacts the generalizability and applicability of research findings.

As the present research focuses on analysing adoption intent for AI-based solutions in agriculture, it needs to understand the stakeholders involved in process of introducing new technology solution and its users. The unit of analysis in the study can be classified in two major categories –

- (a) The largest user of the AI-based solution are **farmers** who are directly involved in agricultural production and economic activities. The majority of activities involving decision making are performed at farm level during pre-production and production stages, for which AI-based solutions are the most suitable for enriching the decisions with appropriate and suitable insights. Farmers are the end-users of digital solutions, and their insights and feedback can help in developing and tailoring these technologies to meet their specific needs and challenges. By understanding their perspectives, developers can create user-friendly and effective tools that address real-world farming problems. Farmers' acceptance and willingness to adopt new technologies are critical for successful implementation. By involving farmers in the design and development process, their concerns and preferences can be addressed, increasing the likelihood of widespread adoption and usage of digital solutions in agriculture. Farmers' input helps in identifying potential barriers and challenges that may hinder the adoption of digital solutions. By understanding their needs and aspirations, solutions can be designed to improve productivity, reduce risks, conserve resources, and enhance profitability.
- (b) For implementation of new technology, a bridge between source of technology development and the end user is essentially required. **Facilitators** are enablers of innovation in agricultural system, for example, agricultural universities, agriculture research institutes, government agriculture departments who reach out farmers for sharing information on new development regarding seeds, pesticides, fertilizers, techniques and practices. Organizations with profit only focus and having no role in enablement of farmers for using new solution or technology are excluded from

the definition of facilitators. By understanding the challenges in agricultural practices adopted by farmers, the facilitators collaboratively work with group of researchers, scientists, and developers to bring out a solution to the identified problems. Facilitators provide improved quality seeds, fertilizers, pesticides, agricultural equipment and technological solution to farmers and enable them with information and training to use. Through direct involvement of agricultural universities and research institutes, a recursive cycle of feedback and improvement in agricultural system and practices gets established which results into increased efficiency and higher production.

3.3 Population and Respondents

India has a significant agricultural sector, with a vast population of farmers. As of 2021, the estimated population of farmers in India is around 118 million, making it one of the largest agrarian populations globally (Ministry of Agriculture & Farmers Welfare Government of India, 2022). These farmers are engaged in various agricultural activities, including crop cultivation, livestock rearing, and horticulture and vary in terms of landholding size, agricultural practices, technology adoption, and socioeconomic backgrounds.

In order to empower farmers with suitable information and knowledge for selection and adoption of new technology, Government of India makes use of its several functionaries such as Agriculture Technology Management Agency (ATMA), Krishi Vigyan Kendras (KVKs) in addition to research institutions (ICAR), State Agricultural Universities (SAUs), Central Agricultural Universities (CAUs) (Ministry of Agriculture & Farmers' Welfare Government of India, 2017). These functionaries act as facilitators and support efficient delivery of the communication and technological improvements and innovation to the farmers. Facilitators also motivate farmers to adopt activities that capture greater value from their produce. The present study excludes private organizations which are involved digital farming solutions as they more focus on organizational profits.

While there are 731 KVKs as shown in Table 3-1, under various host institutions including Central Agricultural Universities (3), Deemed Universities (4), State Agricultural Universities (63), Research Institutes (64), Directorates/Project Directorates (13), National Bureaux (6), National Research Centres (15). KVKs are also broadly distributed under 11 zonal Agricultural Technology Application Research Institutes (ATARI) across India. These units are responsible for scientific research and development for improvement in crops with enhancement in production volume and quality. With mission of farmer-centric growth in agriculture and allied

sectors through application of appropriate technologies in specific agro-ecosystem perspective, KVKs focus on-farm testing to assess the location specificity of agricultural technologies under various farming systems. KVKs also act as knowledge and resource centre of agricultural technologies for supporting initiatives of public, private and voluntary sector in improving the agricultural economy of the district. KVKs provide farm advisories using ICT and other media means on varied subjects of interest of farmers.

Table 3-1: Host Institution-wise distribution of KVKs

Organization	KVKs
State Agricultural University	472
Central Agricultural University	22
ICAR Institutes	66
Non-government Organization	104
Public Sector Undertaking	3
State Govt.	38
Central University	3
Deemed University	8
Other Educational Institution	5
Total	731

3.4 Sampling

The scope of the present research is confined to the states of Punjab and Haryana with total 4.41 million farmers, which represent 3.72% of the total population of farmers in India (Ministry of Agriculture & Farmers Welfare Government of India, 2022). Both the states combined represent 8.35% of the total area of country and contribute to 14.11% of total production of food-grains in India which is significant contribution to the nation's food grain production. Therefore, understanding the perspectives and experiences of farmers in these states regarding use of AI-based solutions in agriculture can provide valuable insights into the adoption and impact of technology in high-intensity farming systems. Moreover, Punjab and Haryana have a relatively well-developed agricultural infrastructure, including irrigation facilities, access to markets, and a strong extension network. This infrastructure may influence the adoption and utilization of digital solutions in agriculture, making it relevant to study the specific challenges and opportunities faced by farmers in these states. Furthermore, Punjab and Haryana have witnessed a significant Green Revolution and subsequent intensification of agriculture. However, this has also led to challenges such as overuse of inputs, declining soil health, and environmental degradation. Exploring the role of digital agriculture in addressing these challenges and promoting sustainable farming practices in these states can provide valuable lessons and strategies that can be extrapolated to other regions facing similar issues.

For the purpose of the study, the focus is on understanding intention of farmers and facilitators for adopting AI-based solutions in agriculture. The primary data is collected from farmers using a combination of stratified sampling and simple random sampling. Stratified sampling involves dividing the population into homogenous subgroups or strata based on relevant characteristics such as geographical location. In the present study, the population is divided at district level and samples were collected mainly from main ten districts in Punjab and eight districts in Haryana which contribute towards high agricultural production across the state. This approach is beneficial because it allows for representation of different segments of the population, ensuring that farmers with varying levels of digital agriculture adoption are included in the sample. It provides a more accurate and comprehensive understanding of the overall adoption patterns in the region. Additionally, it helps in making meaningful comparisons and drawing valid conclusions about the adoption of AI-based solutions among different subgroups of farmers in Punjab and Haryana.

To understand the perspectives of facilitators, the present study uses snowball sampling method to collect data as the target population size is small. This technique helps to identify and access the individuals with relevant inputs and may be difficult to locate through traditional sampling techniques. Snowball sampling helps to reach out participants who possess the necessary knowledge and insights, as these individuals are more likely to be connected to others with similar expertise. The referred participants share their experiences and insights comfortably which leads to richer and more in-depth data. The primary data is collected by contacting agricultural university, extensions and co-operatives and agricultural departments of Punjab and Haryana states in Northern India. These states contribute towards the highest crop production in the country and represent diversified facilitator groups to study adoption intention of AI-based solutions in agriculture.

3.5 Measuring Adoption Intent for AI-based Solutions in Agriculture

The constructs of the research for studying the intent of farmers and facilitators to adopt AI-based solutions are identified in Section 2.5. Based on the identified constructs, two questionnaires are designed for collecting data separately from farmers and facilitators. The questionnaire is developed to obtain the inputs from respondents in a structured manner and analyse it further for achieving the research objectives. The following section describes the procedure in detail.

3.5.1 Scale Formation

Scaling is a technique used to measure and quantify a specific phenomenon, serving the primary research objective (DeVellis, 2012). This process involves identifying the construct and subsequently formulating relevant items associated with the identified construct.

3.5.1.1 Construct Identification

As discussed in Chapter 2, using the lens of three theoretical frameworks, including DoI, UTAUT and TOE, the literature on adoption of digital technologies including AI, machine learning *etc.* in agriculture was studied. After a comprehensive review of literature, based on the dimensions from theoretical frameworks utilized, significant constructs are identified, as explained in Section 2.5. These identified constructs form the basis of integrated framework proposed in the present study.

3.5.1.2 Research Instrument Development

After constructs identification, it becomes essential to determine statements that can effectively capture the viewpoints of farmers and facilitators to adopt AI-based solutions in agriculture. For the purpose of this studying farmers' perceptions, a questionnaire composed of 41 questions is prepared in English and two regional languages (Hindi and Punjabi). The items in the scale are adapted from the relevant sources in literature as illustrated in Appendix 2. The questionnaire has the most of LIKERT scale items which are divided among five sections including *individual characteristics* to gain insight of an individual farmer's approach towards adoption of AI-based solution based on perceived performance expectancy, effort expectancy and risk aversion (12 items); *environmental factors* to evaluate the impact of facilitating conditions, social influence, information availability and financial conditions (14 items); *structural factors* includes study how farmers' links and farming business focus influence their decision to adopt AI-based solution (5 items), the single item corresponding to farm size is analysed separately with demographic factors; *technical factors* intended evaluation of technology compatibility and its challenges related to security and privacy (7 items); *demographic factors* to understand the relationship of adoption performance with demographic conditions of farmers (3 items).

For studying perceptions of facilitators, the data collection in present study uses a questionnaire with 41 questions is prepared in English and two regional languages – Punjabi and Hindi. The questionnaire comprises of five sections with most of the LIKERT scale items to evaluate (a) user-perceived performance expectations, efforts involved in using solution and perceived risks regarding use of these solutions under section *individual characteristics*; (b) the impact of

facilitating conditions, social influence, information availability and financial conditions for adoption of AI-based solutions in agriculture in section *environmental factors*; (c) the influence of *structural factors* such as the formal and informal links; (d) the role of *technology factors* such as compatibility of intelligent solution with existing set-up and its challenges related to security and privacy; and (e) *demographic factors* capturing basic details such as age, education, experience *etc.* in order to understand the adoption preferences based on these factors.

3.5.2 Data Collection

The questionnaire was administered to farmers and facilitators during the period of April 2022 to August 2022 after ethical clearance from Institutional Review Board. The sample size should be representative of the target population and large in number to minimize the sampling error (Grossnickle & Raskin, 2001). Ideally, the sample size selected for research should encompass a minimum of five times the total number of items (Bollen, 2014). As the questionnaire contains 41 items corresponding to the identified constructs, the data was obtained from 495 respondents. Before the survey, the participants were briefed about the available technology solutions using the simplest examples of smartphone applications *e.g.* Plantix (*Plantix Agriculture Application*, 2023), which analyses image of crops using AI and ML algorithms to check health, identify disease and suggest appropriate diagnostic solution. These algorithms are able to utilize crop image, its location and other relevant data like temperature, humidity *etc.* in combination with past learnings available through historic data for providing the recommended action. After addressing their queries, respondents were asked to fill the survey based on their understanding. The survey is completed in pen-and-paper mode. Nine responses were identified invalid because of incomplete responses and were not included in the study, leaving 486 responses used as valid and suitable for further analysis.

To collect data from facilitators The survey was completed for 205 respondents in online and pen-and-paper mode. Participants were briefed about background and purpose of the survey. A brief discussion about the available AI-based solutions was conducted to check their understanding and alignment towards the objective of the survey after which they were asked to rate the items in survey based on their perception. The respondents were contacted from state agricultural universities and agriculture departments in the beginning and gradually the list grew by snowball sampling. Seven incomplete responses were excluded from the study, leaving 198 responses for use in analysis.

3.6 Reliability and Validity of Research Instruments

To ensure the research instrument's consistency and accuracy, it's essential to assess the reliability and validity of the instrument. Reliability refers to the consistency and stability of measurements obtained from the instrument, indicating the extent to which it produces consistent results over time or across different conditions. Validity, on the other hand, refers to the extent to which the instrument measures what it intends to measure, ensuring that it accurately captures the desired construct or concept. Before an appropriate statistical technique is applied, it is crucial to examine whether the items comprising the instrument exhibit satisfactory measurement properties concerning construct validity and reliability (Gefen *et al.*, 2000). The typical methods for conducting such tests involve factor analysis and reliability analysis, as commonly employed (Straub, 1989).

Reliability can be assessed through measures such as test-retest reliability (across time), internal consistency (across items), and interrater reliability (across researchers). Validity can be evaluated using content validity, criterion validity, and construct validity. Ensuring high reliability and validity of instruments is important to enhance the credibility and accuracy of research findings, as it minimizes measurement errors and ensures that the data collected accurately represents the intended concepts or variables. Given the utilization of Likert's scale in this study, the reliability of the instrument is evaluated using the internal consistency method. Average inter-correlation in form of Cronbach's alpha for every item of the questionnaire under each construct is evaluated. Cronbach's alpha measures internal consistency reliability and its value ranges between 0 and 1. Higher alpha values signify enhanced internal consistency among diverse items crafted to gauge various constructs, thereby indicating greater reliability. Reliability coefficient with Cronbach's alpha equal to or greater than 0.7 are commonly regarded as acceptable (Nunnally & Bernstein, 1994). The validity of the instrument was assessed through face validity, as well as through measures of convergent and discriminant validity. These methods collectively affirmed the instrument's satisfactory reliability and validity.

3.7 Data Analysis Methods

Data analysis involves employing various statistical techniques, including descriptive statistics, exploratory factor analysis, and structural equation modeling. A succinct overview of these methods is presented in this section. The data collected from respondents is recorded in spreadsheet format separately for farmers and facilitators. For the purpose of statistical analysis, R software (R Core Team, 2022) is used. R is a powerful open-source programming

language and software environment for statistical analysis and data visualization. It offers a wide range of statistical techniques, data manipulation capabilities, and extensive libraries for data analysis. With its flexibility and community support, R is widely used by researchers and data analysts for data analysis and research purposes.

3.7.1 Descriptive Statistics

Descriptive statistics involve the analysis and summary of data to provide a clear and concise understanding of its key characteristics. Descriptive statistics help to organize, present, and interpret data in a meaningful way, allowing for the identification of patterns, trends, and key features of the dataset. Descriptive statistics serve as a preliminary step in data analysis, providing a comprehensive overview of the data before delving into more advanced statistical techniques and hypothesis testing. Descriptive statistics are employed in this study for dual objectives. Initially, they serve to depict the characteristics of both farmers and facilitators, based on the collected data. It summarizes the data across multiple dimensions including farm size, experience, association with organization, smartphone usage, languages known *etc.* Secondly, descriptive statistics are utilized to gauge the central tendency of the chosen variables within the study through mean values. Moreover, correlations among constructs, tolerance, and variance inflation factors are examined to assess potential multi-collinearity concerns.

3.7.2 Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) is a data reduction technique that identifies underlying dimensions, constructs, or factors from a set of observed variables, and provides insights into the structure of the data (Stevens, 2009). It aims to uncover the structure and relationships within the data, allowing researchers to reduce the complexity of the data and extract meaningful information. EFA explores the inter-relationships among variables and groups them into latent factors based on their shared variance. In the present study, this approach is employed for following reasons: (a) combination of UTAUT, TOE and DOI models is rarely used in the literature and generated fifteen factors, hence reducing number of factors in research model is required; (b) to build parsimony and comprehensiveness in the model for generalization for future use; (c) EFA gives latent factors from the study which make the model more relevant and contextual (Hair *et al.*, 2006). Within the study, factor analysis is employed through the utilization of Principal Component Analysis (PCA) accompanied by varimax rotation. Furthermore, the suitability of the data for factor analysis is assessed using the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (Tabachnick & Fidell, 2019).

3.7.3 Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is a statistical technique used to test the validity of a hypothesized measurement model or factor structure. It is a multivariate analysis method that examines the relationships between observed variables and their underlying latent constructs (Bollen, 2014; Suhr, 2006). CFA aims to assess whether the observed variables align with the proposed factor structure and measure the intended constructs accurately. It evaluates the goodness-of-fit between the observed data and the hypothesized model, providing insights into the adequacy of the measurement model and the presence of any discrepancies. The present study uses CFA for studying proposed model's validity. By analyzing the factor loadings, factor correlations, and model fit indices, CFA helps to validate and refine measurement instruments, providing a rigorous approach to evaluating construct validity.

3.7.4 Convergent Validity and Discriminant Validity

A comprehensive analysis of the literature indicates that factor analysis has been traditionally linked to establishing construct validity (Nunnally & Bernstein, 1994; Thompson & Daniel, 1996). Construct validity refers to the extent to which it is justifiable to draw conclusions from the measurements used in the study to the underlying theoretical constructs that these measurements aim to represent (DeVellis, 2012). Construct validity is evaluate using convergent validity and discriminant validity. Convergent validity is the extent to which measures of the same construct are positively related and provide consistent evidence of the underlying theoretical concept (Hair *et al.*, 2019). Convergent validity is employed to ascertain the extent to which items designed to assess a specific construct indeed capture that intended construct. On the other hand, discriminant validity gauges the degree to which measures of distinct constructs exhibit minimal interrelatedness. It indicates that measures intended to assess different constructs do not measure the same underlying concept or trait (DeVellis, 2012). Discriminant validity, in this context, determines whether individual items are exclusively associated with a single construct or not. In essence, each construct should maintain a distinct separation from the others.

Following this, composite reliability (CR) and average variance extracted (AVE) are calculated using equations (1) and (2) as given below.

$$CR = \frac{(\sum_{i=1}^n \lambda_i)^2}{(\sum_{i=1}^n \lambda_i)^2 + (\sum_{i=1}^n \varepsilon_i)^2} \quad (1)$$

$$AVE = \frac{\sum_{i=1}^n \lambda_i^2}{n} \quad (2)$$

where λ is factor loading and ε is measurement error.

3.7.5 Indices

In Confirmatory Factor Analysis (CFA), several indices are commonly used to assess the goodness-of-fit between the observed data and the hypothesized measurement model. These indices provide information about how well the model fits the data (Hair *et al.*, 2019). Some commonly used indices in CFA include:

1. **Chi-Square (χ^2) Test:** It compares the observed covariance matrix with the model-implied covariance matrix. A non-significant chi-square value indicates a good fit, but it is sensitive to sample size.
2. **Comparative Fit Index (CFI):** It measures the improvement in fit when comparing the proposed model with a baseline model. CFI values range from 0 to 1, with values closer to 1 indicating a better fit.
3. **Tucker-Lewis Index (TLI):** Similar to CFI, TLI also compares the proposed model with a baseline model. TLI values range from 0 to 1, with values closer to 1 indicating a better fit.
4. **Root Mean Square Error of Approximation (RMSEA):** It measures the discrepancy between the hypothesized model and the population covariance matrix. Smaller RMSEA values indicate a better fit, with values below 0.08 are considered acceptable.
5. **Standardized Root Mean Square Residual (SRMR):** It assesses the average discrepancy between the observed and model-implied covariances. Lower SRMR values indicate a better fit, with values below 0.08 typically considered acceptable.

These indices help researchers evaluate the goodness-of-fit of the CFA model and determine whether it adequately represents the data.

3.7.6 Structural Equation Modeling

Structural Equation Modeling (SEM) is a statistical technique used to analyze complex relationships among variables and test theoretical models. It combines factor analysis and regression analysis to examine both the measurement and structural components of a model. SEM helps to investigate the direct and indirect effects of variables, assess model fit, and estimate parameters. SEM is advantageous because it accounts for measurement error, handles multiple latent variables, and can accommodate both observed and latent variables simultaneously. It is widely used in various disciplines, including social sciences, psychology,

economics, and marketing, to study complex phenomena and test theoretical frameworks. By incorporating measurement models and structural equations, SEM provides a comprehensive approach to understanding relationships and testing hypotheses within a single framework.

3.8 Summary

The present research work uses literature review based framework to study intention of farmers and facilitators to adopt AI-based solutions in agriculture. To understand perceptions, questionnaire is prepared separately for farmers and facilitators and data is collected from Punjab and Haryana states which are major contributors of agricultural production in India. The research work uses EFA to identify the latent variables in the proposed model under study for improving the effectiveness of the theoretical model based on literature. Following this, CFA is utilised to validate the proposed model and SEM is used to understand the inter-relationships among constructs and testing the hypotheses in the framework. The next chapter presents analysis of data collected from farmers and facilitators using these analytical techniques.

Chapter 4 Data Analysis and Results

In the previous chapter, the research methods utilised in the present study are discussed. The analysis using those techniques is carried out using R software, which is a highly versatile exploration technique used for multi-variate analysis. The analysis is carried out using descriptive statistics, reliability and factor analysis. In factor analysis, EFA is used to identify the latent variables in the proposed model based on literature to improve its effectiveness. CFA is used for validating the constructs in the model, followed by SEM to understand the relationship among the constructs of model and testing the hypotheses. There are two sections in this chapter – first section presents the analysis carried out for data collected from farmers; and the second section explains the analysis of data collected from facilitators.

4.1 Data Analysis for Farmers

4.1.1 Descriptive Statistics

Before carrying out detailed analysis of the data, descriptive statistics attempts to present a comprehensive overview of the data for its meaningful interpretation in the analysis. Firstly, the descriptive statistics present the profile of the respondents in terms of different dimensions including farm size, experience, association with organization, smartphone usage, languages known *etc.* Secondly, it also presents the data using statistical measures such as central tendency, correlation. The characteristics of respondents included in the present study are summarized in Table 4-1. Representation of farmers from Punjab state is 61% and 39% from Haryana state. The occupation of farming is mainly adopted by dominated by male (75%) in the region. The majority of farmers are young (27%) with age less than 30 years followed by 25% farmers in the age group of 40 to 49 years. Majority of the farmers (24%) are having significant experience in farming for 11 to 20 years. The data indicates that largely the respondents own small and marginal farm size i.e. below 2 hectares. Most of the farmers are connected with co-operatives which act as source of information and support in their farming business. Commonly regional languages are used including Punjabi and Haryanvi and a very high percentage of smartphone usage, 86% farmers is also indicated which is a positive indicator for increasing penetration of digital technology through information dissemination using mobile phone.

Table 4-1: Respondents profile

Respondents	Number in Sample	Percentage (%)
State		
<i>Punjab</i>	295	61%
<i>Haryana</i>	191	39%
Gender		
<i>Female</i>	121	25%
<i>Male</i>	365	75%
Age		
<i>Below 20 years</i>	50	10%
<i>21-29 years</i>	129	27%
<i>30-39 years</i>	109	22%
<i>40-49 years</i>	120	25%
<i>Above 50 years</i>	78	16%
Experience		
<i>Below 4 years</i>	110	23%
<i>5-10 years</i>	106	22%
<i>11-20 years</i>	115	24%
<i>21-30 years</i>	78	16%
<i>More than 30 years</i>	77	16%
Education		
<i>No education</i>	12	2%
<i>Primary school</i>	43	9%
<i>High school</i>	134	28%
<i>Senior Secondary</i>	109	22%
<i>Graduate or above</i>	188	39%
Farm Size		
<i>Marginal (Below 1 ha i.e. < 2.47 acres or killas)</i>	85	17%
<i>Small (1 to 2 ha i.e. 2.47 to 4.94 acres or killas)</i>	147	30%
<i>Semi-medium (2 to 4 ha i.e. 4.94 to 9.88 acres or killas)</i>	140	29%
<i>Medium (4 to 10 ha i.e. 9.88 to 24.71 acres or killas)</i>	77	16%
<i>Large (10 ha and above i.e. above 24.71 acres or killas)</i>	37	8%
Associated with Organization		
<i>Co-operative</i>	243	50%
<i>Extension</i>	17	3%
<i>Agricultural University</i>	111	23%
<i>Private organization</i>	49	10%
<i>Others</i>	66	14%
Languages known		
<i>Regional language</i>	258	53%
<i>Regional language and English</i>	228	47%
Smartphone usage		
<i>No</i>	70	14%
<i>Yes</i>	416	86%

Table 4-2 presents mean, standard deviation and median of the items corresponding to the constructs in the model. The total number of observations are 486 and its mean of the items varies from 2.29 to 4.04.

Table 4-2: Mean, Standard Deviation and Median of the items (N=486)

Item	Mean	Standard Deviation	Median
PEX1	3.99	0.77	4
PEX2	4.04	0.89	4
PEX3	3.98	0.86	4
PEX4	3.93	0.85	4
EEX1	3.93	0.91	4
EEX2	3.78	0.94	4
EEX3	3.72	0.87	4
EEX4	3.71	0.79	4
RAV1	2.68	0.93	3
RAV2	3.21	0.98	3
RAV3	3.30	1.00	4
RAV4	2.68	0.98	2
SIN1	3.71	0.87	4
SIN2	3.56	0.91	4
SIN3	3.74	0.89	4
SIN4	3.81	0.92	4
FAC1	3.19	1.03	3
FAC2	3.17	1.01	3
FAC3	3.27	1.02	3
FAC4	3.24	0.99	3
INF1	3.69	0.85	4
INF2	3.66	0.89	4
INF3	3.72	0.86	4
FIN1	2.29	0.85	2
FIN2	3.30	0.99	3
FIN3	3.58	1.00	4
LNK1	3.77	0.86	4
LNK2	3.79	0.83	4
LNK3	4.02	0.76	4
FBF1	3.90	1.44	5
FBF2	3.93	1.21	4
CMP1	3.46	0.81	4
CMP2	3.80	0.86	4
CMP3	3.72	0.90	4
CMP4	3.74	0.89	4
SPY1	3.77	0.92	4
SPY2	3.91	0.94	4
SPY3	3.92	0.95	4
ITA1	3.94	0.75	4
ITA2	3.88	0.76	4
ITA3	3.92	0.81	4

4.1.2 Reliability Analysis

In the beginning of analysis, the reliability of data is checked using Cronbach's alpha. Table 4-3 shows that each construct has Cronbach's alpha greater than 0.75 after dropping the item "FIN1" with lower alpha value of 0.45. Cronbach's alpha varied from 0.75 to 0.91 which is

considered an acceptable range for this parameter in research methodology (Hair *et al.*, 2006) and indicates good internal consistency among scales used in present study.

Table 4-3: Reliability Analysis using Cronbach's alpha

Constructs	Cronbach's Alpha	Items	Item statistics	Reliability if an item is dropped
Performance Expectancy	0.91	PEX1	0.90	0.88
		PEX2	0.88	0.89
		PEX3	0.88	0.89
		PEX4	0.91	0.88
Effort Expectancy	0.82	EEX1	0.81	0.77
		EEX2	0.77	0.80
		EEX3	0.79	0.78
		EEX4	0.85	0.73
Risk Aversion	0.84	RAV1	0.83	0.80
		RAV2	0.85	0.79
		RAV3	0.83	0.80
		RAV4	0.80	0.82
Facilitating Conditions	0.90	FAC1	0.89	0.86
		FAC2	0.89	0.86
		FAC3	0.88	0.87
		FAC4	0.85	0.88
Social Influence	0.91	SIN1	0.91	0.88
		SIN2	0.88	0.90
		SIN3	0.89	0.89
		SIN4	0.89	0.89
Information Availability	0.90	INF1	0.91	0.86
		INF2	0.90	0.87
		INF3	0.92	0.82
Financial Conditions	0.49	FIN1	0.45	0.75
		FIN2	0.81	0.05
		FIN3	0.81	0.06
Formal and Informal Links	0.79	LNK1	0.86	0.69
		LNK2	0.83	0.72
		LNK3	0.82	0.72
Farming Business Focus	0.84	FBF1	0.94	0.85
		FBF2	0.92	0.63
Compatibility	0.88	CMP1	0.81	0.87
		CMP2	0.87	0.84
		CMP3	0.87	0.84
		CMP4	0.87	0.84
Security and Privacy	0.87	SPY1	0.88	0.84
		SPY2	0.91	0.80
		SPY3	0.89	0.83
Intention to Adopt	0.85	ITA1	0.87	0.82
		ITA2	0.86	0.82
		ITA3	0.91	0.74

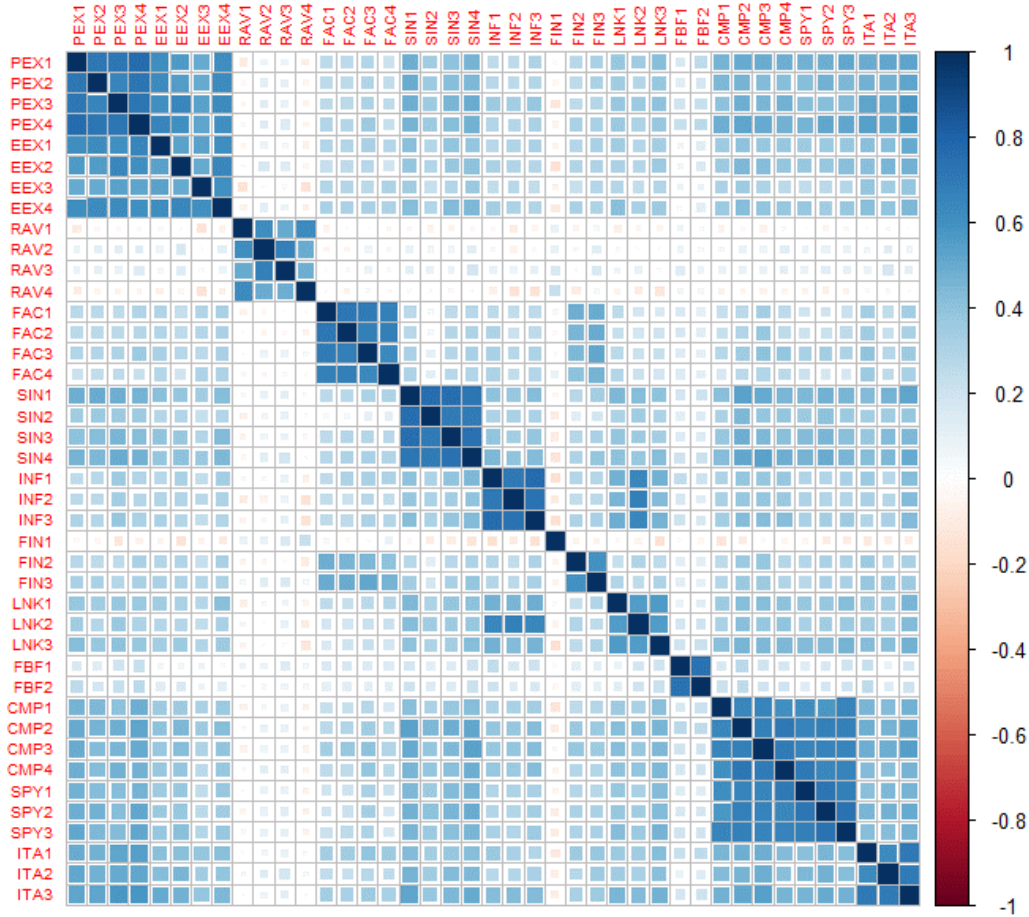


Figure 4.1: Correlation among items from farmers' data

Pearson Product Moment Correlation is computed to examine the correlation among independent variables, which is graphically presented in Figure 4.1. The x-axis and y-axis represent the items being observed in analysis to check their inter-correlation. A correlation coefficient exceeding 0.9 suggests the presence of multi-collinearity (Cohen *et al.*, 2013). However, in the current dataset, the highest correlation coefficient is 0.76, implying the absence of multi-collinearity concerns.

Further, Kleinbaum *et al.* (1988) two different techniques to test multi-collinearity which include Tolerance test and Variance Inflation Factor (VIF). The results using these techniques are presented in Table 4-4. According to the guideline proposed by Hair *et al.* (2006), a tolerance value below 0.1 and a VIF value exceeding 10 signify high collinearity. Upon examination of the tolerance and VIF values in the table, it is evident that all tolerance values surpass 0.1, and all VIF values are below 10. These outcomes collectively suggest the absence of multi-collinearity in the dataset pertaining to farmers.

Table 4-4: Collinearity statistics

Variables	Tolerance	VIF
PEX1	0.287	3.49
PEX2	0.344	2.91
PEX3	0.316	3.17
PEX4	0.256	3.90
EEX1	0.434	2.30
EEX2	0.424	2.36
EEX3	0.497	2.01
EEX4	0.349	2.87
RAV1	0.426	2.35
RAV2	0.398	2.51
RAV3	0.453	2.21
RAV4	0.486	2.06
FAC1	0.339	2.95
FAC2	0.320	3.12
FAC3	0.362	2.76
FAC4	0.386	2.59
SIN1	0.260	3.85
SIN2	0.301	3.33
SIN3	0.315	3.17
SIN4	0.282	3.54
INF1	0.310	3.23
INF2	0.340	2.95
INF3	0.298	3.35
FIN2	0.517	1.93
FIN3	0.475	2.10
LNK1	0.498	2.01
LNK2	0.371	2.70
LNK3	0.486	2.06
FBF1	0.397	2.52
FBF2	0.423	2.36
CMP1	0.412	2.43
CMP2	0.309	3.23
CMP3	0.320	3.12
CMP4	0.315	3.17
SPY1	0.326	3.07
SPY2	0.304	3.29
SPY3	0.322	3.10

4.1.3 Exploratory Factor Analysis

EFA is used to identify the latent variables in the proposed model under study for improving the effectiveness of the theoretical model with relevant and contextual variables for further analysis (Hair *et al.*, 2006). Using common factor analysis further ensures parsimony and comprehensiveness in the model to provide generalised view for future use (Hair *et al.*, 2019). As a pre-check, the appropriateness of the correlation matrix to be used in EFA is assessed

using two tests – (i) Bartlett’s test of sphericity (Bartlett, 1950); and (ii) Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser, 1974). The first assessment using Bartlett’s test of sphericity rejected the hypothesis that the correlation matrix was an identity matrix (chi-square of 3064.842 with 820 degrees of freedom). The KMO measure of sampling adequacy was acceptable with values of 0.70 for the total model and items with values below acceptable level of 0.7 (Hoelzle & Meyer, 2013) *i.e.* farming business focus and risk aversion were excluded. As there was only one item of risk aversion with value 0.77, it was also excluded in the study (Table 4-5). Altogether, these measures indicate that the final correlation matrix is appropriate for EFA (Hair *et al.*, 2019; Tabachnick & Fidell, 2019).

The number of factors extracted for exploratory factor analysis (EFA) should be able to explain the majority of variance with a smaller number of factors. “A delicate balance between comprehensiveness and parsimony is needed to achieve an interpretable solution” (Watkins, 2020). “In the end, the overriding criteria for choosing a particular number of factors are interpretability and theoretical relevance because a factor solution is useful only if it can be interpreted in a meaningful way” (Bandalos, 2018). The scree plot as shown in Figure 4.2 shows that total five factors should be retained which is an optimal balance between comprehensiveness and parsimony. The results confirmed that the factors with eigen value greater than 1 accounted for 62% of total variance using Varimax rotation with principal axes technique in parallel analysis.

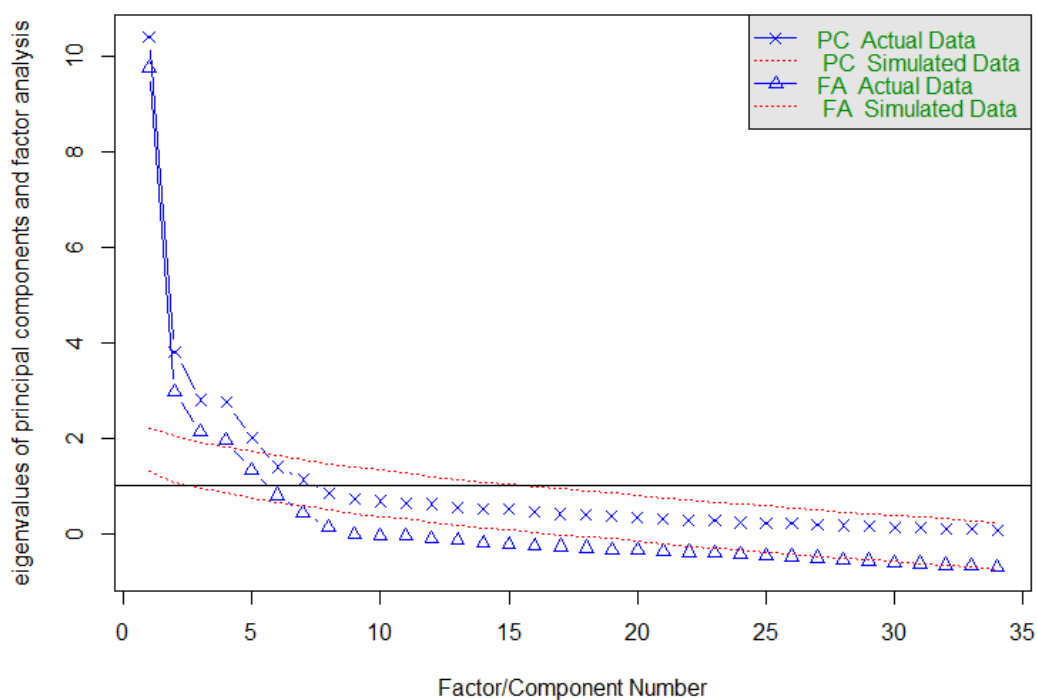


Figure 4.2: Scree Plot for EFA using data from farmers

Table 4-5: Values of KMO

Item	Value of KMO
PEX1	0.85
PEX2	0.83
PEX3	0.85
PEX4	0.81
EEX1	0.73
EEX2	0.87
EEX3	0.79
EEX4	0.87
RAV1	0.55
RAV2	0.70
RAV3	0.77
RAV4	0.63
FAC1	0.73
FAC2	0.81
FAC3	0.84
FAC4	0.74
SIN1	0.85
SIN2	0.81
SIN3	0.87
SIN4	0.79
INF1	0.80
INF2	0.77
INF3	0.75
FIN2	0.76
FIN3	0.81
LNK1	0.76
LNK2	0.76
LNK3	0.85
FBF1	0.51
FBF2	0.55
CMP1	0.75
CMP2	0.87
CMP3	0.84
CMP4	0.90
SPY1	0.85
SPY2	0.86
SPY3	0.73

Table 4-6: Factor loading

Item	Factor-1	Factor-2	Factor-3	Factor-4	Factor-5
PEX1	0.723	0.095	-0.016	0.016	0.226
PEX2	0.754	0.064	0.087	-0.028	0.076
PEX3	0.672	0.168	-0.037	0.12	0.054
PEX4	0.818	0.092	-0.031	0.008	0.193
EEX1	0.605	0.098	0.203	-0.078	0.149
EEX2	0.549	0.157	0.025	0.114	0.097
EEX3	0.564	0.159	0.092	0.109	0.082
EEX4	0.758	0.177	0.112	0.114	0.187
SIN1	0.301	0.784	0.119	0.084	0.22
SIN2	0.185	0.834	-0.208	0.109	0.163
SIN3	0.191	0.785	0.099	0.169	0.219
SIN4	0.259	0.764	0.161	0.199	0.263
FAC1	0.069	-0.100	0.755	0.112	0.095
FAC2	0.069	-0.003	0.754	0.204	0.111
FAC3	0.113	0.07	0.76	0.122	0.15
FAC4	0.090	0.082	0.756	0.023	0.048
INF1	0.050	0.176	0.123	0.804	0.021
INF2	-0.072	0.109	0.078	0.769	0.021
INF3	0.053	0.122	0.214	0.794	0.054
FIN2	-0.005	-0.009	0.583	-0.008	0.057
FIN3	0.038	0.104	0.747	0.082	0.016
LNK1	0.436	-0.031	0.142	0.352	0.38
LNK2	0.227	0.049	0.076	0.792	0.153
LNK3	0.355	0.027	0.011	0.36	0.328
CMP1	0.148	0.050	-0.049	0.032	0.672
CMP2	0.178	0.189	0.108	0.101	0.651
CMP3	0.063	0.200	0.297	0.166	0.666
CMP4	0.167	0.063	0.201	0.074	0.697
SPY1	0.091	0.178	0.065	0.012	0.847
SPY2	0.183	0.178	0.132	-0.016	0.689
SPY3	0.211	0.083	-0.035	0.056	0.819

Factor loadings for all the items is presented in Table 4-6. The value in bold indicates that five factors are getting loaded with items having value greater than 0.5 threshold explaining variance of 62%. According to Awang & others (2015), the item-wise factor loading should ideally exceed 0.5 to be considered acceptable. The model successfully fulfills the prerequisites

for evaluating uni-dimensionality, as all item loadings on their corresponding latent constructs significantly surpass the threshold of 0.5.

After extraction, the latent variables are interpreted by assigning labels as illustrated in Table 4-7. With this outcome, the latent variables revealed a modified research model which had only five factors in place of eleven factors originally. ‘Perceived Expectancy’ and ‘Effort Expectancy’ converged into one factor which was interpreted as ‘User Expectations’. Similarly, the factor ‘Compatibility’ got loaded to Technology factors along with ‘Security and Privacy’. The latent variable for ‘Facilitating conditions’ and ‘Financial conditions’ was interpreted as ‘Facilitating conditions’. The variables ‘Information availability’ and ‘Formal and Informal Link’ got merged with factor ‘Information and Involvement’. The variable of construct ‘Social influence’ loaded uniquely to its own factor, hence no explicit interpretation is required.

Table 4-7: Interpretation of latent factors

Factor	Interpreted variable	Original Constructs	Items	SS Loading	Proportion Variance
Factor-1	User expectations	Performance expectancy	4	5.04	0.15
		Effort expectancy	4		
Factor-2	Technology factors	Compatibility	4	4.60	0.14
		Security and Privacy	3		
Factor-3	Facilitating conditions	Facilitating conditions	4	3.65	0.12
		Financial conditions	2		
Factor-4	Information and Involvement	Information availability	3	3.07	0.11
		Formal and Informal Link	1		
Factor-5	Social Influence	Social Influence	4	2.97	0.10

4.1.4 Confirmatory Factor Analysis

In this section, the reliability and validity of the measurement model (Figure 4.3) is examined. Composite reliability, serving as an indicator of internal consistency, is computed as illustrated in Table 4-8. The significance of composite reliability lies in its ability to evaluate the measurement quality of the construct. A high composite reliability value (usually ranging from 0 to 1) indicates that the observed indicators are highly reliable and consistently measure the underlying construct. This implies that the construct is accurately and consistently captured by the set of indicators, increasing confidence in the validity of the measurement. In general, a composite reliability value of 0.70 or higher is considered acceptable. However, higher values, such as 0.80 or above, are often desired to ensure a high level of internal consistency and

reliability (Hair *et al.*, 2006). In present research, the minimum value of composite reliability observed is 0.874 which indicates acceptable reliability as shown in Table 4-8.

Next, the convergent validity for the constructs is measured. Convergent validity assesses the degree to which different measurement items or scales intended to measure the same construct are positively related to each other (Hair *et al.*, 2006). It is evaluated using average variance extracted (AVE) which is the “grand mean value of the squared loadings of the indicators associated with the construct” as illustrated in equation (2) (Hair *et al.*, 2019).

Table 4-8: Calculation of Composite Reliability, Discriminant Validity, AVE and MSV

Item	PUE	SIN	FAC	INF	TEC	λ^2	AVE (λ^2/n)	MSV	Disc. Validity	e = (1- λ^2)	Comp Rel
PEX1	0.72	.	.	.	.	0.52	0.50	0.69	0.71	0.48	0.888
PEX2	0.76	.	.	.	.	0.58				0.42	
PEX3	0.68	.	.	.	.	0.46				0.54	
PEX4	0.83	.	.	.	.	0.69				0.31	
EEX1	0.69	.	.	.	.	0.48				0.52	
EEX2	0.60	.	.	.	.	0.36				0.64	
EEX3	0.59	.	.	.	.	0.35				0.65	
EEX4	0.76	.	.	.	.	0.58				0.42	
SIN1	.	0.88	.	.	.	0.77	0.74	0.77	0.86	0.23	0.921
SIN2	.	0.81	.	.	.	0.66				0.34	
SIN3	.	0.88	.	.	.	0.77				0.23	
SIN4	.	0.88	.	.	.	0.77				0.23	
FAC1	.	.	0.77	.	.	0.59	0.54	0.66	0.74	0.41	0.874
FAC2	.	.	0.79	.	.	0.62				0.38	
FAC3	.	.	0.81	.	.	0.66				0.34	
FAC4	.	.	0.74	.	.	0.55				0.45	
FIN2	.	.	0.55	.	.	0.30				0.70	
FIN3	.	.	0.72	.	.	0.52				0.48	
INF1	.	.	.	0.83	.	0.69	0.67	0.76	0.82	0.31	0.890
INF2	.	.	.	0.83	.	0.69				0.31	
INF3	.	.	.	0.87	.	0.76				0.24	
LNK2	.	.	.	0.74	.	0.55				0.45	
CMP1	.	.	.	.	0.72	0.52	0.58	0.64	0.76	0.48	0.907
CMP2	.	.	.	.	0.73	0.53				0.47	
CMP3	.	.	.	.	0.78	0.61				0.39	
CMP4	.	.	.	.	0.75	0.56				0.44	
SPY1	.	.	.	.	0.79	0.62				0.38	
SPY2	.	.	.	.	0.77	0.59				0.41	
SPY3	.	.	.	.	0.8	0.64				0.36	

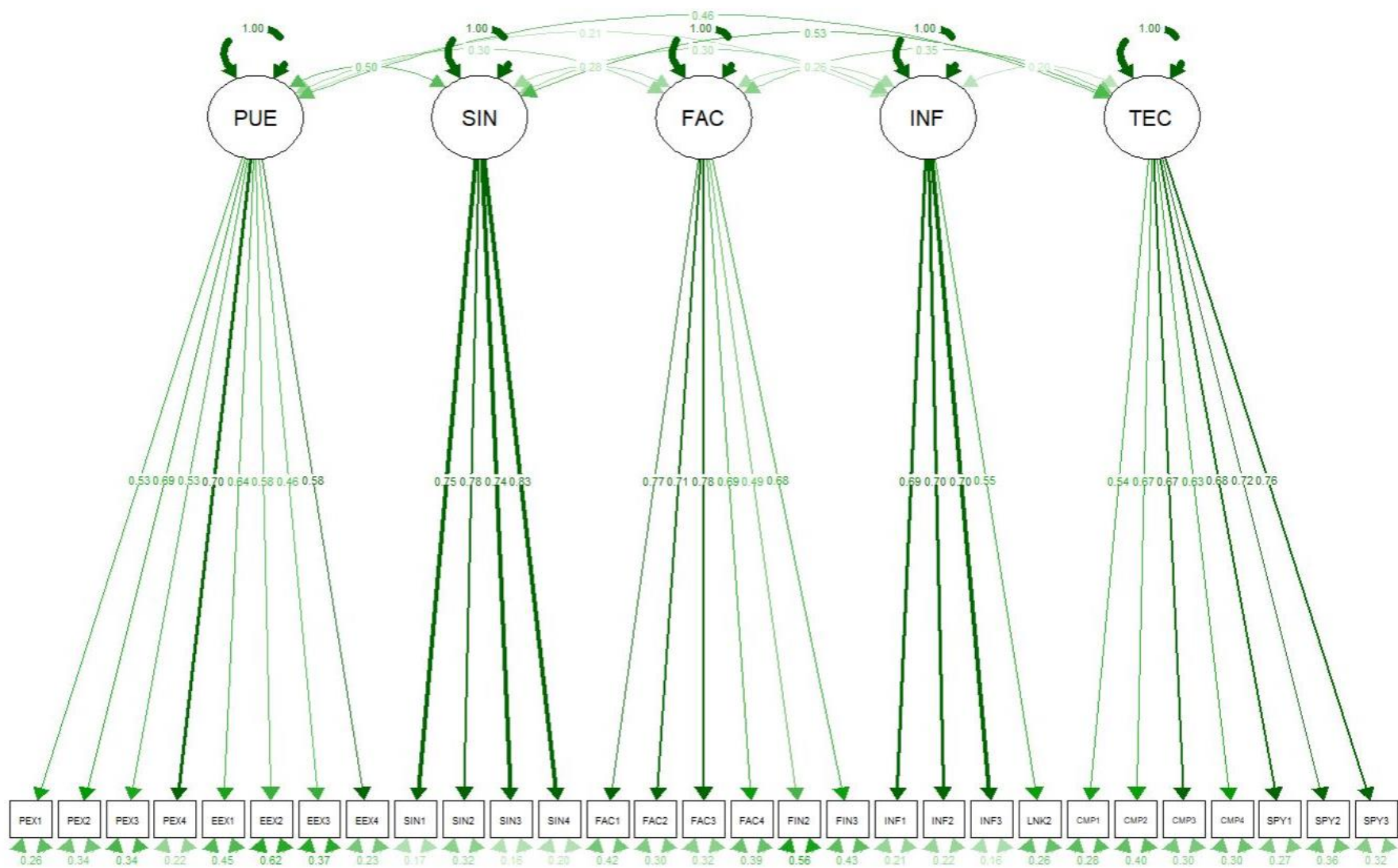


Figure 4.3: Measurement Model for CFA using data from farmers

In literature, the recommended threshold for AVE across all constructs is ≥ 0.5 (Hair *et al.*, 2006). The AVE values for all constructs, as presented in Table 4-8, exceed 0.5, satisfying the necessary criterion. This signifies that all the observed variables in the measurement model are effectively able to converge to their respective latent construct.

As a next step, each construct is evaluated for its discriminant validity. Discriminant validity assesses the extent to which measurement items or scales intended to measure different constructs are different from each other (Hair *et al.*, 2019). The method of evaluating discriminant validity uses the Fornell-Larcker criterion which “compares the square root of the AVE values with the latent variable correlations. In particular, the square root of each construct’s AVE should be greater than its highest correlation with any other construct” (Hair *et al.*, 2019). In cross-loading matrix (Table 4-9), square root of AVE is observed to be greater than correlation coefficient of other constructs, hence, the model is able to meet the criteria of discriminant validity.

Table 4-9: Cross-loading matrix

	PUE	SIN	FAC	INF	TEC	ITA
PUE	0.708					
SIN	0.503	0.863				
FAC	0.296	0.280	0.735			
INF	0.209	0.304	0.261	0.819		
TEC	0.459	0.530	0.352	0.201	0.763	
ITA	0.642	0.503	0.317	0.297	0.511	0.867

The collected model fit values are consolidated in Table 4-10. Each of the fitness indices, which need to surpass a certain threshold for a sound model fit, has met or exceeded their respective threshold values. This outcome underscores the general approval of the measurement model illustrated in Figure 4.3. Additionally, the model's overall acceptability aligns with to Hu & Bentler's (1999) two-index presentation strategy, where RMSEA values should be 0.06 or less, and SRMR values should be below 0.09. The values of CFI is 0.9511 and TLI is 0.9460 (both acceptable greater than 0.9) while RMSEA is 0.0455 and SRMR is 0.061 (both are acceptable below 0.08) (Hair *et al.*, 2019). All the indices of goodness-of-fit indicate the overall acceptability of the measurement model for further analysis.

Table 4-10: Goodness-of-fit indices

Goodness-of-fit indices	Reported values	Recommended value
Normed Chi-square (CMIN/DF)	1.3162	< 3.000
Comparative Fitness Index (CFI)	0.9511	> 0.9000
Goodness of Fit Index (GFI)	0.8160	> 0.9000
Adjusted Goodness of Fit Index (AGFI)	0.7840	> 0.8000
Root Mean Square Error of Approximation (RMSEA)	0.0455	< 0.08
Tucker-Lewis Index (TLI)	0.9460	> 0.9000
Incremental Fit Index (IFI)	0.9510	> 0.9000
Standardized Root Mean Square Residual (SRMR)	0.061	< 0.08

4.1.5 Research Hypotheses

Based on the factors identified in the previous section using EFA, the research hypotheses are formulated towards Research Objective 3 and are stated below and illustrated in Figure 4.4:

H1: *User expectations influence the intention of farmers to use AI-based solutions in agriculture.*

H2: *Technology factors influence the intention of farmers to use AI-based solutions in agriculture.*

H3: *Facilitating conditions influence the intention of farmers to use AI-based solutions in agriculture.*

H4: *Social influence affects the intention of farmers to use AI-based solutions in agriculture.*

H5: *Information and involvement influence the intention of farmers to use AI-based solutions in agriculture.*

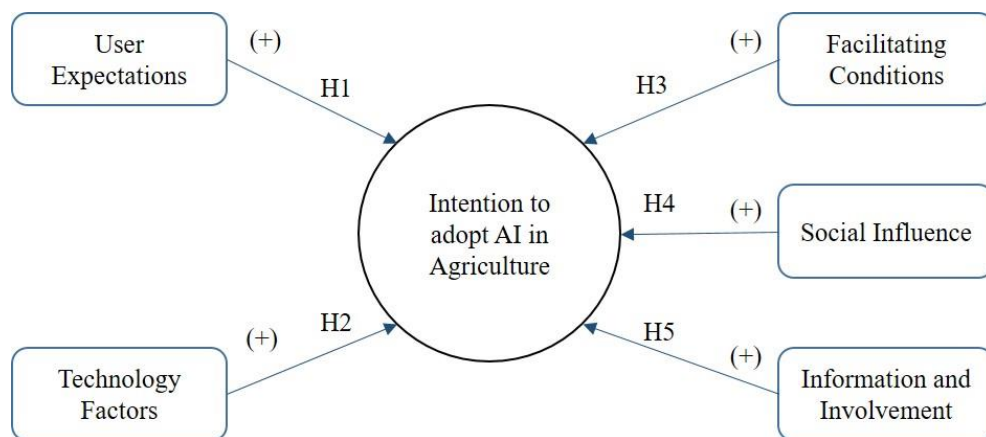


Figure 4.4: Evolved Model for farmers with latent factors using EFA

4.1.6 Structural Equation Modeling

Structural Equation Modeling (SEM) is a statistical method used to examine and validate complex relationships among multiple variables. It integrates measurement models and structural models to assess the direct and indirect effects between variables, allowing for the evaluation of theoretical models and hypotheses. After carrying out EFA for latent variables and CFA for validating the measurement model, an initial structural model was formulated using the provided dimensions, as depicted in Figure 4.5. This structural model was designed to assess the proposed hypotheses. The five factors *User Expectations (PUE)*, *Social influence (SIN)*, *Facilitating Conditions (FAC)*, *Information and Involvement (INF)* and *Technology factors (TEC)* are used as independent variables while *Intention to adopt (ITA)* is used as dependent variable. SEM facilitates to evaluate direct effects between dependent variable and each of the independent variables. This approach enables the testing of construct-level hypotheses directly at the level of construct itself (Ullman & Bentler, 2012).

Table 4-11: Goodness-of-fit indices for Structural Model

Goodness-of-fit indices	Reported values	Recommended value
CMIN/DF	2.420	< 3.000
CFI	0.9293	> 0.9000
GFI	0.822	> 0.9000
AGFI	0.791	> 0.8000
RMSEA	0.0643	< 0.08
TLI	0.9219	> 0.9000
IFI	0.93	> 0.9000
SRMR	0.058	< 0.08

The path analysis is conducted using R software to determine path coefficient for each of the variable. To test hypothesis, the path coefficients, their respective p-value and t-statistics are examined. The achieved model fit indicators are as follows: CMIN/DF as 2.420 (acceptable range from 1 to 5), CFI as 0.929 (acceptable value above 0.90), RMSEA as 0.0643 (acceptable value below 0.08) and GFI as 0.822 (acceptable above 0.90). In overall, these values meet the conditions for a good model fit (Fabrigar *et al.*, 1999; Jackson *et al.*, 2009). Table 4-11 summarizes all the model fit values. The value of R^2 of '*Intention to adopt*' is 80.9% which can explain large amount of variance. Table 4-12 lists the standardized regression weights observed for the model. In Figure 4.5, the structural model with path values showing direct effects is presented. Table 4-13 summarizes the results of hypotheses testing.

Table 4-12: Regression weights for Structural Model

			Standard Estimate	SE	t-Value	2.50% CI	97.50% CI
PUE	→	PEX1	0.895	0.0185	0	0.859	0.932
PUE	→	PEX2	0.853	0.0213	0	0.811	0.895
PUE	→	PEX3	0.895	0.018	0	0.86	0.931
PUE	→	PEX4	0.888	0.0179	0	0.852	0.923
PUE	→	EEX1	0.787	0.0263	0	0.736	0.839
PUE	→	EEX2	0.789	0.0268	0	0.737	0.842
PUE	→	EEX3	0.714	0.0344	0	0.646	0.781
PUE	→	EEX4	0.777	0.0288	0	0.72	0.833
SIN	→	SIN1	0.89	0.021	0	0.849	0.931
SIN	→	SIN2	0.801	0.025	0	0.752	0.85
SIN	→	SIN3	0.827	0.0275	0	0.773	0.881
SIN	→	SIN4	0.824	0.0302	0	0.765	0.883
FAC	→	FAC1	0.877	0.0169	0	0.844	0.91
FAC	→	FAC2	0.862	0.0217	0	0.82	0.905
FAC	→	FAC3	0.825	0.0244	0	0.778	0.873
FAC	→	FAC4	0.821	0.0232	0	0.775	0.866
FAC	→	FIN2	0.58	0.046	0	0.49	0.67
FAC	→	FIN3	0.591	0.0489	0	0.495	0.687
INF	→	INF1	0.858	0.0277	0	0.803	0.912
INF	→	INF2	0.836	0.0246	0	0.788	0.884
INF	→	INF3	0.902	0.019	0	0.865	0.94
INF	→	LNK2	0.745	0.0412	0	0.664	0.826
TEC	→	CMP1	0.732	0.0373	0	0.659	0.805
TEC	→	CMP2	0.885	0.0218	0	0.843	0.928
TEC	→	CMP3	0.823	0.0275	0	0.769	0.877
TEC	→	CMP4	0.83	0.0248	0	0.781	0.878
TEC	→	SPY1	0.809	0.027	0	0.756	0.862
TEC	→	SPY2	0.812	0.0283	0	0.756	0.867
TEC	→	SPY3	0.806	0.0286	0	0.75	0.862
ITA	→	ITA1	0.784	0.0374	0	0.711	0.857
ITA	→	ITA2	0.745	0.0394	0	0.668	0.822
ITA	→	ITA3	0.86	0.0249	0	0.811	0.908

The results show that independent variables *User Expectations (PUE)* influences the dependent factor *Intention to adopt (ITA)* with $\beta=0.35$. Similarly, other independent factors *Technology factors (TEC)*, *Social influence (SIN)*, *Facilitating Conditions (FAC)* and *Information and Involvement (INF)* and influence *Intention to adopt (ITA)* with β values of 0.34, 0.17, 0.13 and 0.07 respectively. Figure 4.5 represents the path analysis to test each hypothesis. In the results, INF ($p=0.221$) turns out to be insignificant. However, all other factors including PUE ($9.73e-06$), SIN ($5.97e-03$), FAC ($1.17e-02$) and TEC ($6.33e-04$) are observed significant.

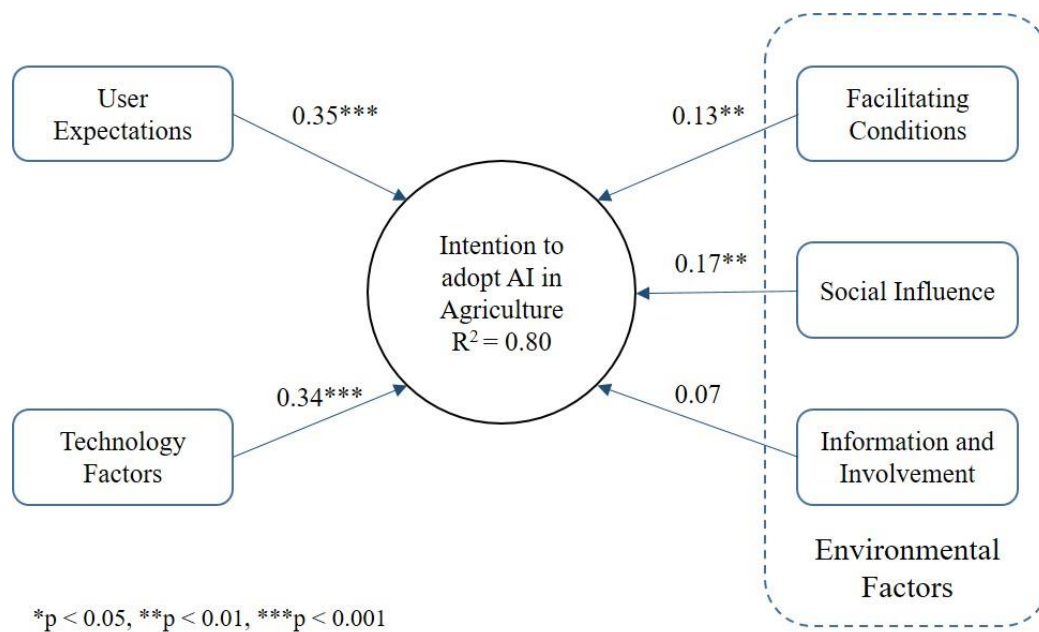


Figure 4.5: Results of Path Analysis for data from farmers

Table 4-13: Hypotheses Substantiation

			Standard Estimate	SE	t-Value	2.50% CI	97.50% CI	Hypothesis Test Results	Hypothesis Decision
ITA	→	PUE	0.3467	0.0784	9.73E-06	0.1931	0.5	Significant and positive	Supported
ITA	→	SIN	0.1744	0.0634	5.97E-03	0.0501	0.299	Significant and positive	Supported
ITA	→	FAC	0.1258	0.0499	1.17E-02	0.028	0.224	Significant and positive	Supported
ITA	→	INF	0.0723	0.0591	2.21E-01	-0.0435	0.188	Non-significant and positive	Not Supported
ITA	→	TEC	0.3385	0.0991	6.33E-04	0.1444	0.533	Significant and positive	Supported

The conclusion that can be drawn from above results is that four out of the five postulated hypotheses are found to be significant and all five exhibit a positive relationship. It can further

be stated that the proposed model presents that user expectations, technology factors, social influence and facilitating conditions significantly influence intention to adopt AI-based solutions in agriculture, while information and involvement of farmers does not significantly influence their intention. The next chapter discusses the results in detail.

4.2 Data Analysis for Facilitators

4.2.1 Descriptive Statistics

This section presents analysis based on descriptive statistics for comprehensive understanding of the data collected from facilitators. The first part of the analysis provides the cross-sectional view of the respondents across various dimensions including farm size, experience, association with organization, smartphone usage, languages known *etc.* In the second part, it presents statistical view of the data. The profile of respondents included in the present study is summarized in Table 4-14 . Representation of facilitators from Punjab state is 57% and 43% from Haryana state. The majority of respondents are male (78%). A large segment of facilitators is young (38%) with age less than 30 years followed by 28% in the age group of 30 to 39 years. Largely, the group of facilitators are graduates and have 5 to 10 years of experience. The facilitators have observed marginal farm sizes below 1 hectare. The organizations with which facilitators are connected mainly include agricultural universities and co-operatives. High percentage of smartphone usage (92%) among facilitators is a positive indicator as it enables for easier connectivity and information sharing.

Table 4-14: Profile of Respondents

Respondents	Number Sample	in Percentage (%)
State		
<i>Punjab</i>	113	57%
<i>Haryana</i>	85	43%
Gender		
<i>Female</i>	44	22%
<i>Male</i>	154	78%
Age		
<i>Below 20 years</i>	-	0%
<i>21-29 years</i>	76	38%
<i>30-39 years</i>	55	28%
<i>40-49 years</i>	44	22%
<i>Above 50 years</i>	23	12%

Experience		
<i>Below 4 years</i>	24	12%
<i>5-10 years</i>	59	30%
<i>11-20 years</i>	51	26%
<i>21-30 years</i>	36	18%
<i>More than 30 years</i>	28	14%
Education		
<i>No education</i>	-	0%
<i>Primary school</i>	-	0%
<i>High school</i>	2	1%
<i>Senior Secondary</i>	46	23%
<i>Graduate or above</i>	150	76%
Farm Size		
<i>Marginal (Below 1 ha i.e. < 2.47 acres or killas)</i>	65	33%
<i>Small (1 to 2 ha i.e. 2.47 to 4.94 acres or killas)</i>	56	28%
<i>Semi-medium (2 to 4 ha i.e. 4.94 to 9.88 acres or killas)</i>	37	19%
<i>Medium (4 to 10 ha i.e. 9.88 to 24.71 acres or killas)</i>	28	14%
<i>Large (10 ha and above i.e. above 24.71 acres or killas)</i>	12	6%
Associated with Organization		
<i>Co-operative</i>	69	35%
<i>Extension</i>	34	17%
<i>Agricultural University</i>	48	24%
<i>Agriculture Department</i>	32	16%
<i>Others</i>	15	8%
Languages known		
<i>Regional language</i>	28	14%
<i>Regional language and English</i>	170	86%
Smartphone usage		
<i>No</i>	16	8%
<i>Yes</i>	182	92%

Table 4-15 presents mean, standard deviation and median of the items corresponding to the constructs in the model. The total number of observations are 198 and its mean of the items varies from 2.76 to 4.33. High value of median for the most of the items indicates that the majority of respondents tend to select responses that are higher on the rating scale for those specific items which signifies that they are in agreement in most of the questions. As *Farming Business Focus* is excluded from the list of variables in this part of study of facilitators as the facilitators have role of enabling farmers for using new technology solution and helping them by resolving their issues. Hence, the specific variable, *Farming Business Focus*, is not suitable for consideration in the study.

Table 4-15: Mean, Standard Deviation and Median of the items (N=198)

Item	Mean	Standard Deviation	Median
PEX1	4.33	0.60	4
PEX2	4.16	0.71	4
PEX3	4.31	0.60	4
PEX4	4.24	0.62	4
EEX1	3.67	1.07	4
EEX2	3.78	0.81	4
EEX3	3.86	0.71	4
EEX4	3.77	0.76	4
RAV1	3.49	0.85	4
RAV2	2.76	1.06	3
RAV3	2.77	1.06	2
RAV4	3.59	0.82	4
SIN1	3.82	0.83	4
SIN2	4.07	0.77	4
SIN3	3.89	0.80	4
SIN4	3.98	0.56	4
FAC1	3.96	0.60	4
FAC2	3.59	0.83	4
FAC3	3.80	0.63	4
FAC4	3.54	0.80	4
INF1	3.84	0.56	4
INF2	3.75	0.68	4
INF3	3.61	0.73	4
FIN1	3.68	0.85	4
FIN2	3.12	1.05	3
FIN3	3.75	0.86	4
STR1	3.97	0.71	4
STR2	4.01	0.76	4
STR3	3.84	0.65	4
CMP1	3.74	0.65	4
CMP2	3.68	0.62	4
CMP3	3.52	0.71	4
CMP4	3.85	0.73	4
SPY1	3.75	0.50	4
SPY2	3.91	0.57	4
SPY3	3.88	0.75	4
ITA1	3.86	0.60	4
ITA2	3.89	0.59	4
ITA3	3.89	0.62	4

4.2.2 Reliability Analysis

In this section, the data reliability is checked using Cronbach's alpha. Table 4-16 shows that item-wise Cronbach's alpha values vary from 0.73 to 0.96 and are above the acceptable threshold of 0.7, thus meeting the criteria of good internal consistency for the scales used in the study of adoption intent for facilitators (Hair *et al.*, 2006).

Table 4-16: Reliability Analysis using Cronbach's alpha

Constructs	Cronbach's Alpha	Items	Item statistics	Reliability if an item is dropped
Performance Expectancy	0.88	PEX1	0.90	0.81
		PEX2	0.85	0.86
		PEX3	0.85	0.84
		PEX4	0.83	0.86
Effort Expectancy	0.80	EEX1	0.76	0.80
		EEX2	0.81	0.78
		EEX3	0.80	0.79
		EEX4	0.79	0.79
Risk Aversion	0.90	RAV1	0.89	0.87
		RAV2	0.89	0.87
		RAV3	0.88	0.88
		RAV4	0.85	0.89
Facilitating Conditions	0.89	FAC1	0.92	0.83
		FAC2	0.90	0.84
		FAC3	0.86	0.87
		FAC4	0.80	0.89
Social Influence	0.89	SIN1	0.90	0.87
		SIN2	0.83	0.89
		SIN3	0.89	0.87
		SIN4	0.88	0.87
Information Availability	0.91	INF1	0.90	0.90
		INF2	0.92	0.89
		INF3	0.87	0.91
Financial Conditions	0.85	FIN1	0.75	0.85
		FIN2	0.83	0.81
		FIN3	0.86	0.79
Formal and Informal Links	0.77	STR1	0.82	0.72
		STR2	0.87	0.66
		STR3	0.81	0.69
Compatibility	0.87	CMP1	0.83	0.87
		CMP2	0.87	0.84
		CMP3	0.84	0.81
		CMP4	0.85	0.84
Security and Privacy	0.74	SPY1	0.73	0.73
		SPY2	0.81	0.63
		SPY3	0.91	0.54
Intention to Adopt	0.94	ITA1	0.91	0.96
		ITA2	0.96	0.88
		ITA3	0.96	0.89

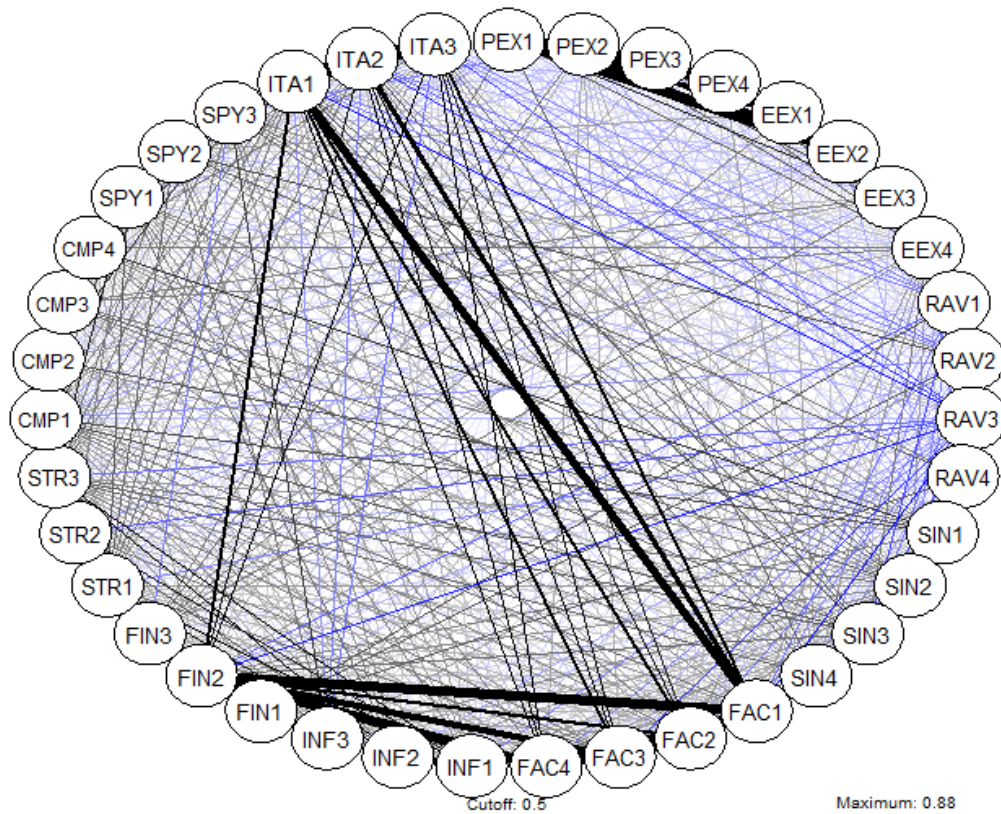


Figure 4.6: Correlation among the items from facilitators' data

Figure 4.6 presents the correlation across all the variables used in the analysis of data collected from facilitators. The highest value of correlation coefficient is 0.88 which indicates no multi-collinearity in the present data. Further, to test multi-collinearity, the two techniques – Tolerance test and VIF are utilized (Kleinbaum *et al.*, 1988). In Table 4-17, the results of these two tests are presented. Hair *et al.* (2006), suggested that tolerance value below 0.1 and a VIF value above 10 indicate high collinearity in the dataset. The results illustrated in Table 4-17 indicate that data being used for analysis is not having multi-collinearity.

Table 4-17: Collinearity statistics

Variables	Tolerance	VIF
PEX1	0.473	2.11
PEX2	0.424	2.36
PEX3	0.396	2.53
PEX4	0.406	2.46
EEX1	0.255	3.92
EEX2	0.391	2.55
EEX3	0.317	3.15
EEX4	0.264	3.78

RAV1	0.536	1.86
RAV2	0.244	4.1
RAV3	0.199	5.01
RAV4	0.368	2.72
SIN1	0.458	2.18
SIN2	0.329	3.04
SIN3	0.22	4.54
SIN4	0.35	2.86
FAC1	0.365	2.74
FAC2	0.319	3.14
FAC3	0.453	2.21
FAC4	0.345	2.89
INF1	0.431	2.32
INF2	0.311	3.21
INF3	0.332	3.01
FIN1	0.459	2.18
FIN2	0.43	2.32
FIN3	0.345	2.89
STR1	0.303	3.3
STR2	0.296	3.38
STR3	0.515	1.94
CMP1	0.388	2.57
CMP2	0.211	4.75
CMP3	0.255	3.92
CMP4	0.364	2.75
SPY1	0.385	2.6
SPY2	0.328	3.05
SPY3	0.318	3.14

4.2.3 Exploratory Factor Analysis

The first part of analysis aims to reveal the underlying structure of the observed variables using Exploratory Factor Analysis (EFA) (Widaman, 2018). As a pre-check for EFA, the correlation matrix is evaluated for its suitability using two tests – (i) Bartlett’s test of sphericity (Bartlett, 1950); and (ii) Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser, 1974). Bartlett’s test of sphericity (1950) rejects the hypothesis that the correlation matrix was an identity matrix (chi-square of 5452.48 with 903 degrees of freedom). KMO test is used to assess the sampling adequacy for factor analysis. With overall KMO measure of sampling adequacy of 0.78, the individual construct of the model has KMO value total ranging from 0.71 to 0.88 (Table 4-18). The acceptable threshold for the KMO test is considered to be 0.7 or higher. Higher KMO values indicate a better fit for factor analysis, indicating that the variables are

more suitable for capturing common underlying factors (Hair *et al.*, 2019; Tabachnick & Fidell, 2019).

Table 4-18: Values of KMO

Item	Value of KMO
PEX1	0.79
PEX2	0.83
PEX3	0.76
PEX4	0.77
EEX1	0.71
EEX2	0.72
EEX3	0.77
EEX4	0.88
RAV1	0.74
RAV2	0.75
RAV3	0.84
RAV4	0.78
SIN1	0.77
SIN2	0.75
SIN3	0.77
SIN4	0.78
FAC1	0.80
FAC2	0.79
FAC3	0.83
FAC4	0.84
INF1	0.82
INF2	0.80
INF3	0.71
FIN1	0.74
FIN2	0.80
FIN3	0.73
STR1	0.85
STR2	0.85
STR3	0.87
CMP1	0.79
CMP2	0.78
CMP3	0.85
CMP4	0.86
SPY1	0.84
SPY2	0.81
SPY3	0.76

The eigenvalue scree plot is a commonly used criterion in factor analysis to determine the number of factors to retain. It is a graphical representation of the eigenvalues obtained from the factor analysis. Eigenvalues represent the amount of variance explained by each factor. Using Parallel Analysis (PA) and Minimum Average Partial (MAP) methods in combination with scree plot is recommended to decide number of latent (Velicer *et al.*, 2000). In the present study, the scree plot as shown in Figure 4.7 indicates that there are five factors with eigenvalue greater than unity. Similarly, the MAP method also suggests that five-factor model is appropriately maintaining the balance between parsimony and comprehensiveness of the proposed model (Watkins, 2020).

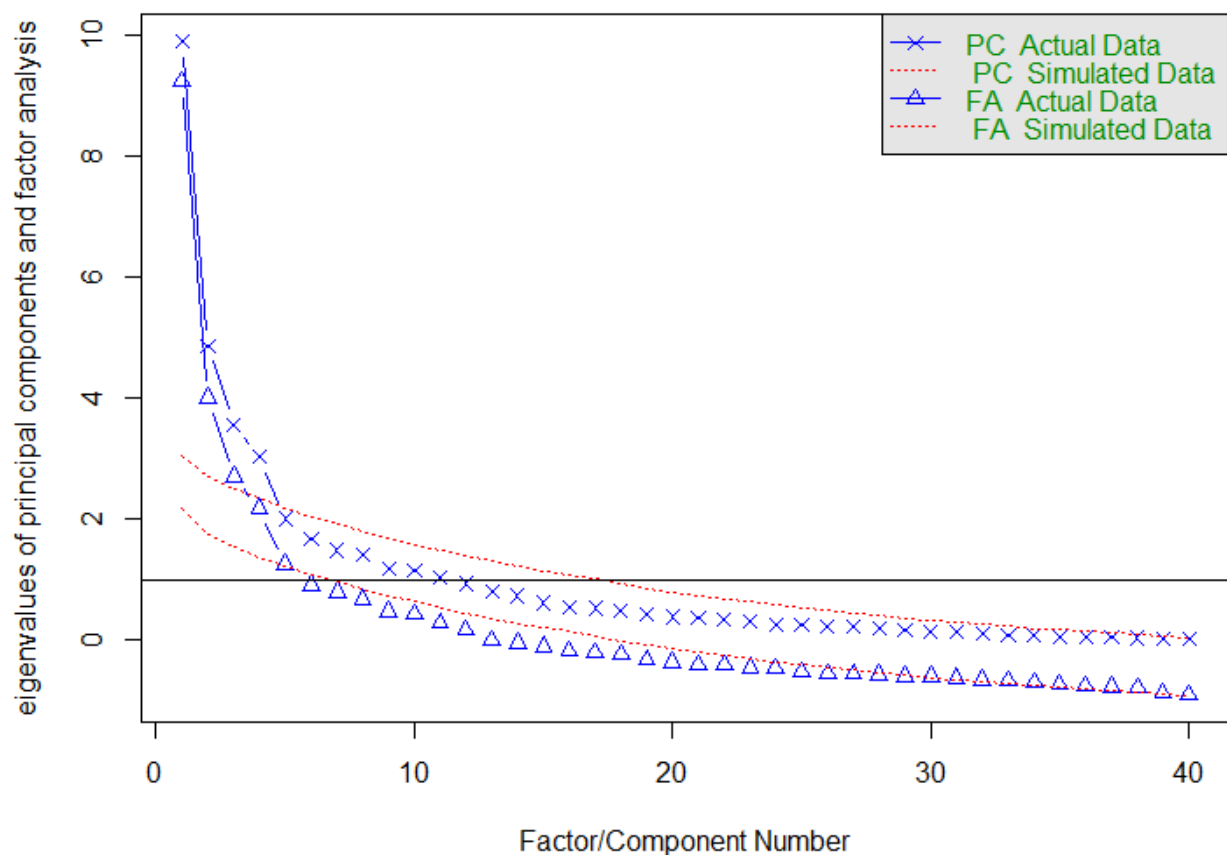


Figure 4.7: Scree plot for EFA using data from facilitators

Table 4-19 shows the factor loading of the constructs using five-factor model explaining variance of 65%. The items with factor loading value above 0.7 threshold (marked in bold) are retained for further analysis. The acceptable value of factor loading against each of the latent variable should have minimum value of 0.5 (Awang & others, 2015). In the present model, the value of all the items loading the latent variable is above the threshold of 0.5, hence it meets the condition of uni-dimensionality.

Table 4-19: Factor loading

Items	Factor-1	Factor-2	Factor-3	Factor-4	Factor-5
PEX1	0.915	0.003	0.021	-0.126	-0.086
PEX2	0.708	-0.058	0.248	-0.147	-0.054
PEX3	0.835	0.070	0.046	-0.065	-0.078
PEX4	0.757	0.045	0.086	-0.031	0.076
EEX1	0.708	0.045	-0.122	0.089	-0.090
EEX2	0.753	-0.102	0.009	0.002	-0.149
EEX3	0.684	-0.067	-0.059	0.040	0.371
EEX4	0.428	-0.109	0.096	-0.303	0.123
RAV1	-0.166	0.035	-0.015	0.822	-0.072
RAV2	-0.035	0.164	-0.060	0.752	-0.085
RAV3	0.042	-0.173	-0.327	0.555	0.054
RAV4	-0.081	0.033	0.059	0.790	-0.062
SIN1	-0.035	0.023	0.208	-0.100	0.428
SIN2	0.217	0.264	0.248	-0.219	0.162
SIN3	0.081	0.134	0.271	-0.494	0.208
SIN4	0.377	0.178	0.034	-0.171	0.090
FAC1	0.018	-0.025	0.856	-0.055	0.185
FAC2	0.102	0.080	0.787	0.083	0.194
FAC3	0.003	0.179	0.816	-0.088	-0.021
FAC4	-0.032	0.062	0.664	0.214	0.109
INF1	-0.109	0.772	0.071	-0.118	0.003
INF2	-0.038	0.804	0.022	0.042	0.089
INF3	0.261	0.535	-0.004	-0.021	0.014
FIN1	-0.051	-0.182	0.234	0.475	0.114
FIN2	0.092	-0.093	0.779	-0.277	-0.042
FIN3	0.303	-0.152	-0.137	0.078	0.233
STR1	-0.149	0.742	-0.050	-0.060	-0.079
STR2	-0.068	0.638	0.194	-0.220	-0.004
STR3	-0.008	0.757	0.124	-0.097	0.173
CMP1	-0.137	0.170	0.163	-0.069	0.689
CMP2	-0.046	0.178	-0.026	0.133	0.868
CMP3	0.109	0.136	-0.004	0.010	0.708
CMP4	-0.003	0.138	0.154	-0.001	0.742
SPY1	-0.067	0.520	0.038	0.105	0.262
SPY2	0.177	0.502	-0.156	0.386	0.149
SPY3	0.070	0.597	-0.075	0.400	0.355

The latent variables extracted from available datasets are interpreted by assigning labels as illustrated in Table 4-20. Based on the interpreted variables, the originally proposed research model with ten independent variables gets condensed to a refined model with five independent variables. Four items of ‘Performance Expectancy’ and two items of ‘Effort Expectancy’ converge into one factor which is interpreted as ‘*User Expectations*’. Similarly, the three items of ‘Facilitating conditions’ and one item of ‘Financial conditions’ get merged under ‘*Facilitating Conditions*’. One item of ‘Risk aversion’ is dropped for its factor loading below 0.7 threshold and is renamed as ‘*Perceived Risks*’. Two items each of ‘Information availability’ and ‘Formal and Informal Links’ are termed as ‘*Information and Involvement*’, while one item of ‘*Compatibility*’ is excluded for its lower factor loading.

Table 4-20: Interpretation of latent factors

Factor	Interpreted variable	Constructs	Items	SS Loading	Proportion Variance
Factor-1	User expectations	Performance expectancy	4	4.90	0.16
		Effort expectancy	2		
Factor-2	Facilitating conditions	Facilitating conditions	3	4.53	0.15
		Financial conditions	1		
Factor-3	Perceived Risks	Risk aversion	3	4.13	0.13
Factor-4	Information and Involvement	Information availability	2	3.59	0.11
		Formal and Informal Links	2		
Factor-5	Compatibility	Compatibility	3	3.37	0.10

4.2.4 Confirmatory Factor Analysis

The reliability and validity of the measurement model as presented in Figure 4.8 is examined in this section. Composite reliability evaluates the measurement quality of the construct. Higher value of composite reliability, such as 0.80 or above, signifies that observed indicators are highly reliable and consistent measure of the underlying construct (Hair *et al.*, 2006). The minimum value of composite reliability observed in the study of facilitators is 0.808 which indicates acceptable reliability as shown in Table 4-21.

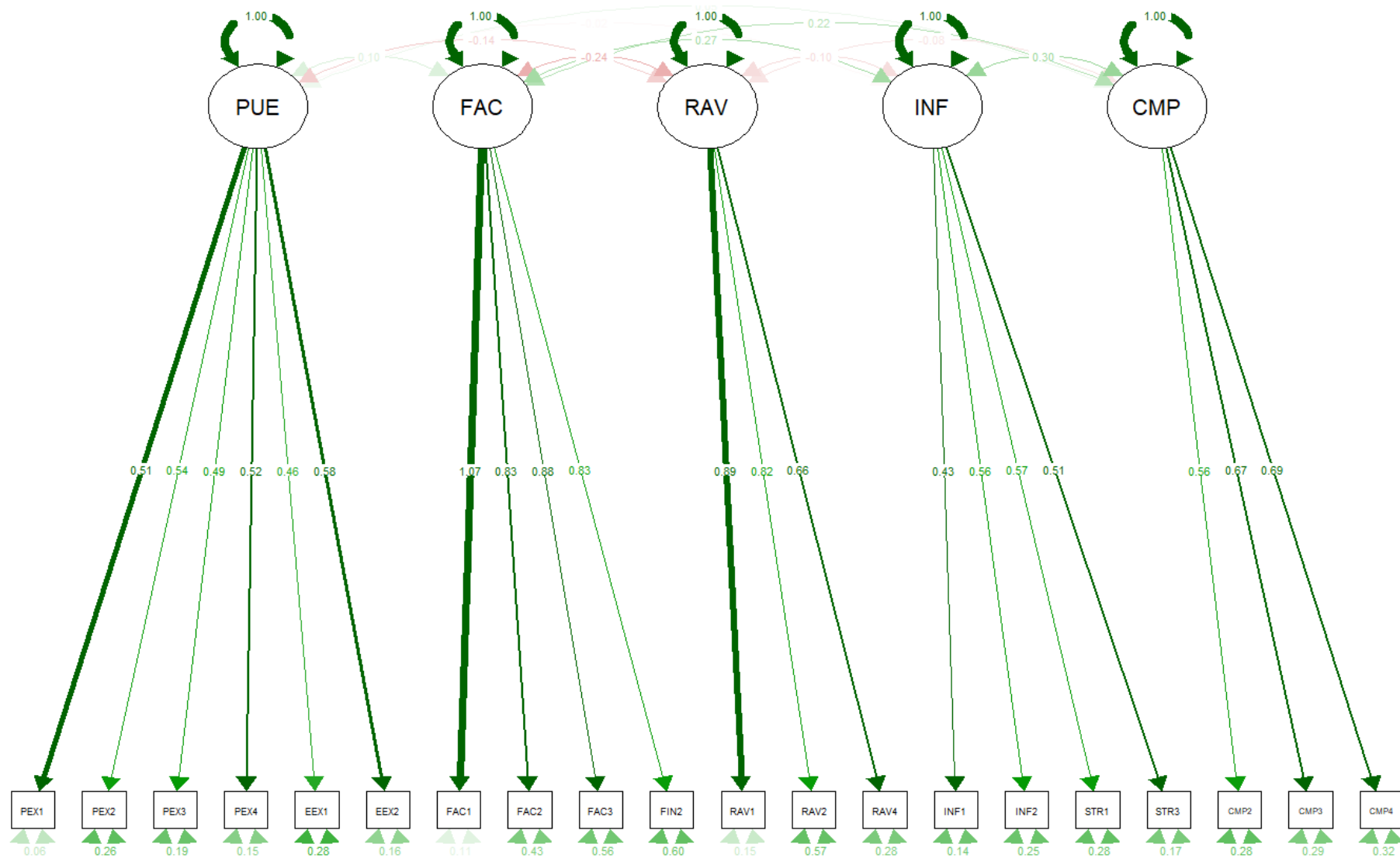


Figure 4.8 Measurement Model for CFA using data from facilitators

In the next step, the constructs are evaluated for convergent validity. By definition, convergent validity estimates the level to which different measures of the same construct are positively related, providing evidence of consistency and agreement among the measurement tools. (Hair *et al.*, 2006). It is assessed by AVE which is recommended to have value ≥ 0.5 for all the constructs (Hair *et al.*, 2006). The value of AVE for all constructs as shown in Table 4-21 is greater than 0.5 which meets the required condition and indicates convergence of all the observed variables to their respective latent construct.

Table 4-21: Calculation of Composite Reliability, Discriminant Validity, AVE and MSV

Items	PUE	FAC	RAV	INF	CMP	λ^2	AVE (λ^2/n)	MSV	Disc. Validi ty	e = (1- λ^2)	Comp Rel
PEX1	0.9	.	.	.	.	0.810	0.604	0.810	0.777	0.190	0.901
PEX2	0.72	.	.	.	.	0.518				0.482	
PEX3	0.75	.	.	.	.	0.563				0.438	
PEX4	0.8	.	.	.	.	0.640				0.360	
EEX1	0.65	.	.	.	.	0.423				0.578	
EEX2	0.82	.	.	.	.	0.672				0.328	
FAC1	.	0.94	.	.	.	0.884	0.662	0.884	0.814	0.116	0.886
FAC2	.	0.79	.	.	.	0.624				0.376	
FAC3	.	0.77	.	.	.	0.593				0.407	
FIN2	.	0.74	.	.	.	0.548				0.452	
RAV1	.	.	0.92	.	.	0.846	0.667	0.846	0.817	0.154	0.856
RAV2	.	.	0.74	.	.	0.548				0.452	
RAV4	.	.	0.78	.	.	0.608				0.392	
INF1	.	.	.	0.75	.	0.563	0.567	0.608	0.753	0.438	0.839
INF2	.	.	.	0.74	.	0.548				0.452	
STR1	.	.	.	0.74	.	0.548				0.452	
STR3	.	.	.	0.78	.	0.608				0.392	
CMP2	.	.	.	.	0.72	0.518	0.584	0.624	0.764	0.482	0.808
CMP3	.	.	.	.	0.78	0.608				0.392	
CMP4	.	.	.	.	0.79	0.624				0.376	

Discriminant validity ensures that the measures of different constructs are distinct and not highly correlated. It demonstrates that the measurement tools are capturing unique aspects of each construct (Hair *et al.*, 2019). The discriminant validity of the measurement model is tested by evaluating cross-correlation among latent variables and its value should not exceed the square root of AVE of each variable. The cross-loading matrix in Table 4-22 depicts that

the study qualifies with discriminant validity since the square root of AVE of each factor (indicated in bold) is greater than correlation value of other factors. These results lead to an interpretation that factors are distinctive in nature with respect to the other factors in the study and thus discriminant validity is established.

Table 4-22: Cross-loading matrix

	PUE	FAC	RAV	INF	CMP	ITA
PUE	0.777					
FAC	0.108	0.813				
RAV	-0.142	-0.237	0.817			
INF	-0.017	0.272	-0.102	0.753		
CMP	0.051	0.225	-0.082	0.300	0.764	
ITA	0.016	0.720	-0.247	0.286	0.316	0.911

The indices of model fitness are summarized in Table 4-23 and meeting the required criteria in overall indicating the acceptability of the measurement model. The model's overall acceptability is also evident based on the two-index presentation strategy proposed by Hu & Bentler's (1999). This strategy considers RMSEA values below 0.06 and SRMR values below 0.09 as indicative of a favorable model fit. The values of CFI is 0.9416 and TLI is 0.9306 (both acceptable greater than 0.9) while RMSEA is 0.0609 and SRMR is 0.0573 (both are acceptable below 0.08) (Hair *et al.*, 2019). All the indices of goodness-of-fit indicate the overall acceptability of the measurement model for further analysis.

Table 4-23: Goodness-of-fit indices

Goodness-of-fit indices	Reported values	Recommended value
Normed Chi-square (CMIN/DF)	1.5187	< 3.000
Comparative Fitness Index (CFI)	0.9416	> 0.9000
Goodness of Fit Index (GFI)	0.8630	> 0.9000
Adjusted Goodness of Fit Index (AGFI)	0.8200	> 0.8000
Root Mean Square Error of Approximation (RMSEA)	0.0609	< 0.08
Tucker-Lewis Index (TLI)	0.9306	> 0.9000
Incremental Fit Index (IFI)	0.9410	> 0.9000
Standardized Root Mean Square Residual (SRMR)	0.0573	< 0.08

4.2.5 Research Hypotheses

Based on the factors identified in the previous section using EFA, the research hypotheses are formulated towards Research Objective 3 and are stated below and illustrated in Figure 4.9:

H1: *User expectations positively influence the intention of facilitators to adopt AI-based solutions in agriculture.*

H2: *Facilitating conditions positively influence the intention of facilitators to adopt AI-based solutions in agriculture.*

H3: *Perceived risks negatively influence the intention of facilitators to adopt AI-based solutions in agriculture.*

H4: *Information and involvement positively affects the intention of facilitators to adopt AI-based solutions in agriculture.*

H5: *Compatibility positively influences the intention of facilitators to adopt AI-based solutions in agriculture.*

These hypotheses are tested using SEM in the next section.

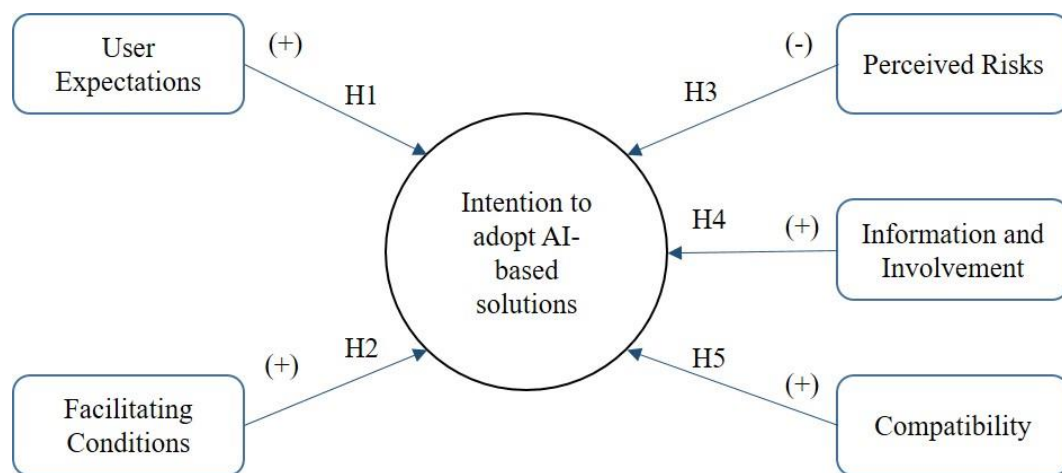


Figure 4.9: Evolved Model for facilitators with latent factors using EFA

4.2.6 Structural Equation Modeling

Structural Equation Modelling (SEM) is a powerful statistical technique that allows researchers to examine complex relationships among variables and test theoretical models. It integrates measurement models and structural models to assess the direct and indirect effects between variables, allowing for the evaluation of theoretical models and hypotheses. Following the steps of EFA, CFA, validation of the measurement model, the formulation of an initial structural model was carried out with dimensions as depicted in Figure 4.9. The primary purpose of this

model is to assess and evaluate the proposed hypotheses. The five factors *User Expectations (PUE)*, *Facilitating Conditions (FAC)*, *Perceived Risks (RAV)*, *Information and Involvement (INF)* and *Compatibility (CMP)* are used as independent variables while *Intention to adopt (ITA)* is used as dependent variable. The evaluation of dependent variable with each independent variable is carried out using SEM.

Table 4-24: Goodness-of-fit indices for Structural Model

Goodness-of-fit indices	Reported values	Recommended value
CMIN/DF	1.9894	< 3.000
CFI	0.911	> 0.9000
GFI	0.849	> 0.9000
AGFI	0.806	> 0.8000
RMSEA	0.070	< 0.08
TLI	0.895	> 0.9000
IFI	0.908	> 0.9000
SRMR	0.055	< 0.08

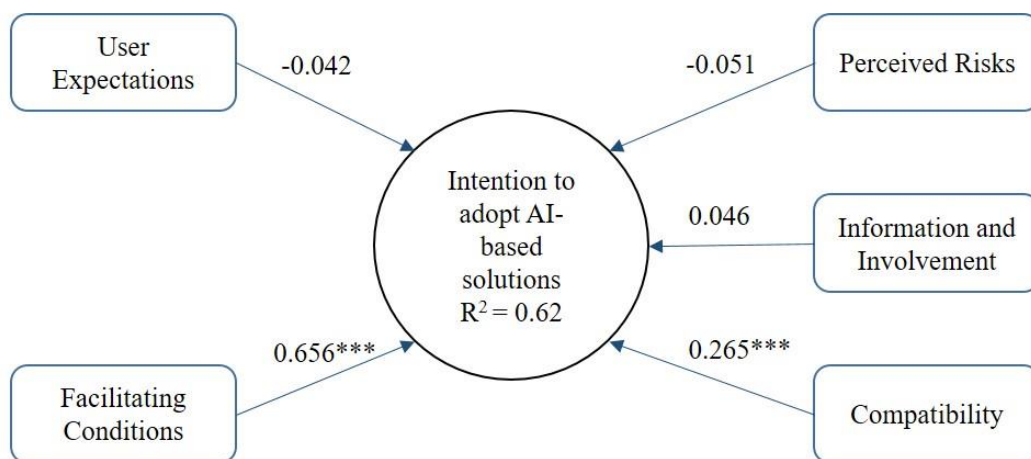
to determine path coefficient for each of the variable. To test hypothesis, the path coefficients, their respective p-value and t-statistics are examined. The achieved model fit indicators are as follows: CMIN/DF as 1.9894 (acceptable value ranges from 1 to 5), CFI as 0.911 (acceptable value above 0.90), RMSEA as 0.070 (acceptable value below 0.08), GFI as 0.849 (acceptable value above 0.90). In overall, these values meet the conditions for a good model fit (Fabrigar *et al.*, 1999; Jackson *et al.*, 2009). Table 4-24 summarizes all the model fit values. The value of R^2 of ‘*Intention to adopt*’ is 62.29% which can explain large amount of variance. Table 4-25 lists the standardized regression weights observed for the model. In Figure 4.10, the structural model with path values showing direct effects is presented. Table 4-26 summarizes the results of hypotheses testing.

Table 4-25: Regression weights for Structural Model

			Standard Estimate	SE	t-Value	2.50% CI	97.50% CI
PUE	→	PEX1	0.888	0.0306	0	0.827	0.948
PUE	→	PEX2	0.763	0.046	0	0.673	0.853
PUE	→	PEX3	0.783	0.0482	0	0.689	0.878
PUE	→	PEX4	0.737	0.0549	0	0.629	0.844
PUE	→	EEX1	0.494	0.0662	0	0.365	0.624
PUE	→	EEX2	0.761	0.0483	0	0.666	0.856
FAC	→	FAC1	0.844	0.0329	0	0.779	0.908
FAC	→	FAC2	0.636	0.0507	0	0.537	0.735

FAC	→	FAC3	0.776	0.0341	0	0.709	0.843
FAC	→	FIN2	0.661	0.0416	0	0.579	0.742
RAV	→	RAV1	0.892	0.0294	0	0.834	0.95
RAV	→	RAV2	0.773	0.033	0	0.708	0.838
RAV	→	RAV4	0.756	0.058	0	0.642	0.869
INF	→	INF1	0.667	0.0694	0	0.531	0.804
INF	→	INF2	0.608	0.0635	0	0.484	0.732
INF	→	STR1	0.707	0.06	0	0.59	0.825
INF	→	STR3	0.811	0.0453	0	0.722	0.9
CMP	→	CMP2	0.755	0.0476	0	0.662	0.848
CMP	→	CMP3	0.828	0.0475	0	0.734	0.921
CMP	→	CMP4	0.735	0.053	0	0.631	0.839
ITA	→	ITA1	0.979	0.0151	0	0.949	1.009
ITA	→	ITA2	0.902	0.0233	0	0.856	0.948
ITA	→	ITA3	0.717	0.04	0	0.638	0.795

The results show that independent variables *User Expectations (PUE)* negatively influences the dependent factor *Intention to adopt (ITA)* with $\beta=-0.0428$. Similarly, other independent factors *Facilitating Conditions (FAC)*, *Perceived Risks (RAV)*, *Information and Involvement (INF)*, and *Compatibility (CMP)* influence *Intention to adopt (ITA)* with β values of 0.6562, -0.0514, 0.0465, and 0.2659 respectively. Figure 4.10 represents the path analysis to test each hypothesis. In the results, PUE ($p=0.600$), RAV ($p=0.464$) and INF ($p=0.550$) turn out to be insignificant. However, other factors including FAC ($p < 0.001$) and CMP ($p < 0.001$) are observed significant.



* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4.10: Results of Path Analysis for data from facilitators

Table 4-26 illustrates values of standardised path with respective levels of significance. The first coefficient between PUE and ITA ($\beta = -0.042$, $p = 0.600$) indicates a low magnitude negative effect of the perceived user expectations on the intention to adopt AI-based solutions in agriculture. As this path has higher p-value than threshold, it is statistically insignificant, thus, it is not supporting H1. The coefficient of path for FAC and ITA ($\beta = 0.656$, $p = 0.000$) demonstrates high positive influence of facilitating conditions on intention to adopt AI-based solutions. The result is significant with positive impact, thus provides support for H2. The characteristics of path between RAV and ITA ($\beta = -0.051$, $p = 0.464$) reveals the impact of perceived risks on the intention to adopt AI-based solutions as negative and insignificant and hence it fails to support H3. The relationship of INF and ITA ($\beta = 0.046$, $p = 0.550$) displays a positive but insignificant effect and does not provide support for H4. The last coefficient of path between CMP on ITA ($\beta = 0.265$, $p = 0.000$) shows high positive effect and significantly provide support for H5. Figure 4.10 graphically represents the path analysis for testing each hypothesis.

Table 4-26: Hypotheses Substantiation

			Standard Estimate	SE	t-Value	2.50% CI	97.50% CI	Hypothesis Test Results	Hypothesis Decision
ITA	→	PUE	-0.0428	0.0818	0.600505	-0.203	0.1175	Non-significant and negative	Not Supported
ITA	→	FAC	0.6562	0.0717	0	0.516	0.7968	Significant and positive	Supported
ITA	→	RAV	-0.0514	0.0702	0.464591	-0.189	0.0863	Non-significant and negative	Not Supported
ITA	→	INF	0.0465	0.0779	0.550412	-0.106	0.1992	Non-significant and positive	Not Supported
ITA	→	CMP	0.2659	0.0738	0.000311	0.121	0.4105	Significant and positive	Supported

From the results, the conclusion is drawn that two out of the five postulated hypotheses are found significant and both have affirmative relationship. It can further be stated that in the proposed model, facilitating conditions and compatibility significantly influence intention to adopt AI-based solutions in agriculture, while user expectations, perceived risks and information and involvement do not significantly influence intention of facilitators. The next chapter discusses the results in detail.

Chapter 5 Discussions, Contributions and Implications

This chapter discusses the overall study carried out on the intention of farmers and facilitators for adoption of AI-based solutions in agriculture. The previous chapters cover a comprehensive literature review on adoption of new technology solutions in agriculture and contributes toward first research objective of the study. Further, based on the literature review, an integrated framework is developed which utilizes three theoretical theories on technology adoption. The developed framework forms the basis of the overall study and fulfils its second research objective. Attributed towards the third research objective of the study, an empirical evaluation of the model is conducted, for which a questionnaire is designed using the variables influencing intention to adopt AI-based solutions in agriculture as identified in the proposed framework. The unit of analysis in the study is taken as farmers, which are end users of the technology, and facilitators, which act as enablers of the new technology in the system.

The discussion on results is presented in this chapter in two parts – the first part discusses highlights of the study on farmers for adopting AI-based solutions in agriculture and the second part presents discussion on the study of facilitators for its adoption. The discussion in each part begins with a concise overview of the study followed by highlights of key characteristics of the respondents. Subsequently, the results are elaborated upon, drawing comparisons with existing literature, and the researcher's insights into the findings are provided. The last section of the chapter presents theoretical and practical implications of this study.

5.1 Discussion on study using Farmers' data

In this part of the study, the analysis on perspectives of farmers is discussed to understand their intention to adopt AI-based solutions in agriculture. Based on the questionnaire, the primary data for study is collected from main ten districts in Punjab and eight districts in Haryana which contribute towards high agricultural production across the state. The samples represent different segments of the population to understand the varying preferences towards adoption of digital agriculture.

The respondents in this part of the study include farmers from Punjab state (61%) and Haryana (39%). Largely, the respondents own small and marginal farms which have size below 2 hectares. Small and marginal farmers often face various challenges such as limited resources, lack of access to credit, and limited technological infrastructure. These constraints can hinder their ability to adopt and integrate digital agriculture solutions effectively. Majority of farmers

are connected with agricultural organizations such as co-operatives which provide them suitable information and support in their farming business. The usage of smartphones by 86% farmers is significant for the adoption of digital agriculture for several reasons. First, smartphones provide farmers with access to a wealth of information and digital tools related to agricultural practices, market trends, weather forecasts, and pest management. This empowers them to make informed decisions and optimize their farming activities. Second, smartphones enable farmers to connect with agricultural experts, extension services, and fellow farmers, facilitating knowledge sharing and collaboration. Third, mobile apps and platforms offer convenient and user-friendly interfaces for accessing digital agricultural solutions, making it easier for farmers to adopt and integrate technology into their practices.

In this study, EFA is utilized to identify underlying dimensions or factors within a set of observed variables using R software, which is a highly versatile exploration technique used for multi-variate analysis. The combination of UTAUT, TOE, and DOI models, which is uncommon in existing literature, and yielded eleven factors which are important for studying adoption of AI-based solutions in agriculture. Using EFA provided five latent factors specific to the study, making the model more relevant and contextual. This also ensures to maintain parsimony and comprehensives in model that can be generalized for future use. Based on the factor loading, five latent factors are identified as: (a) *User expectations*, which is result of combined loading of the variables ‘Perceived Expectancy’ and ‘Effort Expectancy’; (b) *Technology factors*, which is a combination of the variables ‘Compatibility’ and ‘Security and Privacy’; (c) *Facilitating conditions* is the latent variable from the loading of items from variables ‘Facilitating conditions’ and ‘Financial conditions’; (d) *Information and Involvement* is a resultant of loading from items of the variables ‘Information availability’ and ‘Formal and Informal Link’; (e) *Social Influence* is corresponding to its own variable ‘Social influence’.

The evolved model is validated using CFA and hypotheses are formulated as explained in Section 4.1.4 and Section 4.1.5, respectively. After the model is evaluated for its fitness, the path analysis using SEM provides the insights of the contributions by each factor. The results show that the first factor *User Expectations* is highly significant and it represents the performance and effort related expectations of the users from the new technology solution. The level of intention to adopt new technology increases when users relate benefits they are expected to extract from it (Ronaghi & Forouharfar, 2020). The farmers find that the use of intelligent solutions will be useful in their daily farm work and will increase productivity. The use of AI-based solutions will also enable them to accomplish tasks more quickly and enhance chances of higher gains. Further, farmers understand that learning to use and using AI-based

solutions will be easier for them. With highest coefficient (0.35), the factor *User Expectations* becomes the main explanatory variable of the model which leads to the intention to adopt, which is in line with the related studies which highlight the significance of performance and effort expectations (F Caffaro *et al.*, 2020; Cubric, 2020; Heldreth *et al.*, 2021; Shang *et al.*, 2021).

At the second highest level, *technology factors* are contributing towards intention to adopt through its two dimensions – compatibility, security and privacy. Farmers observe that use of AI-based solution in farming is highly compatible to their routine activities and their working style. Also, they understand that using such solutions are highly adaptive and will not make much changes to the existing infrastructure at farm. These observations from the study are supported in the previous literature (Balafoutis *et al.*, 2020; Bryant & Higgins, 2021; Drewry *et al.*, 2019). Farmers are, however, concerned about privacy of data collection from their field and sharing their field related information with other farmers.

Thirdly, the farmers are influenced by the social engagement by local communities, co-operatives and government initiatives. Several programs are run by co-operatives and extensions with objective to promote the use of new technology. These programs involve farmers in activities and demonstrations through which the farmers learn and improve their work practices. This mechanism enhances the level of adoption for new technology and practice (Giua, Materia, *et al.*, 2022; Heldreth *et al.*, 2021; Marius Michels *et al.*, 2020).

At fourth level, *facilitating conditions* play a vital role towards farmers' intention to adopt AI-based solutions in agriculture. The availability of resources required to use the new technology enhances the intention of farmers to adopt it. The resources in form of experiential trainings and infrastructural aids facilitate farmers to gain knowledge and experience of new technology (Giua, Materia, *et al.*, 2022; Marius Michels *et al.*, 2020).

The fifth factor *Information and Involvement* represents availability of information on AI-based solutions and involvement of farmers in agricultural programs. Using the available information, the farmers learn about features and benefits of the new technology which help them to understand it better (Pfeiffer *et al.*, 2021; Smidt, 2021). Through participation in different agricultural events, exhibitions, seminars and activities farmers get familiar with the new technology which enhances their understanding about it and hence influences their intention to adopt it.

5.2 Discussion on study using Facilitators' data

This section presents analysis of perspectives of facilitators regarding their intention to adopt AI-based solutions in agriculture. Based on the questionnaire, the primary data for study is collected from agriculture universities, agriculture department and co-operatives *etc.* using snowball sampling method. The samples represent different segments of respondents involved in enabling adoption new technology to understand their perspective on understanding adoption of digital agriculture. The collected data has representation of facilitators as 57% Punjab state and 43% from Haryana state. Most of the facilitators are graduates and have 5 to 10 years of experience. Largely the facilitators are associated with agricultural universities and co-operatives. The high adoption rate of smartphones (92%) among facilitators is a positive sign, facilitating seamless connectivity and efficient information sharing in the context of the study.

This study employs exploratory factor analysis (EFA) in R software to identify underlying dimensions or factors within a set of observed variables. The unique combination of UTAUT, TOE, and DOI models resulted in eleven factors deemed important for studying the adoption of AI-based solutions in agriculture. Through EFA, five specific latent factors were derived, enhancing the relevance and contextualization of the model. This approach ensures model parsimony and comprehensiveness, allowing for future generalization. Based on factor loading, five latent factors were identified as: (a) *User expectations*, which is result of combined loading of the items from 'Perceived Expectancy' and 'Effort Expectancy'; (b) *Facilitating conditions* is the latent variable from the loading of items from variables 'Facilitating conditions' and 'Financial conditions'; (c) *Perceived risks* represents loading of variable 'Risk aversion'; (d) *Information and Involvement* represents combined loading from variables 'Information availability' and 'Formal and Informal Links'; (e) *Compatibility* is the latent factor resulting from the loading of items from variable 'Compatibility'.

The evolved model is validated using CFA and hypotheses are formulated as explained in Section 4.2.4 and Section 4.2.5, respectively. After the model is evaluated for its fitness, the path analysis using SEM provides the insights of the contributions by each factor. The results of path analysis show that the first factor *User Expectations* is negatively influencing the intention of facilitators to adopt AI-based solution in agriculture. This depicts that although facilitators perceive high expectations from the new technology in terms of its usefulness, productivity, speed, monetary gain, clear understanding and easy to learn features, the adoption intention is low which indicates that there are challenges in adopting this technology despite

its known benefits. Additionally, this factor is observed to be insignificant in the present study, thus for discovering and analysing challenges in adopting the new technology, other factors are analysed in detail as below.

The study findings support that *Facilitating Conditions* have significantly high and positive effect on intention of facilitators to adopt AI-based solutions in agriculture. The lower rating of constructs implies that present conditions regarding the new technology in terms of required knowledge, resources, technical support and financial assistance are lacking which acts as a deterrent to its adoption (Giua, Materia, *et al.*, 2022; Marius Michels *et al.*, 2020). With this observation, *Facilitating Conditions* represents an important aspect in present study which indicates the need to increase focus on knowledge and skill building activities including training, deploying sufficient resources and arranging technical and financial support. Aligned to this track, the initiatives by governments in collaboration with private sector organizations can materialize the vision of increasing adoption level.

The study reveals negative influence of *Perceived Risks* on the adoption intention of facilitators. With lower coefficient value ($\beta = -0.051$) of this construct, its effect is smaller in magnitude and moreover it is observed to be insignificant in the present study ($p = 0.464$). The study highlights the concerns regarding the new technology in terms of its high cost, efficiency and technical risks. Many of the facilitators are concerned about the initial cost involved in deploying the new technology while others have apprehensions on its performance (Barnes *et al.*, 2019; Bryant & Higgins, 2021; Pathak *et al.*, 2019; Salimi *et al.*, 2020; Shang *et al.*, 2021). The input to AI-based solution in form of crop image of top side of leaf provides healthy analysis even if its bottom side is infected with pests. Such inefficient behaviour of the new technology offers deterrence to its adoption.

The awareness about the recent developments and involvement in associated activities have positive effect on the adoption intention. However, the present study shows that the construct *Information and Involvement* is not significant. Although the facilitators are able to receive appropriate the content of information in timely fashion, their intention to adopt the new technology is feeble in view of the less favouring conditions (Pfeiffer *et al.*, 2021; Smidt, 2021). With high involvement in activities of agricultural universities, research institutions and other organizations, the awareness about new technology is made available to the users adequately.

The fifth construct '*Compatibility*' is positively influencing towards intention to adopt AI-based solution. The high value of its coefficient ($\beta = 0.265$), its effect is high on the adoption intention and the construct is observed significant ($p=0.000$) in the present study. The

compatibility of the new technology solution with existing work practices, farmer's work style and existing set-up at farm (Balafoutis *et al.*, 2020; Bryant & Higgins, 2021; Drewry *et al.*, 2019) plays vital role in understanding end-user requirements and delivering the expectations. At the same time, it is very critical that the existing set-up used by farmers should be supporting the new technology which swiftly increases its adoption.

5.3 Contributions

The findings of present study make multiple theoretical contributions to the body of knowledge. Firstly, the study presents a concise, relevant and contextual research model evolved using common factor analysis on the conceptual model based on the IS theories from literature. This study presents comprehensive analysis of the factors influencing the adoption of AI-based solutions in agriculture. By combining the UTAUT, TOE, and DOI models, the study provides a holistic framework that captures multiple dimensions of technology adoption. The use of exploratory factor analysis (EFA) helps identify underlying factors specific to the study context, ensuring the model's relevance and contextual applicability.

Secondly, the result of the study specifically highlights the key areas to be focused instead of aiming at the generalised set of constructs to increase the adoption level of new technology. The identification of five latent factors through exploratory factor analysis enhances the model's robustness and generalizability across diverse agricultural contexts. This, in turn, enables stakeholders to tailor their approaches to specific regions and crops, maximizing the impact of digital technology adoption. This study's findings shed light on the key factors that drive or hinder the adoption of digital technology in agriculture, providing valuable insights for researchers, solution developers, and policymakers. The study's contribution lies in its potential to inform the development of targeted interventions, strategies, and policies that promote the successful adoption and implementation of digital technologies in agricultural settings.

Thirdly, the study indicates that the availability of favouring conditions significantly encourages facilitators to adopt advanced technologies in order to increase the yield with productivity and boosts their progression towards sustainable agriculture. Furthermore, this study's contribution is crucial as it addresses the specific needs and challenges faced by farmers and facilitators in adopting AI-based solutions in agriculture. By examining factors such as user perceived benefits, information availability, user involvement, compatibility with existing work practices, and perceived risks, the study offers a nuanced understanding of the adoption behaviour.

Moreover, the study's focus on facilitators is particularly valuable as it sheds light on the support structures and incentives required to promote technology adoption at various levels of the agricultural ecosystem. By highlighting the significance of facilitators' role, the study underscores the need for collaborative efforts involving researchers, policymakers, extension workers, and technology providers to facilitate technology uptake.

In addition to enriching the existing literature on agricultural technology adoption, this study sets a precedent for future research in emerging economies. Its methodological approach, utilizing exploratory factor analysis and regression analysis, can serve as a guide for researchers exploring adoption behaviour in other sectors or regions.

In conclusion, this study's multifaceted approach, comprehensive analysis, and meaningful insights make it a valuable resource for advancing the understanding of digital technology adoption in agriculture. Its findings can inspire evidence-based strategies, policy formulation, and technology design, ultimately fostering sustainable agricultural development and ensuring food security in a digitally evolving world.

5.4 Implications

5.4.1 Theoretical Implications

The theoretical implications of this study are significant as they contribute to the existing body of knowledge in the field of technology adoption and agricultural innovation. Firstly, by integrating and applying established theoretical frameworks such as UTAUT, TOE, and DOI models, this study demonstrates the usefulness of combining multiple theoretical perspectives to gain a comprehensive understanding of technology adoption behaviour in the agricultural context. This highlights the importance of considering various factors and their inter-relationships when studying complex phenomena like the adoption of AI-based solutions.

Secondly, the identification of five latent factors through exploratory factor analysis adds to the theoretical understanding of the specific drivers and barriers to adoption in the agricultural sector. The findings provide empirical evidence for the relevance and applicability of these factors, thereby contributing to the refinement and validation of existing theories related to technology adoption.

Furthermore, this study's focus on facilitators and their role in technology adoption extends the theoretical understanding beyond individual farmers. It emphasizes the significance of the broader agricultural ecosystem and the need to consider the influence and support of facilitators

such as extension workers, technology providers, and policymakers in promoting technology adoption.

In overall, the study's theoretical implications lie in enhancing our understanding of the factors influencing technology adoption, expanding the application of existing theories, and emphasizing the importance of facilitators in the adoption process. These insights can inform future research and theory development in the field of agricultural innovation, technology adoption, and related disciplines, ultimately leading to more effective strategies and interventions for promoting the adoption of digital technologies in agriculture.

5.4.2 Practical Implications

The practical implications of this study are significant for various stakeholders involved in the agricultural sector. Firstly, the findings can inform policymakers and government agencies about the importance of promoting and supporting the adoption of digital technology in agriculture. They can use the insights to develop targeted policies, incentives, and programs to encourage farmers and facilitators to embrace digital solutions.

Secondly, the study provides valuable insights for agricultural technology developers and solution providers. They can better understand the specific factors that drive adoption and tailor their products and services accordingly. This can lead to the development of user-friendly and contextually relevant digital solutions that address the needs and challenges of farmers and facilitators.

Thirdly, the study can benefit extension agencies and agricultural advisors who work closely with farmers. They can utilize the findings to educate and train farmers on the benefits and practical aspects of adopting digital technology in their farming practices. This can help bridge the knowledge gap and build the necessary skills and confidence among farmers to effectively use digital tools.

Overall, the practical implications of this study revolve around improving the adoption and implementation of digital technology in agriculture, thereby enhancing productivity, sustainability, and profitability for farmers and facilitators.

5.5 Summary

This chapter discusses the research work on the intention of farmers and facilitators to adopt AI-based solutions in agriculture. It begins with a literature review and the development of an integrated framework based on three theoretical theories on technology adoption. The study collects primary data through questionnaires from farmers and facilitators in Punjab and

Haryana, India. The analysis of farmers' data reveals that user expectations, technology factors, social influence, facilitating conditions, and information and involvement are important factors influencing their intention to adopt AI-based solutions. For facilitators, the research finds that facilitating conditions, perceived risks, information and involvement, and compatibility are significant factors affecting their adoption intention. The findings contribute to the body of knowledge by providing a holistic framework for understanding technology adoption in agriculture, identifying specific factors for targeted interventions, and highlighting the role of facilitators in promoting adoption.

Chapter 6 Conclusions and Future Scope

The research work focuses on the identifying and analysing factors influencing adoption of AI-based solutions in agriculture. In the previous chapters, the literature review has been conducted to identify and analyse the factors impacting intention to adopt AI-based solution in agriculture, attributing to Research Objective-1. Section 2.5 presents development of an integrated framework based on analysis of existing theoretical models towards fulfilment of Research Objective-2. Chapter 4 presents data analysis and results of the study to empirically evaluate the developed framework contributing to the Research Objective-3. This chapter discusses the conclusion and limitations from present study. It further highlights the suggestions for future research work.

6.1 Conclusion

This study examines the intention of farmers and facilitators to adopt AI-based solutions in agriculture. The research objectives are achieved through a comprehensive literature review, the development of an integrated framework based on three theoretical models, and an empirical evaluation using a questionnaire. The study focused on farmers as end users and facilitators as enablers of the technology.

The overall study is divided into three parts, contributing to its three research objectives. The first part of the present study explored the literature to propose a framework by integrating the concepts from UTAUT, TOE and DOI to explain the intention of farmers and facilitators to adopt AI-based solutions in agriculture. A systematic literature review is carried out to identify the factors influencing adoption decision for AI-based solutions.

The second part of the study brings an integrated framework which constitutes key factors influencing decision to adopt AI-based solutions in agriculture. Based on this model, a research instrument in form of a questionnaire is administered for farmers and facilitators in states of Punjab and Haryana which are significant contributors towards overall agricultural produce of India.

In the third part, analytical techniques such as EFA, CFA and SEM are utilized to analyse and empirically evaluate the model. The findings indicate that farmers are more likely to adopt the new technology when it garners their performance and effort expectations while meeting the technical dimensions of compatibility and security. This study also highlights the significance of environmental factors playing critical role in increasing the acceptance of new solution

through technical, financial support. The results have practical implications for enhancing adoption by preparing for use of this transformative technology. These findings offer AI-based solution providers to devise strategy to increase the adoption level among farmers by designing and developing solutions suitable to their requirements and expectations. While the present study has observed intention of farmers towards adoption of AI-based solutions in Indian context, future research can examine validity of this framework for other emerging economies. Moreover, the present study offers a generalized view of adoption behaviour of farmers, while future studies can focus on specific crops or agricultural domains where AI finds large number of applications.

Further, the findings indicate that facilitators are more likely to adopt the new technology when they get adequately available facilitating conditions for its use. End-users need to be provided with the required knowledge, resources, technical support and financial assistance to encourage its adoption which demands an active role of government in collaboration with private sector organizations to provide the required facilities. This study also highlights the significance of the compatibility feature of AI-based solution for its adaptability to the existing set-up of farmers. The solution designers need to embed this feature as a critical requirement for higher acceptance of the new technology. Building infrastructural conditions and ensuring compatibility of solution will foster trust of the users and will, thus, increase its adoption to achieve SDG goal of zero hunger by increasing agricultural production.

The study contributes to the body of knowledge by presenting a concise and contextually relevant research model that combines the UTAUT, TOE, and DOI models. The identification of specific latent factors through exploratory factor analysis enhances the model's robustness and generalizability. The findings provide valuable insights for researchers, solution developers, and policymakers in designing targeted interventions, strategies, and policies to promote the successful adoption of AI-based solutions in agriculture.

The work highlights the need for focused efforts to improve facilitating conditions and address perceived risks to increase adoption levels. Collaborative initiatives involving government and private sector organizations can play a crucial role in providing knowledge, resources, and financial support. Furthermore, the study emphasizes the importance of compatibility with existing practices and the availability of information and involvement in promoting technology adoption.

Overall, this research work contributes to the understanding of the factors influencing the adoption of AI-based solutions in agriculture and provides practical implications for promoting

their adoption. By addressing the specific needs and challenges faced by farmers and facilitators, the study paves the way for the successful integration of AI technology in agriculture, leading to improved productivity, sustainability, and decision-making in the sector.

6.2 Limitations

Despite its contributions, this study has certain limitations as discussed in this section. Firstly, the present study empirically evaluates the proposed conceptual model in Indian context, which may limit the generalizability of the findings to other contexts or populations. The cultural, economic, and technological factors specific to India may have influenced the adoption patterns and outcomes observed. The effectiveness of this model can be empirically validated across other emerging economies.

Secondly, this study employs a generalised context of agriculture for adoption of AI-based solution which can be further analysed for specific domains of agriculture. For instance, investigating the application of AI in agriculture value chains, such as storage, transportation, and distribution, could shed light on how these solutions can enhance efficiency and reduce wastage.

Hence, addressing these limitations would strengthen the understanding of AI adoption and its impact on agricultural practices and productivity.

6.3 Suggestions for future research

The present study is an attempt to identify significant factors influencing adoption of AI-based solutions in agriculture based on empirical analysis of data collected from facilitators in North India. The results of present study can be further validated using data from other region to generalize the model used and to provide an enhanced picture to the policy-makers for better decisions.

In future research, it would be valuable to explore the long-term effects of AI adoption in agriculture and its impact on sustainable farming practices. This could involve studying the environmental consequences of AI integration, such as its influence on resource consumption, pesticide usage, and biodiversity.

Conducting a comparative analysis of AI adoption in different agricultural sectors, such as crop farming, livestock management, and precision agriculture, could provide valuable insights into sector-specific challenges and opportunities.

Exploring the role of AI in enhancing food security and resilience to climate change could also be a relevant area of investigation, as AI has the potential to optimize crop yields, predict weather patterns, and improve disaster preparedness.

Examining the impact of AI-based solutions on smallholder farmers and their access to resources and markets could shed light on the equitable distribution of benefits and the potential for inclusive agricultural development.

Furthermore, investigating the ethical considerations and data privacy issues related to AI adoption in agriculture would be essential to ensure responsible and transparent use of technology.

Studying the cost-benefit analysis of AI adoption in agriculture, including initial investment, operational costs, and potential returns, could help farmers and policymakers make informed decisions about adopting these technologies. Also, analyzing the scalability and interoperability of AI-based solutions across different farm sizes and regions would provide insights into the potential for widespread adoption and integration.

Exploring the role of government policies and incentives in promoting AI adoption in agriculture could identify ways to foster an enabling environment for technology uptake.

Lastly, investigating the social implications of AI adoption, including its effects on employment dynamics, farmer livelihoods, and rural communities, would provide a comprehensive understanding of the broader implications of AI in agriculture.

References

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211.
- Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Algharabat, R. (2018). Examining factors influencing Jordanian customers' intentions and adoption of internet banking: Extending UTAUT2 with risk. *Journal of Retailing and Consumer Services*, 40, 125–138.
- Aljawder, A., & Al-Karaghoul, W. (2022). The adoption of technology management principles and artificial intelligence for a sustainable lean construction industry in the case of Bahrain. *Journal of Decision Systems*, 1–30.
- Aubert, B. A., Schroeder, A., & Grimaudo, J. (2012). IT as enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology. *Decision Support Systems*, 54(1), 510–520. <https://doi.org/10.1016/j.dss.2012.07.002>
- Awang, P., & others. (2015). *SEM made simple: A gentle approach to learning Structural Equation Modeling*. MPWS Rich Publication, Bangi.
- Balafoutis, A. T., van Evert, F. K., & Fountas, S. (2020). Smart farming technology trends: Economic and environmental effects, labor impact, and adoption readiness. *Agronomy*, 10(5). <https://doi.org/10.3390/agronomy10050743>
- Balogh, P., Bai, A., Czibere, I., Kovach, I., Fodor, L., Bujdos, A., Sulyok, D., Gabnai, Z., & Birkner, Z. (2021). Economic and Social Barriers of Precision Farming in Hungary. *AGRONOMY-BASEL*, 11(6). <https://doi.org/10.3390/agronomy11061112>
- Bandalos, D. L. (2018). *Measurement theory and applications for the social sciences*. Guilford Publications.
- Barnes, A. P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., van der Wal, T., & Gómez-Barbero, M. (2019). Exploring the adoption of precision agricultural technologies: A cross regional study of EU farmers. *Land Use Policy*, 80, 163–174. <https://doi.org/10.1016/j.landusepol.2018.10.004>
- Bartlett, M. S. (1950). Tests of significance in factor analysis. *British Journal of Psychology*.
- Batte, M T. (2005). Changing computer use in agriculture: Evidence from Ohio. *Computers and Electronics in Agriculture*, 47(1), 1–13. <https://doi.org/10.1016/j.compag.2004.08.002>

- Batte, Marvin T., & Arnholt, M. W. (2003). Precision farming adoption and use in Ohio: Case studies of six leading-edge adopters. *Computers and Electronics in Agriculture*, 38(2), 125–139. [https://doi.org/10.1016/S0168-1699\(02\)00143-6](https://doi.org/10.1016/S0168-1699(02)00143-6)
- Behera, R. K., Bala, P. K., & Dhir, A. (2019). The emerging role of cognitive computing in healthcare: A systematic literature review. *International Journal of Medical Informatics*, 129, 154–166. <https://doi.org/10.1016/j.ijmedinf.2019.04.024>
- Benyam, A. A., Soma, T., & Fraser, E. (2021). Digital agricultural technologies for food loss and waste prevention and reduction: Global trends, adoption opportunities and barriers. *Journal of Cleaner Production*, 323. <https://doi.org/10.1016/j.jclepro.2021.129099>
- Bollen, K. A. (2014). *Structural Equations with Latent Variables*. Wiley.
- Bronson, K., & Knezevic, I. (2016). *Big Data in Food and Agriculture, Big Data \& Society*. January-June.
- Bryant, M., & Higgins, V. (2021). Securitising uncertainty: Ontological security and cultural scripts in smart farming technology implementation. *Journal of Rural Studies*, 81, 315–323. <https://doi.org/10.1016/j.jrurstud.2020.10.051>
- Caffaro, F., Micheletti Cremasco, M., Roccato, M., & Cavallo, E. (2020). Drivers of farmers' intention to adopt technological innovations in Italy: The role of information sources, perceived usefulness, and perceived ease of use. *Journal of Rural Studies*, 76, 264–271. <https://doi.org/10.1016/j.jrurstud.2020.04.028>
- Caffaro, Federica, & Cavallo, E. (2019). The effects of individual variables, farming system characteristics and perceived barriers on actual use of smart farming technologies: Evidence from the piedmont region, northwestern Italy. *Agriculture (Switzerland)*, 9(5). <https://doi.org/10.3390/agriculture9050111>
- Caplan, S., Tilt, B., Hoheisel, G., & Baugher, T. A. (2014). Specialty Crop Growers' Perspectives on Adopting New Technologies. *HORTTECHNOLOGY*, 24(1), 81–87. <https://doi.org/10.21273/HORTTECH.24.1.81>
- Carolan, M. (2018). ``Smart' Farming Techniques as Political Ontology: Access, Sovereignty and the Performance of Neoliberal and Not-So-Neoliberal Worlds. *SOCIOLOGIA RURALIS*, 58(4), 745–764. <https://doi.org/10.1111/soru.12202>
- Carrer, M. J., de Souza Filho, H. M., & Batalha, M. O. (2017). Factors influencing the adoption

- of Farm Management Information Systems (FMIS) by Brazilian citrus farmers. *Computers and Electronics in Agriculture*, 138, 11–19. <https://doi.org/10.1016/j.compag.2017.04.004>
- Castle, M. H., Lubben, B. D., & Luck, J. D. (2016). *Factors influencing the adoption of precision agriculture technologies by Nebraska producers*.
- CEMA. (2017). *Digital Farming: what does it really mean?* https://www.cema-agri.org/images/publications/position-papers/CEMA_Digital_Farming_-_Agriculture_4.0__13_02_2017_0.pdf
- Chaudhary, S., & Suri, P. K. (2021). Framework for agricultural e-trading platform adoption using neural networks. *International Journal of Information Technology (Singapore)*, 13(2), 501–510. <https://doi.org/10.1007/s41870-020-00603-9>
- Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2013). *Applied multiple regression/correlation analysis for the behavioral sciences*. Routledge.
- Cubric, M. (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. *Technology in Society*, 62. <https://doi.org/10.1016/j.techsoc.2020.101257>
- D’Antoni, J. M., Mishra, A. K., & Joo, H. (2012). Farmers’ perception of precision technology: The case of autosteer adoption by cotton farmers. *Computers and Electronics in Agriculture*, 87, 121–128. <https://doi.org/10.1016/j.compag.2012.05.017>
- Daberkow, S. G., & McBride, W. D. (2003). Farm and operator characteristics affecting the awareness and adoption of precision agriculture technologies in the US. *Precision Agriculture*, 4(2), 163–177. <https://doi.org/10.1023/A:1024557205871>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340.
- DeVellis, R. F. (2012). *Scale Development: Theory and Applications*. SAGE Publications.
- Drewry, J. L., Shutske, J. M., Trechter, D., Luck, B. D., & Pitman, L. (2019). Assessment of digital technology adoption and access barriers among crop, dairy and livestock producers in Wisconsin. *Computers and Electronics in Agriculture*, 165. <https://doi.org/10.1016/j.compag.2019.104960>
- El-Gayar, O. F., Ambati, L. S., & Nawar, N. (2019). Wearables, artificial intelligence, and the

- future of healthcare. In *AI and Big Data's Potential for Disruptive Innovation* (pp. 104–129). <https://doi.org/10.4018/978-1-5225-9687-5.ch005>
- Elferink, M., & Schierhorn, F. (2016). Global Demand for Food is Rising. Can we meet it. *Harvard Business Review*, 7(04), 2016.
- Engås, K. G., Raja, J. Z., & Neufang, I. F. (2023). Decoding technological frames: An exploratory study of access to and meaningful engagement with digital technologies in agriculture. *Technological Forecasting and Social Change*, 190, 122405.
- Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, 4(3), 272.
- FAO. (2020). Food Security and Nutrition in the World. In *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*.
- Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behaviour: An introduction to theory and research*. Addison-Wesley.
- Fishman, R., Ghosh, M., Mishra, A., Shomrat, S., Laks, M., Mayer, R., Jog, A., Ben-Dor, E., & Shacham-Diamand, Y. (2020). Digital Villages: A Data-Driven Approach to Precision Agriculture in Small Farms. *Sensornets*, 161–166.
- Fuentes, S., Gonzalez Viejo, C., Cullen, B., Tongson, E., Chauhan, S. S., & Dunshea, F. R. (2020). Artificial intelligence applied to a robotic dairy farm to model milk productivity and quality based on cow data and daily environmental parameters. *Sensors*, 20(10), 2975.
- Gabriel, A., Gandorfer, M., & Spykman, O. (2021). Use of and barriers to digital technologies in agriculture Perspectives from farming and the trade media. *Berichte Über Landwirtschaft*, 99(1).
- Gacar, A., Aktas, H., & Ozdogan, B. (2017). Digital agriculture practices in the context of agriculture 4.0. *Pressacademia*, 4(2), 184–191. <https://doi.org/10.17261/pressacademia.2017.448>
- Gallardo, R. K., Grant, K., Brown, D. J., McFerson, J. R., Lewis, K. M., Einhorn, T., & Sazo, M. M. (2019). Perceptions of precision agriculture technologies in the U.S. fresh apple industry. *HortTechnology*, 29(2), 151–162. <https://doi.org/10.21273/HORTTECH04214-18>

- Gefen, D., Straub, D., & Boudreau, M.-C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, 4(1), 7.
- Giua, C., Cristiana, V., & Camanzi, L. (2022). Technology in Society Smart farming technologies adoption : Which factors play a role in the digital transition ? *Technology in Society*, 68(January), 101869. <https://doi.org/10.1016/j.techsoc.2022.101869>
- Giua, C., Materia, V. C., & Camanzi, L. (2022). Smart farming technologies adoption: Which factors play a role in the digital transition? *Technology in Society*, 68(September 2021), 101869. <https://doi.org/10.1016/j.techsoc.2022.101869>
- Gizelis, C. A., Nestorakis, K., Misargopoulos, A., Nikolopoulos-Gkamatsis, F., Kefalogiannis, M., Palaiogeorgou, P., Christonasis, A. M., Boletis, K., Giamalis, T., & Charisis, C. (2022). Decision support using AI: the data exploitation at telecoms in practice. *Journal of Decision Systems*, 1–19.
- Gómez-Chabla, R., Real-Avilés, K., Morán, C., Grijalva, P., & Recalde, T. (2018). IoT applications in agriculture: A systematic literature review. *ICT for Agriculture and Environment: Second International Conference, CITAMA 2019, Guayaquil, Ecuador, January 22-25, 2019, Proceedings*, 68–76.
- Griva, A., Dennehy, D., Pappas, I., Mäntymäki, M., Pouloudi, N., Dwivedi, Y. K., & Schmarzo, B. (2022). Artificial intelligence and analytics in practice. In *Journal of Decision Systems* (pp. 1–7). Taylor & Francis.
- Groher, T., Heitkämper, K., & Umstätter, C. (2020). Digital technology adoption in livestock production with a special focus on ruminant farming. *Animal*, 14(11), 2404–2413. <https://doi.org/10.1017/S1751731120001391>
- Groher, T., Heitkämper, K., Walter, A., Liebisch, F., & Umstätter, C. (2020). Status quo of adoption of precision agriculture enabling technologies in Swiss plant production. *Precision Agriculture*, 21(6), 1327–1350. <https://doi.org/10.1007/s11119-020-09723-5>
- Grossnickle, J., & Raskin, O. (2001). *Handbook of Online Marketing Research*. McGraw-Hill.
- Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., Black, W. C., & Anderson, R. E. (2019). *Multivariate Data Analysis (Eighth)*. Cengage Learning EMEA.
- Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate*

- data analysis 6th Edition. *Pearson Prentice Hall*. New Jersey. *Humans: Critique and Reformulation*. *Journal of Abnormal Psychology*, 87, 49–74.
- Haque, A., Islam, N., Samrat, N. H., Dey, S., & Ray, B. (2021). Smart farming through responsible leadership in Bangladesh: Possibilities, opportunities, and beyond. *Sustainability (Switzerland)*, 13(8). <https://doi.org/10.3390/su13084511>
- Hayat, N., Al Mamun, A., Nasir, N. A. M., Selvachandran, G., Nawli, N. B. C., & Gai, Q. S. (2020). Predicting sustainable farm performance-Using hybrid structural equation modelling with an artificial neural network approach. *Land*, 9(9). <https://doi.org/10.3390/LAND9090289>
- Heldreth, C., Akrong, D., Holbrook, J., & Su, N. M. (2021). What Does AI Mean for Smallholder Farmers? A Proposal for Farmer-Centered AI Research. *Interactions*, 28(4), 56–60. <https://doi.org/10.1145/3468004>
- Hildebrand, C., Hoffman, D., Logg, J. M., Yang, H. H. J., & Yeomans, M. (2020). Resisting Artificial Intelligence: When Do Decision-Makers Avoid or Use Algorithmic Input? *Academy of Management Proceedings*, 2020(1), 17721.
- Hoehle, H., Scornavacca, E., & Huff, S. (2012). Three decades of research on consumer adoption and utilization of electronic banking channels: A literature analysis. *Decision Support Systems*, 54(1), 122–132.
- Hoelzle, J. B., & Meyer, G. J. (2013). *Exploratory factor analysis: Basics and beyond*.
- Holzinger, A., Weippl, E., Tjoa, A. M., & Kieseberg, P. (2021). Digital Transformation for Sustainable Development Goals (SDGs) - A Security, Safety and Privacy Perspective on AI. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 12844 LNCS, 1–20. https://doi.org/10.1007/978-3-030-84060-0_1
- Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55.
- Huang, S., Welch, C., Iliev, Y., & Rossello, V. (2018). The technical and commercial increment of the fusion of big data analysis, artificial intelligence and earth observation. *Proceedings of the International Astronautical Congress, IAC, 2018-Octob*. <https://www.scopus.com/inward/record.uri?eid=2-s2.0->

- Isgin, T., Bilgic, A., Forster, D. L., & Batte, M. T. (2008). Using count data models to determine the factors affecting farmers' quantity decisions of precision farming technology adoption. *Computers and Electronics in Agriculture*, 62(2), 231–242. <https://doi.org/10.1016/j.compag.2008.01.004>
- Jaafar, H., & Kharroubi, S. A. (2021). Views, practices and knowledge of farmers regarding smart irrigation apps: A national cross-sectional study in Lebanon. *Agricultural Water Management*, 248. <https://doi.org/10.1016/j.agwat.2021.106759>
- Jackson, D. L., Gillaspay Jr, J. A., & Purc-Stephenson, R. (2009). Reporting practices in confirmatory factor analysis: an overview and some recommendations. *Psychological Methods*, 14(1), 6.
- Jellason, N. P., Robinson, E. J. Z., & Ogbaga, C. C. (2021). Agriculture 4.0: Is Sub-Saharan Africa Ready? *Applied Sciences (Switzerland)*, 11(12). <https://doi.org/10.3390/app11125750>
- Jha, K., Doshi, A., Patel, P., & Shah, M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture*, 2, 1–12. <https://doi.org/https://doi.org/10.1016/j.aiia.2019.05.004>
- Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, 39(1), 31–36.
- Khanna, M., Atallah, S. S., Kar, S., Sharma, B., Wu, L., Yu, C., Chowdhary, G., Soman, C., & Guan, K. (2022). Digital transformation for a sustainable agriculture in the United States: Opportunities and challenges. *Agricultural Economics*, 53(6), 924–937.
- Kleinbaum, D. G., Kupper, L. L., & KE, M. (1988). Applied regression analysis and other multivariable methods PWS-Kent. *Boston, Massachusetts*.
- Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS - Wageningen Journal of Life Sciences*, 90–91. <https://doi.org/10.1016/j.njas.2019.100315>
- Kumar, A. (2020). *National strategy for artificial intelligence*.
- Kumar, D., Samalia, H. V., & Verma, P. (2017). Factors influencing cloud computing adoption by small and medium-sized enterprises (SMEs) in India. *Pacific Asia Journal of the*

- Kumar, R. (2021). Managing Business in the Digital Era--The use of IT and Analytics for Process Transformation. In *Journal of Decision Systems* (Vol. 30, Issue 4, pp. 410–413). Taylor & Francis.
- Kumar, S. (2018). *Understanding Different Issues of Unit of Analysis in a Business Research Journal of General Management research*.
- Lambert, D. M., Paudel, K. P., & Larson, J. A. (2015). Bundled adoption of precision agriculture technologies by cotton producers. *Journal of Agricultural and Resource Economics*, 40(2), 325–345. <https://www.scopus-com-puchd.knimbus.com/inward/record.uri?eid=2-s2.0-84936774736&partnerID=40&md5=9c48bc8961c309a8e1007c392c2eccf4>
- Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The technology acceptance model: Past, present, and future. *Communications of the Association for Information Systems*, 12(1), 50.
- Li, B., Ding, J., Wang, J., Zhang, B., & Zhang, L. (2021). Key factors affecting the adoption willingness, behavior, and willingness-behavior consistency of farmers regarding photovoltaic agriculture in China. *Energy Policy*, 149. <https://doi.org/10.1016/j.enpol.2020.112101>
- Li, W., Clark, B., Taylor, J. A., Kendall, H., Jones, G., Li, Z., Jin, S., Zhao, C., Yang, G., Shuai, C., Cheng, X., Chen, J., Yang, H., & Frewer, L. J. (2020). A hybrid modelling approach to understanding adoption of precision agriculture technologies in Chinese cropping systems. *Computers and Electronics in Agriculture*, 172. <https://doi.org/10.1016/j.compag.2020.105305>
- Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors (Switzerland)*, 18(8), 1–29. <https://doi.org/10.3390/s18082674>
- Liang, T.-P., Kohli, R., Huang, H.-C., & Li, Z.-L. (2021). What Drives the Adoption of the Blockchain Technology? A Fit-Viability Perspective. *Journal of Management Information Systems*, 38(2), 314–337. <https://doi.org/10.1080/07421222.2021.1912915>
- Liu, W., Shao, X.-F., Wu, C.-H., & Qiao, P. (2021). A systematic literature review on applications of information and communication technologies and blockchain technologies

- for precision agriculture development. *Journal of Cleaner Production*, 298. <https://doi.org/10.1016/j.jclepro.2021.126763>
- McLeod, M. S., Payne, G. T., & Evert, R. E. (2016). Organizational ethics research: A systematic review of methods and analytical techniques. *Journal of Business Ethics*, 134(3), 429–443.
- Michels, M, Fecke, W., Feil, J.-H., Musshoff, O., Pigisch, J., & Krone, S. (2020). Smartphone adoption and use in agriculture: empirical evidence from Germany. *Precision Agriculture*, 21(2), 403–425. <https://doi.org/10.1007/s11119-019-09675-5>
- Michels, M, von Hobe, C.-F., & Musshoff, O. (2020). A trans-theoretical model for the adoption of drones by large-scale German farmers. *Journal of Rural Studies*, 75, 80–88. <https://doi.org/10.1016/j.jrurstud.2020.01.005>
- Michels, M, von Hobe, C.-F., von Ahlefeld, P. J., & Musshoff, O. (2021). The adoption of drones in German agriculture: a structural equation model. *Precision Agriculture*. <https://doi.org/10.1007/s11119-021-09809-8>
- Michels, Marius, Bonke, V., & Musshoff, O. (2020). Understanding the adoption of smartphone apps in crop protection. *Precision Agriculture*, 21(6), 1209–1226. <https://doi.org/10.1007/s11119-020-09715-5>
- Ministry of Agriculture & Farmers’ Welfare Government of India. (2017). *Report of the Committee on Doubling Farmers’ Income, Volume. XI. X(1)*, 1–164. <https://farmer.gov.in/imagedefault/DFI/DFI10.pdf%0Ahttp://dx.doi.org/10.1016/j.inpa.2015.11.002> Vol-
- Ministry of Agriculture & Farmers Welfare Government of India. (2022). *Agricultural Statistics at a Glance, 2022*. 1–280.
- Mitchell, S., Weersink, A., & Bannon, N. (2021). Adoption barriers for precision agriculture technologies in canadian crop production. *Canadian Journal of Plant Science*, 101(3), 412–416. <https://doi.org/10.1139/cjps-2020-0234>
- Molina-Maturano, J., Verhulst, N., Tur-Cardona, J., Guarena, D. T., Gardezabal-Monsalve, A., Govaerts, B., & Speelman, S. (2021). Understanding Smallholder Farmers’ Intention to Adopt Agricultural Apps: The Role of Mastery Approach and Innovation Hubs in Mexico. *AGRONOMY-BASEL*, 11(2). <https://doi.org/10.3390/agronomy11020194>

- Monteleone, S., de Moraes, E. A., de Faria, B. T., Aquino Junior, P. T., Maia, R. F., Neto, A. T., & Toscano, A. (2020). Exploring the adoption of precision agriculture for irrigation in the context of agriculture 4.0: The key role of internet of things. *Sensors (Switzerland)*, 20(24), 1–32. <https://doi.org/10.3390/s20247091>
- Mukherjee, A., Misra, S., & Raghuwanshi, N. S. (2019). A survey of unmanned aerial sensing solutions in precision agriculture. *Journal of Network and Computer Applications*, 148, 102461.
- Nowak, B. (2021). Precision Agriculture: Where do We Stand? A Review of the Adoption of Precision Agriculture Technologies on Field Crops Farms in Developed Countries. *Agricultural Research*. <https://doi.org/10.1007/s40003-021-00539-x>
- Nunnally, J. C., & Bernstein, I. H. (1994). The assessment of reliability. *Psychometric Theory*.
- Pathak, H. S., Brown, P., & Best, T. (2019). A systematic literature review of the factors affecting the precision agriculture adoption process. *Precision Agriculture*, 20(6), 1292–1316. <https://doi.org/10.1007/s11119-019-09653-x>
- Patrício, D. I., & Rieder, R. (2018). Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Computers and Electronics in Agriculture*, 153, 69–81. <https://doi.org/10.1016/j.compag.2018.08.001>
- Paustian, M., & Theuvsen, L. (2017). Adoption of precision agriculture technologies by German crop farmers. *Precision Agriculture*, 18(5), 701–716. <https://doi.org/10.1007/s11119-016-9482-5>
- Pfeiffer, J., Gabriel, A., & Gandorfer, M. (2021). Understanding the public attitudinal acceptance of digital farming technologies: a nationwide survey in Germany. *Agriculture and Human Values*, 38(1), 107–128. <https://doi.org/10.1007/s10460-020-10145-2>
- Pierpaoli, E., Carli, G., Pignatti, E., & Canavari, M. (2013). Drivers of Precision Agriculture Technologies Adoption: A Literature Review. *Procedia Technology*, 8(Haicta), 61–69. <https://doi.org/10.1016/j.protcy.2013.11.010>
- Pivoto, D., Waquil, P. D., Talamini, E., Finocchio, C. P. S., Dalla Corte, V. F., & de Vargas Mores, G. (2018). Scientific development of smart farming technologies and their application in Brazil. *Information Processing in Agriculture*, 5(1), 21–32. <https://doi.org/10.1016/j.inpa.2017.12.002>

- Pivoto, Dieisson, Barham, B., Waquil, P. D., Foguesatto, C. R., Dalla Corte, V. F., Zhang, D., & Talamini, E. (2019). Factors influencing the adoption of smart farming by Brazilian grain farmers. *International Food and Agribusiness Management Review*, 22(4), 571–588. <https://doi.org/10.22434/IFAMR2018.0086>
- Plantix Agriculture Application*. (2023). <https://plantix.net/en/>
- R Core Team. (2022). *R: A Language and Environment for Statistical Computing*. <https://www.r-project.org/>
- Rathod, P., & Dixit, S. (2020). Precision dairy farming: Opportunities and challenges for India. *INDIAN JOURNAL OF ANIMAL SCIENCES*, 90(8), 1083–1094.
- Reim, W., Parida, V., & Örtqvist, D. (2015). Product--Service Systems (PSS) business models and tactics--a systematic literature review. *Journal of Cleaner Production*, 97, 61–75.
- Report of the Committee on Doubling Farmers' Income*. (2018).
- Rodzalan, S. A., Yin, O. G., & Mohd Noor, N. N. (2020). A foresight study of artificial intelligence in the agriculture sector in Malaysia. *International Journal of Advanced Science and Technology*, 29(6), 447–462. <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85084045169&partnerID=40&md5=c2ef86553f623b640a054229baa2e6da>
- Rogers, E. M. (2003). Elements of diffusion. *Diffusion of Innovations*, 5(1.38).
- Ronaghi, M. H., & Forouharfar, A. (2020). A contextualized study of the usage of the Internet of things (IoTs) in smart farming in a typical Middle Eastern country within the context of Unified Theory of Acceptance and Use of Technology model (UTAUT). *Technology in Society*, 63. <https://doi.org/10.1016/j.techsoc.2020.101415>
- Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Frontiers in Sustainable Food Systems*, 2, 87.
- Salimi, M., Pourdarbani, R., & Nouri, B. A. (2020). Factors Affecting the Adoption of Agricultural Automation Using Davis's Acceptance Model (Case Study: Ardabil). *Acta Technologica Agriculturae*, 23(1), 30–39. <https://doi.org/10.2478/ata-2020-0006>
- Samantaray, S. D., & Pant, D. (2017). Development of Knowledge Mining Techniques For Spatial Decision Support System. *International Journal of Computer Engineering & Technology*, 8(6).

- Scur, G., da Silva, A. V. D., Mattos, C. A., & Gonçalves, R. F. (2023). Analysis of IoT adoption for vegetable crop cultivation: Multiple case studies. *Technological Forecasting and Social Change*, 191, 122452.
- Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., & Rasch, S. (2021). Adoption and diffusion of digital farming technologies - integrating farm-level evidence and system interaction. *Agricultural Systems*, 190. <https://doi.org/10.1016/j.agsy.2021.103074>
- Sharma, R., Kamble, S. S., Gunasekaran, A., Kumar, V., & Kumar, A. (2020). A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Computers & Operations Research*, 119, 104926.
- Shutske, J. M., Trechter, D., Luck, B. D., Drewry, J. L., DeWitte, M. J., Pitman, L., & Kluz, M. (2018). Assessment of digital capacity, needs and access barriers among crop, dairy and livestock producers. *ASABE 2018 Annual International Meeting*. <https://doi.org/10.13031/aim.201801320>
- Skevas, T., & Kalaitzandonakes, N. (2020). Farmer awareness, perceptions and adoption of unmanned aerial vehicles: evidence from Missouri. *International Food and Agribusiness Management Review*, 23(3), 469–485. <https://doi.org/10.22434/IFAMR2019.0151>
- Smidt, H. J. (2021). Factors affecting digital technology adoption by small-scale farmers in agriculture value chains (AVCs) in South Africa. *Information Technology for Development*. <https://doi.org/10.1080/02681102.2021.1975256>
- Sood, A., Bhardwaj, A. K., & Sharma, R. K. (2022). Towards sustainable agriculture: key determinants of adopting artificial intelligence in agriculture. *Journal of Decision Systems*, 1–45.
- Sood, A., Sharma, R. K., & Bhardwaj, A. K. (2021). Artificial intelligence research in agriculture: a review. *Online Information Review*.
- Stevens, J. P. (2009). *Applied Multivariate Statistics for the Social Sciences*. Routledge.
- Straub, D. W. (1989). Validating instruments in MIS research. *MIS Quarterly*, 147–169.
- Suhr, D. D. (2006). *Exploratory or confirmatory factor analysis?*
- Tabachnick, B. G., & Fidell, L. S. (2019). *Using Multivariate Statistics*.
- Takácsné György, K., Lámfalusi, I., Molnár, A., Sulyok, D., Gaál, M., Keményné Horváth, Z., Domán, C., Illés, I., Kiss, A., Péter, K., & Kemény, G. (2018). Precision agriculture in

- Hungary: Assessment of perceptions and accounting records of FADN arable farms. *Studies in Agricultural Economics*, 120(1), 47–54. <https://doi.org/10.7896/j.1717>
- Tamirat, T. W., Pedersen, S. M., & Lind, K. M. (2018). Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany. *Acta Agriculturae Scandinavica Section B: Soil and Plant Science*, 68(4), 349–357. <https://doi.org/10.1080/09064710.2017.1402949>
- Tey, Y. S., & Brindal, M. (2012). Factors influencing the adoption of precision agricultural technologies: A review for policy implications. *Precision Agriculture*, 13(6), 713–730. <https://doi.org/10.1007/s11119-012-9273-6>
- Tey, Y. S., & Brindal, M. (2022). A meta-analysis of factors driving the adoption of precision agriculture. *Precision Agriculture*, 23(2), 353–372. <https://doi.org/10.1007/s11119-021-09840-9>
- Thomas, R. J., O'Hare, G., & Coyle, D. (2023). Understanding technology acceptance in smart agriculture: A systematic review of empirical research in crop production. *Technological Forecasting and Social Change*, 189, 122374.
- Thompson, B., & Daniel, L. G. (1996). Factor analytic evidence for the construct validity of scores: A historical overview and some guidelines. In *Educational and psychological measurement* (Vol. 56, Issue 2, pp. 197–208). Sage Publications Sage CA: Thousand Oaks, CA.
- Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *Processes of technological innovation*. Lexington books.
- Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, 14(3), 207–222.
- Ullman, J. B., & Bentler, P. M. (2012). Structural equation modeling. *Handbook of Psychology, Second Edition*, 2.
- United Nations. (2022). *Day of 8 Billion*. United Nations. <https://www.un.org/en/dayof8billion>
- Vaithilingam, S., Nair, M., Macharia, M., & Venkatesh, V. (2022). Mobile communication and use behavior of the urban poor in a developing country: A field study in Malaysia. *International Journal of Information Management*, 63, 102440.

- Vecchio, Y., De Rosa, M., Adinolfi, F., Bartoli, L., & Masi, M. (2020). Adoption of precision farming tools: A context-related analysis. *Land Use Policy*, 94. <https://doi.org/10.1016/j.landusepol.2020.104481>
- Velicer, W. F., Eaton, C. A., & Fava, J. L. (2000). Construct explication through factor or component analysis: A review and evaluation of alternative procedures for determining the number of factors or components. *Problems and Solutions in Human Assessment*, 41–71.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 27(3), 425–478. <http://www.jstor.org/stable/30036540>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157–178.
- Verdouw, C., Wolfert, S., & Tekinerdogan, B. (2016). Internet of things in agriculture. *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources*, 11. <https://doi.org/10.1079/PAVSNNR201611035>
- Walton, J. C., Larson, J. A., Roberts, R. K., Lambert, D. M., English, B. C., Larkin, S. L., Marra, M. C., Martin, S. W., Paxton, K. W., & Reeves, J. M. (2010). Factors Influencing Farmer Adoption of Portable Computers for Site-Specific Management: A Case Study for Cotton Production. *Journal of Agricultural and Applied Economics*, 42(2), 193–209. <https://doi.org/10.1017/s1074070800003400>
- Watkins, M. W. (2020). *A step-by-step guide to exploratory factor analysis with R and RStudio*. Routledge.
- Widaman, K. F. (2018). On common factor and principal component representations of data: Implications for theory and for confirmatory replications. *Structural Equation Modeling: A Multidisciplinary Journal*, 25(6), 829–847.
- Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big Data in Smart Farming – A review. *Agricultural Systems*, 153, 69–80. <https://doi.org/10.1016/j.agsy.2017.01.023>
- World Bank. (2016). The World Bank: Agricultural Land (% of Land Area). *World Bank*. <https://data.worldbank.org/indicator/AG.LND.AGRI.ZS>

- Yoon, C., Lim, D., & Park, C. (2020). Factors affecting adoption of smart farms: The case of Korea. *Computers in Human Behavior*, 108. <https://doi.org/10.1016/j.chb.2020.106309>
- Zambon, I., Cecchini, M., Egidi, G., Saporito, M. G., & Colantoni, A. (2019). Revolution 4.0: Industry vs. agriculture in a future development for SMEs. *Processes*, 7(1). <https://doi.org/10.3390/pr7010036>
- Zhai, Z., Martínez, J. F., Beltran, V., & Martínez, N. L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Computers and Electronics in Agriculture*, 170. <https://doi.org/10.1016/j.compag.2020.105256>

Appendix

Appendix-1

Criteria for Quality Evaluation

Criteria	Evaluation Parameter	Answer Options (Score)	Description
QE-1	Nature of the analysis used in the study	▪ Qualitative (+2), ▪ Quantitative (+1.5), ▪ Mixed (+3.5)	Classification based on research method utilized in the study
QE-2	Explanation of advantages and limitations	▪ Yes (+2), ▪ No (0), ▪ Partially (+1)	Classification based on advantages and limitations mentioned in the study. Partial score when either advantage or limitation is explained in the study.
QE-3	Justifiable output of the study	▪ Yes (+2), ▪ No (0), ▪ Partially (+1)	Classification based justifiable output from the study. Partial score if technique is explained in a limited manner.
QE-4	Rating based on the publication avenues.	▪ Sum(Number of Citations, H-index) > 100 (+2), ▪ Sum(Number of Citations, H-index) ranges from 50 to 99 (+1.5), ▪ Sum(Number of Citations, H-index) ranges from 1 to 49 (+1.0), ▪ Sum(Number of Citations, H-index) = 0 or data not available (0)	Classification based on sum of number of citations of respective article and H-index of journal

Appendix 2

Items generation for constructs adapted from literature

A. Items generation for farmers

Construct and Source	Adapted Scale Items
Performance Expectancy (Giua, Cristiana, et al., 2022; Venkatesh et al., 2003)	PEX1: I would find the use of intelligent solutions useful in my daily farm work. PEX2: I think the use of intelligent solutions increases productivity at farm. PEX3: Using the intelligent solutions enables me to accomplish tasks more quickly. PEX4: Using the intelligent solutions will increase my chances of higher gains.
Effort Expectancy (Giua, Cristiana, et al., 2022; Venkatesh et al., 2003)	EEX1: My interaction with intelligent solutions would be clear and understandable. EEX2: It would be easy for me to become skillful at using the intelligent solution. EEX3: I would find the intelligent solutions easy to use. EEX4: Learning to operate the intelligent solutions will be easy for me.
Risk Aversion (W. Li et al., 2020)	RAV1: Intelligent solutions may increase the costs of farming. RAV2: Intelligent solutions may not improve efficiency at farms. RAV3: Intelligent solutions may not increase my income. RAV4: Intelligent solutions may have technical risks.
Social influence (W. Li et al., 2020; Liang et al., 2021),	SIN1: Local communities encourage me to use intelligent solutions in farms. SIN2: Government encourages me to use intelligent solutions in farms. SIN3: Co-operatives encourage me to use intelligent solutions in farms. SIN4: Intelligent solutions will help me to get a high positive profile amongst other farmers.
Facilitating Conditions (Giua, Cristiana, et al., 2022; Vaithilingam et al., 2022; Venkatesh et al., 2003)	FAC1: I have the basic knowledge necessary to use intelligent solution. FAC2: I have the resources necessary to use the intelligent solution. FAC3: If I am in difficulty with the use of intelligent solution, there are people who would provide me with assistance or support. FAC4: I have access to the financial assistance I need to use intelligent solution
Information Availability (Balogh et al., 2021)	INF1: I am informed about most things related to the development of my own field. INF2: I obtain most of the information on farm developments in a timely manner. INF3: I obtain the most information on local community events in a timely manner.
Financial Conditions (Skevas & Kalaitzandonakes, 2020).	FIN1: For using intelligent solutions in farm, I am concerned with its initial purchase cost. FIN2: I have sufficient funds to invest in intelligent solutions for better results. FIN3: I can easily deploy and start using intelligent solutions if I get financial assistance.
Formal and informal links (Aubert et al., 2012).	LNK1: I believe that association as member with co-operative / extension / university / other organization helps me to gain latest information and support in farming. LNK2: I attend and participate in agricultural programmes / events to enhance my professional knowledge. LNK3: I prefer to get agriculture information from my friends, relatives and family members.
Farming Business Focus (B. Li et al., 2021; Vecchio et al., 2020)	FBF1: The ownership of farm I work in is: sole owner / Joint ownership / On Lease from Government/ On Lease from private owner FBF2: I work for farming business as: full-time / part-time/ seasonal farming/outsourced.
Compatibility (Aubert et al., 2012; Yoon et al., 2020)	CMP1: Using intelligent solutions is compatible with most aspects of my farm work. CMP2: Using intelligent solutions fits my work style. CMP3: Using intelligent solutions fits well with existing set-up at my farm.

	CMP4: Using intelligent solutions is compatible with my culture and value system.
Security and Privacy (Liang <i>et al.</i> , 2021; Skevas & Kalaitzandonakes, 2020; Yoon <i>et al.</i> , 2020)	SPY1: When I think about using intelligent solutions in farm, I am concerned with privacy related issues of neighbouring farmers. SPY2: I am concerned about sharing information of my field with others. SPY3: I am concerned about security issues while using intelligent solutions.
Intention to adopt (Venkatesh <i>et al.</i> , 2003)	ITA1: I intend to use intelligent solutions in future. ITA2: I predict to use intelligent solutions in future. ITA3: I plan to use intelligent solutions in future.

B. Items generation for facilitators

Construct and Source	Adapted Scale Items
Performance Expectancy (Giua, Cristiana, <i>et al.</i> , 2022; Venkatesh <i>et al.</i> , 2003)	PEX1: I think intelligent solutions are useful in daily farm work. PEX2: I think the use of intelligent solutions increases productivity at farms. PEX3: I think the use of intelligent solutions enables to accomplish tasks more quickly. PEX4: I think using the intelligent solutions will increase chances of higher gains.
Effort Expectancy (Giua, Cristiana, <i>et al.</i> , 2022; Venkatesh <i>et al.</i> , 2003)	EEX1: I think interaction of farmers with intelligent solutions would be clear and understandable. EEX2: It would be easy for farmers to become skilful at using the intelligent solution. EEX3: I think farmers would find the intelligent solutions easy to use. EEX4: I think learning to operate the intelligent solutions is easy for farmers.
Risk Aversion (W. Li <i>et al.</i> , 2020)	RAV1: I think intelligent solutions may increase the costs of farming. RAV2: I think intelligent solutions may not improve efficiency at farms. RAV3: I think intelligent solutions may not increase income for farmers. RAV4: I think intelligent solutions may have technical risks.
Social influence (W. Li <i>et al.</i> , 2020; Liang <i>et al.</i> , 2021),	SIN1: Local communities encourage us to deploy intelligent solutions in farms. SIN2: Government encourages us to deploy intelligent solutions in farms. SIN3: Co-operatives encourage us to deploy intelligent solutions in farms. SIN4: Intelligent solutions will help us to get a high positive profile amongst peer organizations.
Facilitating Conditions (Giua, Cristiana, <i>et al.</i> , 2022; Vaithilingam <i>et al.</i> , 2022; Venkatesh <i>et al.</i> , 2003)	FAC1: I have the basic knowledge necessary to deploy and provide support for intelligent solutions. FAC2: I have the resources necessary to deploy, use and provide support for intelligent solutions. FAC3: If I am in difficulty with the installation or service of intelligent solution, there are people who would provide me with assistance or support. FAC4: I have access to the financial assistance I need to deploy and provide support for intelligent solution.
Information Availability (Balogh <i>et al.</i> , 2021)	INF1: I am informed about most things related to the development of my own field. INF2: I obtain most of the information on farm developments in a timely manner. INF3: I obtain feedback from users of intelligent solutions in a timely manner.
Financial Conditions (Skevas & Kalaitzandonakes, 2020).	FIN1: For deploying intelligent solutions in farm, I am concerned with the initial investment. FIN2: I have sufficient funds to invest in intelligent solutions for better results. FIN3: I can easily deploy and provide support for intelligent solutions if I get financial assistance.
Formal and informal links (Aubert <i>et al.</i> , 2012).	LNK1: I believe that association as member with research institute /university / other organization helps me to gain latest information and support in farming.

	LNK2: I attend and participate in agricultural programmes / events to enhance my professional knowledge.
	LNK3: I prefer to get agriculture information from my friends, relatives and family members.
Farming Business Focus (B. Li <i>et al.</i> , 2021; Vecchio <i>et al.</i> , 2020)	FBF1: I believe intelligent solutions are preferred by: individual farmers/Co-operatives/Large agricultural companies using own land for crop production/ Large agricultural companies using leased land for crop production FBF2: I believe intelligent solutions are preferred by: full-time farmers / part-time farmers/ agricultural companies for short term production/ agricultural companies for long term production.
Compatibility (Aubert <i>et al.</i> , 2012; Yoon <i>et al.</i> , 2020)	CMP1: Using intelligent solutions is compatible with most aspects of farm work. CMP2: Using intelligent solutions easily fits farmer's work style. CMP3: Using intelligent solutions fits well with existing set-up at farm. CMP4: Intelligent solutions are compatible with my culture and value system.
Security and Privacy (Liang <i>et al.</i> , 2021; Skevas & Kalaitzandonakes, 2020; Yoon <i>et al.</i> , 2020)	SPY1: While using intelligent solutions, farmers have concerns related to privacy of neighbouring farmers. SPY2: Farmers are concerned about sharing information of their field with other farmers. SPY3: Farmers are concerned for security issues while using intelligent solutions.
Intention to adopt (Venkatesh <i>et al.</i> , 2003)	ITA1: I / our organization intend(s) to deploy and provide support for intelligent solutions in future. ITA2: I / our organization predict(s) to deploy and provide support for intelligent solutions in future. ITA3: I / our organization plan(s) to deploy and provide support for intelligent solutions in future.

Appendix 3
List of Publications

Paper-1:	
Title:	Artificial Intelligence Research in Agriculture: A Review
Authors:	Amit Sood, Dr. Amit Kumar Bhardwaj Dr. R. K. Sharma
Journal:	Online Information Review (Emerald Publishers) (ABDC Category B)
Date of Publication:	29 December 2021

Paper-2:	
Title:	Towards sustainable agriculture: key determinants of adopting artificial intelligence in agriculture
Authors:	Amit Sood, Dr. Amit Kumar Bhardwaj Dr. R. K. Sharma
Journal:	Journal of Decision Systems (Taylor & Francis) (ABDC Category B)
Date of Publication:	14 December 2022

Paper-3:	
Title:	Empirical Analysis and Evaluation of Factors Influencing Adoption of AI-based Automation Solutions for Sustainable Agriculture
Authors:	Amit Sood, Dr. Amit Kumar Bhardwaj Dr. R. K. Sharma
Conference:	International Conference on Agriculture Centric Computing (ICA-23)
Date of Acceptance:	15 April 2023

Paper-4:	
Title:	Perceptions of facilitators towards adoption of AI-based solutions for Sustainable Agriculture
Authors:	Amit Sood, Dr. Amit Kumar Bhardwaj Dr. R. K. Sharma
Journal:	Journal of Decision Systems (Taylor & Francis) (ABDC Category B)
Date of Publication:	Communicated (Revised manuscript script submitted on 1 st April 2023)
