

**PADDY FARMERS' INTENTION TO FULLY
ADOPT SMART FARMING TECHNOLOGIES:
EXAMINING THE ROLE OF OVERALL
PERCEIVED VALUE AND TECHNOLOGY
READINESS**

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by

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TABLE OF CONTENTS

ACKNOWLEDGEMENT	ii
TABLE OF CONTENTS.....	iii
LIST OF TABLES	x
LIST OF FIGURES	xii
LIST OF ABBREVIATIONS	xiii
LIST OF APPENDICES	xiv
ABSTRAK	xv
ABSTRACT	xvii
CHAPTER 1 INTRODUCTION.....	1
1.1 Chapter Introduction	1
1.2 The Emergence of Smart Farming Technologies (SFTs).....	1
1.3 Malaysia Context and the Potential of SFTs	5
1.4 The Paddy Industry in Malaysia and The Urgency of SFTs	8
1.5 Problem Statement	12
1.6 Research Objectives	18
1.7 Research Questions	18
1.8 Significance of the Study	19
1.8.1 Theoretical Significance.....	19
1.8.2 Practical Significance	21
1.9 Definition of Key Terms	24
1.10 Chapter Summary.....	26
CHAPTER 2 LITERATURE REVIEW.....	28
2.1 Chapter Introduction	28
2.2 The Paradigm of Smart Farming Technologies (SFTs)	28
2.3 Past Work on the Adoption of Smart Farming Technologies (SFTs)	40

2.3.1	Theory Utilization in SFTs Adoption Research.....	41
2.3.1(a)	An Overview of Dominant Theories in SFTs Adoption	42
2.3.1(b)	The Rationale for a Value-Centric Approach in SFTs Adoption.....	43
2.3.1(c)	The Value-Based Adoption Model (VAM): A Foundational Framework.....	45
2.3.1(d)	The Theory of Consumption Values (TCV): Decomposing the Value Construct	48
2.3.1(e)	The VAM-TCV Integration: A Synthesized Framework for SFTs Adoption.....	51
2.3.2	Drivers Enhancing the Overall Perceived Value of SFTs.....	53
2.3.2(a)	A Synthesis of Global SFTs Adoption Drivers	53
2.3.2(b)	Key Drivers in the Malaysian Context	57
2.3.2(c)	Justification for Selecting PE, FC, and FIP as Focal Drivers	60
2.3.3	Barriers Detracting from the Overall Perceived Value of SFTs	62
2.3.3(a)	A Synthesis of Global SFTs Adoption Barriers	62
2.3.3(b)	Key Barriers in the Malaysian Context	65
2.3.3(c)	Justification for Selecting PCO, PCX, and PUN as Focal Barriers.....	68
2.3.4	Farmer Predispositions: Technology Readiness as a Key Moderator	70
2.3.4(a)	The Under-Explored Role of Moderation in SFTs Adoption Research.....	70
2.3.4(b)	Technology Readiness (TR) as a Holistic Psychological Construct	71
2.3.4(c)	Justifying Technology Readiness as a Potential Moderator in the Malaysian SFTs Context.....	73
2.3.5	Analytical Approaches: A Rationale for a Hybrid PLS-SEM and ANN	75
2.3.5(a)	The Prevailing Analytical Landscape in SFTs Adoption Research.....	75

2.3.5(b)	The Need for Complementary Methods	76
2.3.5(c)	The Hybrid PLS-SEM and ANN Approach: An Integrated Solution.....	78
2.4	Field Insights on SFTs Adoption in the Malaysian Paddy Industry	80
2.4.1	High Cost and Limited Economic Returns	81
2.4.2	Older Farmer Demographics and Risk Aversion	83
2.4.3	Small, Fragmented Landholdings and Part-Time Farming.....	84
2.4.4	Technological Mismatch and Infrastructure Gaps	85
2.4.5	Low Digital Literacy and Limited Training.....	86
2.4.6	Policy and Institutional Barriers.....	87
2.4.7	Service Provider and Operational Constraints	89
2.4.8	Concluding Synthesis.....	90
2.5	Recapitulation of Research Gaps	91
2.6	Hypotheses' Development and Research Framework.....	96
2.6.1	Perceived Efficiency (PE) and OPV	97
2.6.2	Facilitating Conditions (FC) and OPV.....	98
2.6.3	Financial Incentive Policy (FIP) and OPV.....	99
2.6.4	Perceived Cost (PCO) and OPV.....	100
2.6.5	Perceived Complexity (PCX) and OPV	101
2.6.6	Perceived uncertainty (PUN) and OPV.....	102
2.6.7	OPV and Farmers' Adoption Intention of SFTs (INT).....	104
2.6.8	The Mediating Role of OPV	106
2.6.9	The Moderating Role of Technology Readiness (TR).....	108
2.6.10	Control Variables	112
2.6.11	Research Framework and Hypotheses Summary.....	113
2.7	Chapter Summary.....	114
CHAPTER 3 METHODOLOGY.....		116
3.1	Chapter Introduction	116

3.2	Research Philosophy	116
3.3	Research Design	118
3.4	Target Population and Sampling Considerations	120
3.4.1	Target Population: Malaysian Paddy Farmers	120
3.4.2	Sampling Selection: Focusing on Key Rice-Producing States.....	121
3.4.3	Sampling Design	123
3.4.4	Sample Size	125
3.5	Survey Instruments & Operationalization of Research Constructs.....	126
3.5.1	Perceived Efficiency (PE)	127
3.5.2	Facilitating Conditions (FC)	127
3.5.3	Financial Incentive Policy (FIP)	128
3.5.4	Perceived Cost (PCO)	129
3.5.5	Perceived Complexity (PCX).....	130
3.5.6	Perceived Uncertainty (PUN).....	131
3.5.7	Overall Perceived Value (OPV).....	132
3.5.8	Adoption Intention of SFTs (INT)	135
3.5.9	Technology Readiness (TR).....	136
3.5.10	Control Variables	139
3.6	Pre-testing.....	141
3.7	Questionnaire Translation into the Malay Language	144
3.8	Questionnaire Structure	144
3.9	Data Collection Procedures	147
3.10	Data Analysis	150
3.10.1	Straight-lining Responses.....	150
3.10.2	Missing Values Treatment	150
3.10.3	Detection of Outliers	151
3.10.4	Examining The Assumptions of Multivariate Analysis	152

3.10.4(a)	Normality	152
3.10.4(b)	Homoscedasticity	153
3.10.4(c)	Linearity	153
3.10.4(d)	Autocorrelation or Absence of correlated error	153
3.10.5	Common Method Variance (CMV)	154
3.10.6	The Statistical Assessment of The Research Model	157
3.10.6(a)	The PLS-SEM Approach	157
3.10.6(b)	Artificial Neural Networks (ANN) Approach	165
3.11	Ethical Considerations	168
3.12	Chapter Summary	168
CHAPTER 4	DATA ANALYSIS AND RESULTS	169
4.1	Chapter Introduction	169
4.2	Initial Overall Data Response Rate	169
4.3	Data Screening & Cleaning	170
4.3.1	Inclusion & Exclusion Criteria Check	170
4.3.2	Data Entry Errors	170
4.3.3	Straight-line Answers	171
4.3.4	Missing Values Treatment	171
4.3.4(a)	Step 1: Assessment of the Extent and Pattern of Missing Data	171
4.3.4(b)	Step 2: Diagnosis of the Missing Data Mechanism	172
4.3.4(c)	Step 3: Imputation using Maximum Likelihood Estimation (MLE)	172
4.3.4(d)	Step 4: Post-Imputation Verification	172
4.3.5	Outlier Detection	173
4.4	Final Overall Response Rate	173
4.5	Assessment of Multivariate Analysis Assumptions	174
4.5.1	Normality	174

4.5.2	Homoscedasticity	175
4.5.3	Linearity	175
4.5.4	Autocorrelation or Absence of Correlated Error.....	176
4.6	Common Method Variance (CMV)	176
4.7	Non-response Bias.....	178
4.8	Descriptive Analysis of The Respondents' Profile	179
4.8.1	Demographic Characteristics of Respondents.....	179
4.8.2	Awareness and Usage of SFTs.....	182
4.8.3	Preferred Sources of SFTs Information	183
4.9	Statistical Analysis of The Research Model	186
4.9.1	PLS-SEM Analysis	186
4.9.1(a)	The Assessment of the Measurement Model.....	187
4.9.1(b)	The Assessment of The Structural Model	194
4.9.1(c)	The Assessment of The Mediating Role of OPV	201
4.9.1(d)	The Assessment of The Moderating Role of Technology Readiness	202
4.9.2	Artificial Neural Network (ANN) Assessment	205
4.10	Chapter Summary.....	210
CHAPTER 5 CONCLUSION AND FUTURE RECOMMENDATIONS....		211
5.1	Chapter Introduction	211
5.2	The Study Recapitulation	211
5.3	Discussion of The Findings of Direct Relationships.....	214
5.3.1	H1: The Relationship between PE and OPV.....	215
5.3.2	H2: The Relationship between FC and OPV	216
5.3.3	H3: The Relationship between FIP and OPV.....	218
5.3.4	H4: The Relationship between PCO and OPV.....	220
5.3.5	H5: The Relationship between PCX and OPV.....	222
5.3.6	H6: The Relationship between PUN and OPV	225

5.3.7	H7: The Relationship between OPV and Adoption Intention of SFTs	227
5.4	Discussion of The Findings on Indirect Relationship	230
5.4.1	Discussion of the Mediating Impact of OPV (H8).....	230
5.4.2	Discussion of the Moderating Effect of Technology Readiness (H9)	234
5.5	Implications of the Study	237
5.5.1	Theoretical Implications.....	237
5.5.2	Practical Implications	242
5.5.2(a)	Enhancing the Drivers of Perceived Value (PE, FC, and FIP)	243
5.5.2(b)	Mitigating the Barriers to Perceived Value (PCO, PCX, and PUN)	244
5.5.2(c)	Leveraging the Centrality of Overall Perceived Value (OPV)	246
5.5.2(d)	Tailoring Interventions based on Technology Readiness (TR)	247
5.6	Limitations and Future Directions.....	249
5.7	Chapter Summary.....	252
	REFERENCES.....	254
	APPENDICES	
	LIST OF PUBLICATIONS	

LIST OF TABLES

	Page
Table 2.1 Recent and relevant research on SFTs adoption.	31
Table 2.2 Summary of Hypotheses.	114
Table 3.1 Overview of the Malaysian Paddy industry in 2021.....	122
Table 3.2 Inclusion & exclusion criteria of the targeted respondents.	124
Table 3.3 The measurement of Perceived Efficiency (PE).	127
Table 3.4 The measurement of Facilitating Conditions (FC).....	128
Table 3.5 The measurement of Financial Incentive Policy (FIP).	129
Table 3.6 The measurement of Perceived Cost (COS).	130
Table 3.7 The measurement of Perceived Complexity (PCX).....	131
Table 3.8 The measurement of Perceived Uncertainty (PUN).....	132
Table 3.9 The measurement of Functional Value (FV).	133
Table 3.10 The measurement of Monetary Value (MV).....	134
Table 3.11 The measurement of Conditional Value (CV).	135
Table 3.12 The measurement of adoption intention of SFTs (INT).....	136
Table 3.13 The measurement of Motivators (MOTV).....	137
Table 3.14 The measurement of Inhibitors (INHB).....	138
Table 3.15 Dummy Coding Scheme for Control Variables.	141
Table 3.16 The structure of the questionnaire.....	145
Table 3.17 The items of Attitude Toward the Colour Blue.	156
Table 3.18 The assessment of the reflective measurement model.	160
Table 3.19 The assessment of the formative measurement model.....	161
Table 3.20 The assessment of the structural model.	162
Table 4.1 The final overall response rate.	173

Table 4.2	The results of the Full Collinearity Test (FCT).	177
Table 4.3	The results of the MLMV approach.	177
Table 4.4	Test of Homogeneity of Variances Based on Mean.	178
Table 4.5	Demographic information of the respondents.	180
Table 4.6	Reflective measurement model assessment - 1st stage.	188
Table 4.7	The HTMT ratio matrix – 1st Stage.	190
Table 4.8	Reflective measurement model assessment - 2nd stage.	192
Table 4.9	The HTMT ratio matrix – 2nd Stage.	193
Table 4.10	The formative measurement model assessment for OPV.	194
Table 4.11	The results of the structural model assessment.	199
Table 4.12	Out-of-sample predictive performance.	201
Table 4.13	RMSE values for A & B ANN models.	207
Table 4.14	Sensitivity analysis for Models A & B.	208
Table 4.15	Comparison of the findings from PLS-SEM and ANN.	209

LIST OF FIGURES

	Page
Figure 1.1 Brief Overview of the NAP 2.0.	7
Figure 1.2 Key actors in the Malaysian upstream paddy production chain.	9
Figure 2.1 The Value-based adoption model (Kim et al., 2007).	46
Figure 2.2 Antecedents of SFTs adoption, adopted from Osrof et al. (2023).	54
Figure 2.3 Conceptual Research Framework.	113
Figure 3.1 Minimum sample size using the G*power software.	125
Figure 3.2 An illustration of the mediation model.	163
Figure 3.3 An illustration of the two-stage approach.	164
Figure 4.1 Normality test results.	174
Figure 4.2 Homoscedasticity assessment with Loess Fit Line.	175
Figure 4.3 The results of the Auto-correlation test.	176
Figure 4.4 Preferred sources of information on SFTs among paddy farmers. ..	184
Figure 4.5 The research model - the first stage of the disjoint approach.	187
Figure 4.6 PLS Algorithm - the second stage of the disjoint approach.	191
Figure 4.7 Redundancy analysis.	193
Figure 4.8 Bootstrapping of the model without the moderator.	198
Figure 4.9 The results of bootstrapping the model with the moderator.	202
Figure 4.10 The moderating effect of MOTV on OPV→INT.	204
Figure 4.11 The moderating effect of INHB on OPV→INT.	204
Figure 4.12 ANN Model A.	206
Figure 4.13 ANN Model B.	206

LIST OF ABBREVIATIONS

SFTs	Smart Farming Technologies
INT	Adoption Intention of SFTs
OPV	Overall Perceived Value
TR	Technology Readiness
MOTV	Motivators
INHB	Inhibitors
PE	Perceived Efficiency
FC	Facilitating Conditions
FIP	Financial Incentive Policy
PCO	Perceived Cost
PCX	Perceived Complexity
PUN	Perceived Uncertainty
VAM	Value-based Adoption Model
TCV	Theory of Consumption Values
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
DOI	Diffusion of Innovations
TPB	Theory of Planned Behavior
SOC	Second-Order Construct
FOC	First-Order Construct
MAFS	Ministry of Agriculture and Food Security
IADA	Integrated Agriculture Development Area
MADA	Muda Agricultural Development Authority
KADA	Kemubu Agricultural Development Authority
MARDI	Malaysian Agricultural Research and Development Institute
DOA	Department of Agriculture
PPK	Pertubuhan Peladang Kawasan
FAO	Food and Agriculture Organization

LIST OF APPENDICES

Appendix A	The Survey – English Version
Appendix B	The Survey – Malay Version
Appendix C	Missing Values, Patterns, and Treatment
Appendix D	Outliers' Removed Cases
Appendix E	Linearity Assessment
Appendix F	Control Variables Analysis
Appendix G	Some Pictures of Field Visits & Data Collection

**NIAT PESAWAH PADI UNTUK MENGGUNAKAN TEKNOLOGI
PERTANIAN PINTAR SEPENUHNYA: MENGAJAI PERANAN NILAI
KESELURUHAN DAN KESIAPSIAGAAN TEKNOLOGI**

ABSTRAK

Teknologi Pertanian Pintar mempunyai potensi besar untuk meningkatkan produktiviti, mengoptimumkan sumber, dan mempromosikan kelestarian dalam sektor pertanian. Pertanian moden menghadapi pelbagai cabaran yang kompleks dan saling berkait, yang lazimnya tidak dapat ditangani sepenuhnya oleh satu teknologi tunggal. Cabaran ini merangkumi aspek seperti kesihatan tanah, pengurusan air, kawalan perosak, serta pengoptimuman hasil. Namun begitu, kadar penggunaan Teknologi Pertanian Pintar masih rendah di negara membangun seperti Malaysia. Meskipun pelbagai inisiatif telah diperkenalkan oleh pihak kerajaan, kebanyakan petani masih bergantung kepada amalan pertanian tradisional. Ini menunjukkan wujudnya jurang antara dasar dan amalan, yang memerlukan kajian berasaskan bukti bagi mengenalpasti dan menangani faktor-faktor asas yang mempengaruhi penggunaan Teknologi Pertanian Pintar. Kajian terkini menekankan peranan persepsi nilai dalam kalangan pesawah padi terhadap penggunaan Teknologi Pertanian Pintar, memandangkan aspek ini masih kurang diterokai, khususnya berkaitan dengan kerumitan nilai dan faktor-faktor yang mempengaruhinya. Tambahan pula, literatur menyediakan pandangan yang terhad dan tidak konsisten mengenai peranan Kesiapsiagaan Teknologi, di mana pesawah padi sering digambarkan sebagai tidak bersedia untuk menghadapi perubahan teknologi. Oleh itu, kajian ini menggunakan pendekatan berfokuskan nilai dengan mengintegrasikan Model Penerimaan Berasaskan Nilai dan Teori Nilai Penggunaan untuk meneroka pemuat dan halangan

yang mempengaruhi nilai keseluruhan yang dirasakan serta niat penggunaan Teknologi Pertanian Pintar, dengan Kesiapsiagaan Teknologi sebagai pemboleh ubah penyederhana. Data tinjauan daripada 351 pesawah padi dianalisis dengan menggunakan gabungan PLS-SEM dan ANN, iaitu satu pendekatan baharu dalam penyelidikan penggunaan Teknologi Pertanian Pintar. Penemuan utama menunjukkan bahawa Kecekapan yang Dirasakan, Keadaan Pemudahcaraan, dan Polisi Insentif Kewangan secara signifikan meningkatkan Nilai Keseluruhan yang Dirasakan, sekali gus menekankan keperluan untuk mewujudkan ekosistem dan dasar yang menyokong. Menariknya, Kos yang Dirasakan memberi kesan positif kepada Nilai Keseluruhan yang Dirasakan, manakala Kerumitan dan Ketidakpastian yang Dirasakan tidak menunjukkan sebarang kesan. Hasil ini mencabar andaian tradisional dan memberikan pandangan baharu mengenai peranan penyumberan luar Teknologi Pertanian Pintar dan dinamika kos-nilai dalam sektor pertanian. Tambahan pula, Nilai Keseluruhan yang Dirasakan muncul sebagai peramal paling berpengaruh, dengan nilai bersyarat menjadi keutamaan pesawah padi diikuti oleh nilai fungsional dan nilai kewangan. Analisis penyederhanaan menunjukkan bahawa tahap Motivator yang tinggi (iaitu optimisme dan inovasi) melemahkan kebergantungan petani terhadap Nilai Keseluruhan yang Dirasakan, manakala tahap Penghalang yang tinggi (iaitu Ketidakselesaian dan Ketidakselamatan) menguatkannya. Ini mencadangkan bahawa pesawah padi yang lebih enggan cenderung bergantung kepada Nilai Keseluruhan yang Dirasakan untuk mengurangkan kebimbangan mereka. Analisis ANN menyokong dapatan PLS-SEM, walaupun dengan sedikit perbezaan dari segi kedudukan. Kajian ini memajukan pemahaman tentang penggunaan Teknologi Pertanian Pintar dengan menekankan peranan kritikal Nilai Keseluruhan yang Dirasakan dan Kesiapsiagaan Teknologi, di samping menawarkan pandangan strategik untuk merapatkan jurang antara dasar dan amalan dalam sektor pertanian.

**PADDY FARMERS' INTENTION TO FULLY ADOPT SMART FARMING
TECHNOLOGIES: EXAMINING THE ROLE OF OVERALL PERCEIVED
VALUE AND TECHNOLOGY READINESS**

ABSTRACT

Smart Farming Technologies (SFTs) hold significant potential for enhancing productivity, optimizing resource utilization, and promoting sustainability in agriculture. Modern farming faces a complex array of interconnected challenges, from soil health and water management to pest control and yield optimization, that a single technology cannot adequately address. However, adoption rates remain low in developing countries like Malaysia, where many farmers still rely on traditional practices despite government initiatives. This highlights a gap between policy and practice, necessitating evidence-based research to address the underlying factors influencing SFTs adoption. While recent studies emphasize the role of farmers' value perceptions in SFTs adoption, this notion remains underexplored, especially concerning the value complexity and the factors that shape it. Additionally, the literature provides limited and inconsistent insights into the role of Technology Readiness (TR), where farmers are often portrayed as resistant to technological change. Therefore, this study adopted a value-centric approach, integrating the Value-Based Adoption Model (VAM) and the Theory of Consumption Values (TCV), to explore the drivers and barriers influencing farmers' Overall Perceived Value (OPV) and adoption intentions, with TR as a moderating factor. Survey data from 351 paddy farmers were analyzed using a hybrid PLS-SEM and ANN, a novel approach in SFTs adoption research. Key findings revealed that Perceived Efficiency, Facilitating Conditions, and Financial Incentive Policy significantly enhance OPV, emphasizing

the need for supportive ecosystems and policies. Surprisingly, Perceived Cost positively affects OPV while Perceived Complexity and Uncertainty showed no impact. This outcome challenges traditional assumptions and provides fresh insights into the role of outsourcing SFTs and the cost-value dynamic in agriculture. Moreover, OPV emerged as the most influential predictor, with conditional value as the top priority for farmers, followed by functional and monetary values. The moderating analysis showed that high Motivators (optimism and innovativeness) weaken farmers' dependence on OPV, while high Inhibitors (discomfort and insecurity) strengthen it, suggesting that reluctant farmers rely more on OPV to mitigate their concerns. The ANN analysis supported the PLS-SEM results with a slightly different ranking. This study advances the understanding of SFTs adoption by highlighting the critical roles of OPV and TR, offering strategic insights to bridge the gap between policy and practice in the agriculture sector.

CHAPTER 1

INTRODUCTION

1.1 Chapter Introduction

This chapter provides an overview of the research context and its foundation. It begins by introducing the emergence of Smart Farming Technologies (SFTs) and their transformative potential in modern agriculture. Next, it contextualizes SFTs within Malaysia, highlighting their specific opportunities and challenges. The discussion then narrows to the paddy industry in Malaysia, emphasizing the critical need for adopting SFTs to address pressing challenges. The chapter further establishes the research focus by presenting the problem statement, which identifies the core issues driving this study. It then details the research objectives and questions that shape the investigation. The chapter also outlines the study's theoretical and practical significance, underlining its contribution to knowledge and real-world applications. Lastly, it provides definitions of key terms for conceptual clarity and concludes with a summary, setting the stage for subsequent chapters.

1.2 The Emergence of Smart Farming Technologies (SFTs)

Agriculture is undergoing a profound and rapid transformation, driven by the widespread integration of advanced digital and data-centric technologies (Alam et al., 2023; Büyüközkan & Uztürk, 2024; Klerkx et al., 2019). This technological shift, often described using terms like “Precision Agriculture,” “Digital Agriculture,” “Smart Farming,” or “Agriculture 4.0”, signifies more than a linear upgrade of existing methods (Abbasi et al., 2022; da Silveira et al., 2021; Maffezzoli et al., 2022). Instead, it constitutes a complex socio-technical disruption that redefines farm labor, farmer identity, and decision-making processes (Daniel et al., 2025; Martin et al., 2022).

Acknowledging this complexity is critical, as much of the literature on SFTs adoption has been critiqued for oversimplifying adoption processes and adopting a technology-deterministic lens (Daniel et al., 2025; Giua et al., 2022). These innovations represent a paradigm shift toward more data-driven, precise, automated, and interconnected agricultural systems (Javaid et al., 2022; Prakash et al., 2023).

The fundamental importance of SFTs in modern agriculture lies in their potential to address some of the most pressing global challenges. This includes increasing food production sustainably to meet growing demand, conserving scarce natural resources (e.g., water, land, inputs), mitigating and adapting to climate change, improving farm profitability, and enhancing the resilience and sustainability of food systems (Azlan et al., 2024b; Balyan et al., 2024; Ingram et al., 2022). Traditional agricultural practices are increasingly inadequate to meet these complex and intersecting demands (Shang et al., 2021).

Conceptually, the literature presents several overlapping frameworks for understanding these technologies. Precision Agriculture initially focused on site-specific input management using tools like GPS and sensors (Klerkx et al., 2019). Digital Agriculture broadened this scope to include farm-wide data collection, management, and analytics (Ingram et al., 2022). Today, Smart Farming and Agriculture 4.0 encompass a wider ecosystem of technologies, such as IoT, AI, robotics, big data analytics, cloud computing, and sensor networks, that support intelligent, adaptive, and often automated farming (Abbasi et al., 2022; da Silveira et al., 2021; Javaid et al., 2022; Maffezzoli et al., 2022). The “smartness” of these technologies lies in their capacity for real-time data collection, advanced processing and interpretation for decision-making, precise control, and integration across farm systems (Azlan et al., 2024b; Hashim et al., 2024).

Importantly, the full benefits of SFTs are realized not through isolated tools but via integrated systems. The agricultural production process is inherently complex, with multiple interdependent variables (Klerkx et al., 2019). Optimizing one element, such as irrigation, without addressing others like nutrient management or pest control may yield limited gains. As Maffezzoli et al. (2022) note, the significant impacts of Agriculture 4.0 are achieved through the joint application of multiple technologies. Interconnected smart systems (e.g, sensors feeding data to analytics platforms and then to automation tools) work best as cohesive bundles. A single soil sensor, for example, becomes far more valuable when its data is linked to a mobile app, a decision-support system, and a responsive irrigation device. This systemic, integrative approach underpins this study's definition of SFTs as a bundled suite of complementary technologies and its focus on farmers' intention to adopt them.

SFTs span the entire agricultural value chain, pre-field (e.g., seed and genetic innovation), in-field (e.g., planting, monitoring, harvesting), and post-field (e.g., processing, logistics) (da Silveira et al., 2021). This study focuses specifically on in-field technologies, where individual farmers make most operational decisions and where the immediate impacts of digital technologies are most visible (Azlan et al., 2024b; Osrof et al., 2023). For instance, smart automated machinery, such as GPS-guided precision planters and harvesters with yield-mapping capabilities and variable-rate application systems, can optimize resource use and improve crop monitoring (Abbasi et al., 2022; Martin et al., 2022; Prakash et al., 2023). Similarly, drones equipped with multispectral or thermal sensors that monitor crop health, pest outbreaks, and water stress, and can also perform precision spraying to optimize pesticide and fertilizer use (Baharin et al., 2023; Hashim et al., 2024). Sensors for soil moisture, weather conditions, and laser-guided land leveling enable precise, real-time,

and site-specific data collection, which is crucial for efficient irrigation and field management (Prakash et al., 2023; Santoso et al., 2024). Likewise, mobile applications and Farm Management Information Systems (FMIS) serve as integration hubs that consolidate sensor, drone, and machinery data to support decision-making, recordkeeping, and remote monitoring (Thomas et al., 2023; Tummers et al., 2019).

These technologies are designed to work in synergy: sensors collect field-level data; drones offer aerial diagnostics and perform targeted applications; smart machinery executes data-driven operations; and FMIS platforms synthesize and visualize the data to guide actions. Partial adoption may yield limited value compared to full-system integration. This synergistic functionality underlies the growing view that SFTs should be considered not as isolated tools, but as interdependent components of an integrated digital farming ecosystem (Azlan et al., 2024a).

Despite these advancements and their potential, the global adoption of SFTs remains uneven and low, especially in developing regions (Diana et al., 2024; Gemtou et al., 2024a; Ingram et al., 2022; Tey & Brindal, 2022). Adoption rates in countries like Canada, Australia, and Sweden hover around 35% (Das V et al., 2019), while in the U.S., over 40% of crop farmers were using tools like variable-rate application and yield mapping by 2016 (Hellerstein & Vilorio, 2019). In contrast, Europe reported an adoption rate of only 25% (European Parliament et al., 2016). The gap is even more pronounced in developing economies, where adoption is hindered by high initial costs, limited digital infrastructure and connectivity, low digital literacy, and insufficient institutional support (da Silveira et al., 2023; FAO, 2022; Kroupová et al., 2025; Mana et al., 2024).

Nevertheless, SFTs hold significant promise for smallholder farmers. Studies have shown that engaging farmers in co-designing technologies improves contextual

fit and increases adoption likelihood (Birner et al., 2021; Pawera et al., 2024). By tailoring integrated SFTs solutions to specific socio-economic and agro-ecological contexts, their diffusion can be accelerated, even in resource-constrained settings (Amoussouhoui et al., 2024). There is, therefore, a critical need for further research on the underlying drivers of smallholder adoption of integrated SFTs in developing countries (Azlan et al., 2024a; Diana et al., 2024). A deeper understanding of these drivers is essential to fostering equitable access to smart farming and unlocking the broader development potential of agricultural digitalization.

1.3 Malaysia Context and the Potential of SFTs

The agricultural sector has historically served as a cornerstone of Malaysia's economy. However, its contribution to national GDP has declined considerably, reflecting broader structural challenges (World Bank, 2024). In 2023, agriculture ranked fourth in GDP contribution (7.4%), behind services, manufacturing, and mining (The Ministry of Economy, 2023). Additionally, the Department of Agriculture reported that 119,273 hectares of arable land lay idle in 2018, undermining national self-sufficiency efforts (Dardak et al., 2022). This land underutilization, combined with relatively low yields, places Malaysia behind regional counterparts, such as Indonesia, Thailand, and Vietnam, in agricultural productivity (En & Hui, 2023; World Bank, 2020). Malaysia is also lagging in the development and adoption of Smart Farming Technologies (SFTs), despite their recognized potential, an issue this study aims to examine from a farmer adoption perspective (Wee & Hui, 2023).

Several factors underlie these challenges, including low income linked to poor yields, a weak agribusiness environment, limited youth participation, financial constraints, and the slow adoption of modern technologies (MAFS, 2021; Saili et al.,

2024). In particular, Malaysian smallholder farmers face high input costs and technical difficulties in using advanced agricultural tools (Lazim et al., 2020). These issues are central to understanding adoption barriers. Further compounding the situation are unpredictable weather patterns and natural disasters such as floods and droughts (Dardak et al., 2022). An aging farming population, often resistant to change and hesitant to adopt new technologies, also poses a socio-cultural hurdle (Rahman et al., 2023; Ravindran et al., 2024). Although a variety of SFTs, such as drones, irrigation systems, farm automation, and precision farming tools, are available (Azlan et al., 2024b; Diana et al., 2024), smallholder farmers largely continue to rely on traditional methods (Adnan et al., 2022; Danuri et al., 2019). This technological inertia is often attributed to limited digital literacy, inadequate training, and insufficient support infrastructure, which are key human capital and systemic constraints that shape the broader adoption environment (Baharin et al., 2023; Hamid et al., 2024).

In response to these challenges, the Malaysian government has launched several forward-looking policies to promote smart agriculture. Strategic documents such as the National Fourth Industrial Revolution Policy (4IR) 2021–2030, the 12th Malaysia Plan (2021–2025), the Shared Prosperity Vision 2030, and the National Agro-Food Policy 2021–2030 (NAP 2.0) all emphasize the integration of SFTs. Among them, NAP 2.0 explicitly positions the adoption of advanced technologies as central to transforming the agri-food sector into one that is sustainable, resilient, and high-tech (MAFS, 2021). **Figure 1.1** provides a brief overview of NAP 2.0, illustrating how SFTs are envisioned to enhance productivity, build economic resilience, and strengthen Malaysia’s competitiveness in the global agri-food market (MAFS, 2021). It also highlights the role of SFTs in uplifting smallholder livelihoods, attracting private investment, and safeguarding natural resources.



Figure 1.1 Brief Overview of the NAP 2.0.

Adapted from BERNAMA TV,
<https://x.com/BernamaTV/status/1452874968581107715/photo/2>

In line with these national priorities and the gaps identified in the literature regarding adoption drivers and barriers among smallholder farmers in Malaysia (Wee & Ting, 2023; Ravindran et al., 2024), this study aims to provide an evidence-based analysis of the factors influencing farmers' decisions to adopt SFTs. While other agricultural sectors like palm oil and rubber are undeniably significant contributors to the Malaysian economy, the paddy industry was selected as the sole focus of this study for several critical reasons pertinent to SFTs adoption. First, the paddy sector is predominantly comprised of smallholder farmers, whose adoption decisions are often constrained by unique socio-economic factors, making them a crucial demographic for

understanding the challenges of SFTs uptake (Hashim et al., 2024; Rusli et al., 2023; Saili et al., 2024). This contrasts with palm oil and rubber, which are commercial commodities and often involve larger, more corporate entities with different resource capacities and adoption dynamics.

Next, paddy's role as the nation's primary staple food directly links SFTs adoption in this sector to pressing national food security and self-sufficiency agendas (Hashim et al., 2024; MAFS, 2021). The current production deficit and the identified low SFTs adoption rates within this specific group of farmers highlight an urgent need for further investigation (Ahmad et al., 2024; Zaman et al., 2023). Focusing on paddy thus allows for a detailed exploration of SFTs adoption within a context of high national importance and distinct smallholder characteristics, providing a manageable yet critical scope for this research. By shedding light on the underlying factors, this research could equip policymakers with new insights needed to craft effective strategies that accelerate the adoption of SFTs among smallholder farmers.

1.4 The Paddy Industry in Malaysia and The Urgency of SFTs

In Malaysia, rice (paddy) is the cornerstone of the national diet and a critical component of food security, yet domestic production consistently falls short of meeting national demand (Hashim et al., 2024; Ravindran et al., 2024; Zaman et al., 2023). For the past two decades, Malaysia has relied on imports for approximately 30-40% of its annual rice consumption (Department of Statistics Malaysia, 2022). This dependency was starkly highlighted during the COVID-19 pandemic, which led to supply chain disruptions, food shortages, price surges, and panic-buying (Zaman et al., 2023). The situation was further exacerbated when Thailand, a key rice exporter, temporarily halted exports, compelling Malaysia to source shortfalls from India and

underscoring the urgent need to achieve greater self-sufficiency in rice production (Dorairaj & Govender, 2023). This urgency is reflected in ambitious policy targets under the National Agrofood Policy 2.0 (NAP 2.0), which aims to achieve a rice self-sufficiency level (SSL) of 75% by 2025 and 80% by 2030, positioning technological advancement as a strategic imperative (Harun et al., 2024).

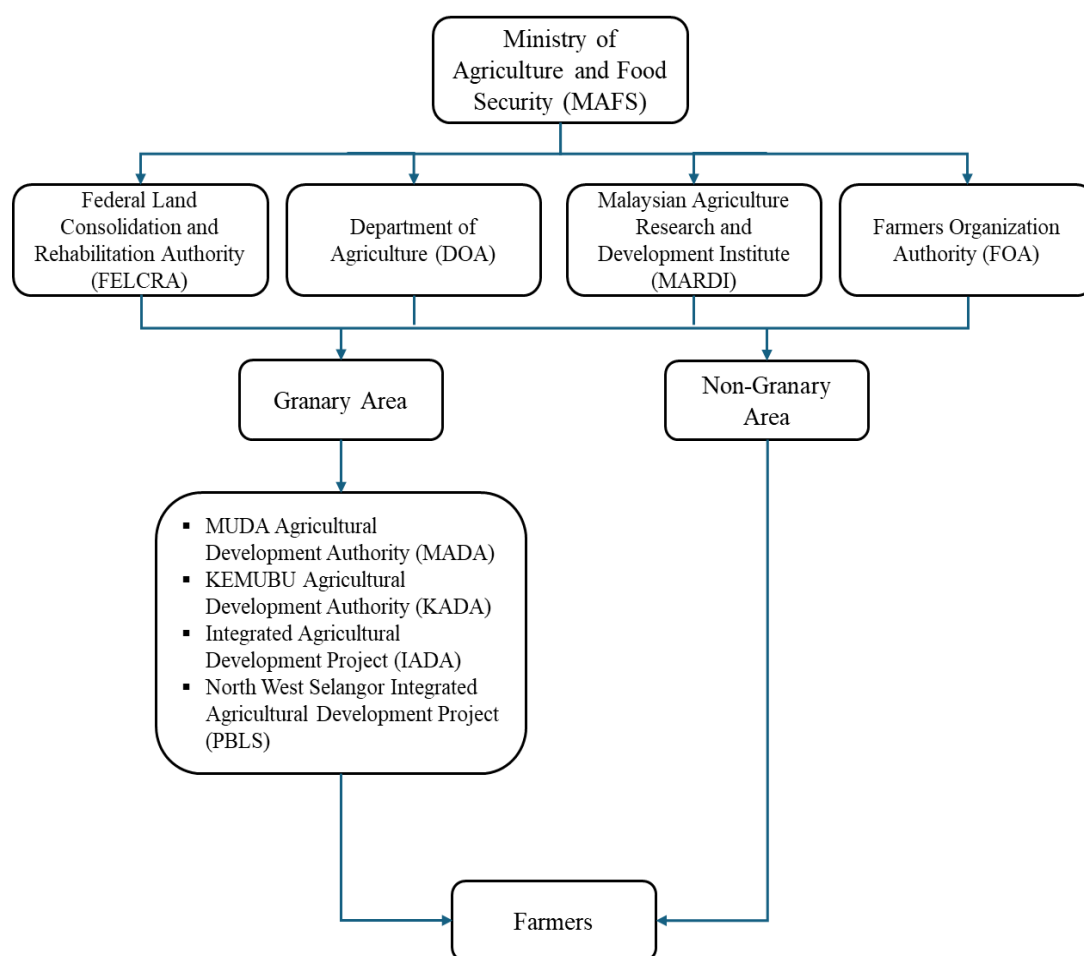


Figure 1.2 Key actors in the Malaysian upstream paddy production chain.
Adapted from Rahmat et al. (2019).

Paddy cultivation is extensive, spanning 647,859 hectares, with Peninsular Malaysia accounting for 81% of this area and over 89% of the total output (DOA, 2022). The sector employs around 190,093 farmers, predominantly smallholders operating on relatively small plots of land (DOA, 2022; Saili et al., 2024). **Figure 1.2** illustrates the key actors and support systems within Malaysia's upstream paddy

production chain. Cultivation is largely concentrated in designated granary areas (e.g., MADA, KADA, IADA) with sophisticated irrigation, supplemented by numerous secondary and minor granaries (Rahmat et al., 2019). Despite this scale, national rice self-sufficiency hovers around 67-70% (Dorairaj & Govender, 2023). The Malaysian paddy industry faces a confluence of persistent challenges: rising input costs, low productivity compared to regional counterparts, increasing environmental uncertainties such as erratic weather patterns and water scarcity, and a significant labor shortage exacerbated by an aging farmer demographic and the reluctance of younger generations to enter the sector (Dardak et al., 2022; Hashim et al., 2024; Kharim & Rosdi, 2024; Rahim et al., 2022; Ravindran et al., 2024; Saili et al., 2024).

SFTs, as part of the broader Agricultural Industrial Revolution 4.0 (IR4.0), present significant opportunities to address these multifaceted challenges. SFTs encompass a range of data-driven tools, such as drones, smart automated machinery, sensor devices, and mobile apps, designed to optimize resource use, enhance decision-making, and improve yields (Azlan et al., 2024b; Hashim et al., 2024; Prakash et al., 2023). The adoption of such modern technologies is seen as a crucial strategy for enhancing efficiency and profitability along the entire paddy production value chain (Kharim & Rosdi, 2024). For instance, drones can significantly reduce time and labor for pesticide/fertilizer application, and evidence suggests they can improve resource efficiency and overall productivity (Baharin et al., 2023; Harun et al., 2024; Saili et al., 2024). Collectively, these technologies offer the potential to transform traditional paddy farming into a more productive, cost-effective, and sustainable practice.

However, despite government initiatives and these apparent opportunities, the adoption of a comprehensive suite of SFTs by Malaysian paddy farmers remains slow and fragmented (Hashim et al., 2024; MAFS, 2021). Even with the positive reception

of technologies like drones, recent studies note a "growing phenomenon of technology rejection" or significant hesitation among farmers (Kharim & Rosdi, 2024). Many still harbor doubts about the effectiveness and efficiency of SFTs compared to traditional methods, like pesticide spraying (Harun et al., 2024). The Malaysian SFTs adoption landscape is thus characterized by an 'adoption lag', particularly among the predominant smallholder farmers (Ahmad et al., 2024) (Ahmad et al., 2024; Wee & Hui, 2023). While individual technologies, like drones, are gaining traction, often through service providers, integrating a bundle of SFTs into daily farming practices remains rare (Baharin et al., 2023; Harun et al., 2024; Hashim et al., 2024).

Multiple, interconnected barriers contribute to this limited uptake. High upfront costs and ongoing maintenance expenses make SFTs financially prohibitive for many smallholders with limited access to capital or credit (Ahmad et al., 2024; Baharin et al., 2023; Ravindran et al., 2024; Saili et al., 2024). Infrastructure deficits, such as poor internet connectivity in rural areas and a lack of technical advisory services, further restrict SFTs' deployment (Ahmad et al., 2024; Baharin et al., 2023; Hamid et al., 2024; Saili et al., 2024). Moreover, many older farmers lack the digital literacy and technical skills needed to operate these tools and often perceive them as overly complex (Baharin et al., 2023; Rusli et al., 2023; Saili et al., 2024). These practical limitations are compounded by perceptual barriers, including skepticism about the utility of new technologies, uncertainty about their benefits, mistrust of information sources, and fears of data misuse (Shaffril et al., 2018; Zaman et al., 2023). For instance, widespread misperceptions about the inefficacy of drone spraying continue to circulate among farming communities in some regions (Kharim & Rosdi, 2024). Furthermore, deep-rooted traditional farming practices and a general resistance

to change, especially among the aging farmer population, can hinder the adoption of novel SFTs (Adnan & Nordin, 2021; Rahman et al., 2023).

While individual technologies, like drones, are gaining traction, often through service providers, integrating a bundle of SFTs into daily farming practices remains rare (Baharin et al., 2023; En & Hui, 2023; Harun et al., 2024; Hashim et al., 2024). Achieving the transformative potential of smart agriculture in Malaysia's paddy sector, therefore, necessitates moving beyond the sporadic adoption of individual tools towards the integrated uptake of a bundle of SFTs (Azlan et al., 2024a; da Silveira et al., 2021). Hence, further research is essential, given that the decision to adopt agricultural innovations is influenced by a complex interplay of socioeconomic, socio-psychological, and contextual factors (Adnan & Nordin, 2021; Ahmad et al., 2024; Zaman et al., 2023). Accordingly, this study aims to provide a more nuanced understanding of the factors influencing paddy farmers' decisions to embrace this broader, integrated suite of SFTs.

1.5 Problem Statement

Malaysia's agricultural sector, particularly the paddy industry, is at a critical juncture, striving for transformation through the integration of advanced technologies into traditional farming practices (6Wresearch, 2024; Azlan et al., 2024b; Saili et al., 2024). SFTs, comprising diverse data-driven tools such as remote sensing, drones, automated machinery with smart capabilities (e.g., temperature sensing, geolocation, resource optimization), and farm information management platforms and apps, hold substantial promise (Abbasi et al., 2022; Javaid et al., 2022; Prakash et al., 2023). These technologies can deliver real-time data to empower farmers, boosting productivity, enabling more sustainable agricultural practices through efficient

resource management (e.g., water, fertilizer, pesticide), and improving resilience to climate-related disruptions (Balyan et al., 2024; Hashim et al., 2024). This vision aligns with Malaysia's national ambition to build a tech-driven, sustainable agri-food sector that ensures food security and economic resilience (MAFS, 2021; Ravindran et al., 2024). Importantly, the transformative impact is best realized through the adoption of a bundle of SFTs that optimizes farming operations holistically, from land preparation to harvesting (da Silveira et al., 2021; Maffezzoli et al., 2022).

Despite promising technological developments and strong governmental support, such as through the National Agrofood Policy 2.0, the adoption of SFTs among Malaysian paddy farmers remains notably low and fragmented (Ahmad et al., 2024; MAFS, 2021; Ravindran et al., 2024; Wee & Hui, 2023). This "adoption lag," especially pronounced among smallholder paddy farmers, who are vital to national food security, poses a serious challenge to agricultural modernization (Baharin et al., 2023; Hamid et al., 2024; Saili et al., 2024). These farmers, often operating with tight margins and limited capital, face considerable deterrents (Ahmad et al., 2024; Islam et al., 2024; Jamaluddin et al., 2025). These include high perceived costs of acquiring, operating, and maintaining SFTs; the perceived need for specialized training and digital skills; and concerns about long-term sustainability and uncertain returns on investment (6Wresearch, 2024; Baharin et al., 2023; Jamaluddin et al., 2025; Saili et al., 2024). These challenges are compounded by practical issues such as inadequate rural infrastructure, low awareness of SFTs' benefits, and perceptions of inaccessible or insufficient funding mechanisms (Ahmad et al., 2024; En & Hui, 2023; Hamid et al., 2024; Ravindran et al., 2024; Sabirin et al., 2022). As a result, some farmers may employ individual modern tools, leaving the full potential of diverse SFTs largely unrealized. This limited adoption underscores an urgent need for a deeper

understanding of the underlying factors shaping farmers' decisions to adopt diverse SFTs (Diana et al., 2024; Dibbern et al., 2024; Gemtou et al., 2024b; Kroupová et al., 2025). Accordingly, this study seeks to offer new insights into farmers' adoption behavior by addressing several key research gaps.

First, a fundamental reason behind the adoption gap may lie in an incomplete understanding of how Malaysian paddy farmers perceive the value of using SFTs. Value perception is a primary driver of farmers' actions (Faridi et al., 2020). This significance has also been highlighted in several studies on SFTs adoption (e.g., de Witt et al., 2021; Ingram et al., 2022; Marshall et al., 2022). For farmers, adoption involves weighing substantial financial and operational shifts against potential productivity and sustainability gains (Saili et al., 2024; Santoso et al., 2024). This value assessment is not merely about a single technology but about the collective worth of a bundle of SFTs designed to address diverse farming challenges (da Silveira et al., 2021; Maffezzoli et al., 2022). Therefore, this study adopts a value-centric approach by utilizing the Value-Based Adoption Model (VAM) (Kim et al., 2007). VAM's strength lies in positioning *perceived value* as a core mediator influencing adoption behavior (Kim et al., 2007). Additionally, this framework allows a deeper exploration of how farmers' perceived value is shaped by the various drivers and barriers they often face (Osrof et al., 2023; Pedersen et al., 2024).

Second, although VAM offers a strong foundation, it often conceptualizes value unidimensionally and has rarely been applied in the SFTs context (Osrof et al., 2023; Zeithaml et al., 2020). The limited studies that do reference VAM (e.g., Jayashankar et al., 2018) fail to unpack the multidimensional nature of value in complex adoption decisions. Recent scholarship increasingly calls for the decomposition of value into multiple dimensions (Tanrikulu, 2021; Zeithaml et al.,

2020). To address this, the study integrates VAM with the Theory of Consumption Values (TCV) (Sheth et al., 1991), which has been effectively applied in other complex technology domains (e.g., García-Monleón et al., 2023; Turel et al., 2010). This integration enables the operationalization of Overall Perceived Value (OPV) as a formative second-order construct comprising Functional (FV), Monetary (MV), and Conditional (CV) Values. In particular, this study defines OPV as farmers' holistic and subjective assessment of the net worth of adopting SFTs. This judgment is formed through a cognitive trade-off between benefits and sacrifices (Zeithaml, 1988). In this study, these benefits and sacrifices are understood through multiple dimensions, including SFTs' practical utility (FV), their economic viability (MV), and the availability of a supportive and enabling ecosystem (CV) (Sheth et al., 1991). This decomposition is critical in the context of SFTs, which are often technologically complex and financially demanding. This integrated VAM-TCV approach offers more granular and actionable insights than VAM alone by identifying which value dimensions exert the strongest influence on Malaysian paddy farmers. It thus enables a deeper understanding of the decision-making calculus farmers employ and supports the development of more targeted strategies to enhance perceived value across the dimensions that matter most, thereby facilitating greater adoption.

Third, this study investigates how multiple contextually relevant drivers and barriers shape farmers' OPV and their subsequent adoption intentions. Existing literature has explored several SFT-related adoption factors (e.g., Diana et al., 2024; Dibbern et al., 2024; Fragomeli et al., 2024; Kroupová et al., 2025; Pedersen et al., 2024). However, this study focuses on Perceived Efficiency (PE), Facilitating Conditions (FC), and Financial Incentive Policy (FIP) as drivers, and Perceived Cost (PCO), Perceived Complexity (PCX), and Perceived Uncertainty (PUN) as barriers.

These factors are contextually relevant to Malaysia, where SFTs adoption is still emerging, and most farmers, primarily smallholders, are navigating the challenges and opportunities of adopting these technologies (e.g., Ahmad et al., 2024; En & Hui, 2023; Hashim et al., 2024; MAFS, 2021; Zaman et al., 2023). Some of these factors, particularly PE, PCO, and PCX, are integral to the original VAM model, while others (e.g., FC, FIP, and PUN) extend VAM's applicability by being tested for the first time in this context (Mahmud et al., 2021).

Fourth, this study pioneers the investigation of Technology Readiness (TR) as a moderating variable in the context of SFTs adoption. Farmers' readiness is a critical factor influencing the successful uptake of SFTs (Owusu-Sekyere et al., 2024; Rose & Bhattacharya, 2023). Furthermore, their psychological predispositions play a significant role in shaping openness to digital solutions (Jamaluddin et al., 2025; Mohd Nor et al., 2024). This is particularly relevant when considering diverse SFTs, which may appear more complex or intimidating than individual tools. The literature reveals inconsistent patterns in farmers' readiness to adopt SFTs. For example, while some express positive attitudes toward IoT-based applications (Dixit et al., 2023), others show uncertainty regarding the performance and effectiveness of autonomous vehicles for weed control (Tran et al., 2023). Farmers' optimism about the potential benefits of SFTs is often counterbalanced by concerns about their reliability and profitability (Rakholia et al., 2024). These psychological predispositions are especially pertinent in the Malaysian paddy context, where attitudes toward technology vary considerably across age groups and levels of exposure (Hamid et al., 2024; Rusli et al., 2023). Although some studies have explored TR as a predictor of SFTs adoption, they have generally employed narrow conceptualizations like technical knowledge (Haberli et al., 2017; Schukat & Heise, 2021) or have failed to test its moderating role as

recommended (Shi et al., 2022). This study adopts a more comprehensive definition of TR, encompassing both Motivators (innovativeness and optimism) and Inhibitors (insecurity and discomfort), as conceptualized by Parasuraman (2000). This two-factor model offers a robust and theoretically grounded framework for understanding the often conflicting attitudes individuals hold toward technology, as supported by the meta-analysis conducted by Blut and Wang (2020). Accordingly, this study contends that understanding farmers' general perceptions of technology is essential for advancing research on SFTs adoption. By empirically testing TR as a moderator, this research contributes a novel and more nuanced perspective, shedding light on how individual differences condition the value-intention relationship in SFTs adoption.

Finally, most prior studies on SFTs adoption rely solely on SEM or regression-based methods, potentially overlooking complex non-linear decision patterns (Osrof et al., 2023; Wang et al., 2024b). While PLS-SEM, as applied here, is effective for theory testing and modeling interactive relationships such as moderation, it may miss hidden patterns. Thus, this study employs a hybrid PLS-SEM and Artificial Neural Network (ANN) approach to address a methodological gap. This dual-stage approach leverages the explanatory strengths of SEM and the pattern recognition capacity of ANN (Leong et al., 2024). In particular, it captures both linear and non-linear effects to deliver a more robust and predictive understanding of the factors influencing farmers' intentions to adopt SFTs (Leong et al., 2024; Wang et al., 2024b).

1.6 Research Objectives

This research addressed the following primary objectives:

1. To investigate the impact of the drivers: Perceived Efficiency (PE), Facilitating Conditions (FC), and Financial Incentive Policy (FIP), on Malaysian paddy farmers' Overall Perceived Value of SFTs.
2. To examine the influence of the barriers: Perceived Cost (PCO), Perceived Complexity (PCX), and Perceived Uncertainty (PUN), on Malaysian paddy farmers' Overall Perceived Value of SFTs.
3. To explore the impact of Overall Perceived Value (OPV) on Malaysian paddy farmers' adoption intentions of SFTs.
4. To assess the role of OPV in mediating the relationship between the drivers: PE, FC, FIP, and Malaysian paddy farmers' adoption intentions of SFTs.
5. To examine the role of OPV in mediating the relationship between the barriers: PCO, PCX, PUN, and Malaysian paddy farmers' adoption intentions of SFTs.
6. To evaluate the role of Malaysian paddy farmers' Technology Readiness (Motivators and Inhibitors) in moderating the relationship between OPV and their adoption intentions of SFTs.

1.7 Research Questions

The current research intended to answer the following questions:

1. Do the drivers: PE, FC, and FIP, affect Malaysian paddy farmers' OPV?
2. Do the barriers: PCO, PCX, and PUN, affect Malaysian paddy farmers' OPV?
3. Does OPV foster Malaysian paddy farmers' Adoption Intentions of SFTs?

4. Does OPV mediate between the drivers: PE, FC, FIP, and Malaysian paddy farmers' Adoption Intentions of SFTs?
5. Does OPV mediate between the barriers: PCO, PCX, PUN, and Malaysian paddy farmers' Adoption Intentions of SFTs?
6. Do Malaysian paddy farmers' Technology Readiness (Motivators and Inhibitors) moderate the relationship between OPV and their Adoption Intentions of SFTs?

1.8 Significance of the Study

1.8.1 Theoretical Significance

This study offers several contributions to the literature on SFTs adoption. First, it responded to the increasing demand for deeper exploration of the factors influencing farmers' adoption of SFTs, addressing the persistently low and fragmented adoption rates, particularly in developing countries such as Malaysia (e.g., Ahmad et al., 2024; Azlan et al., 2024a; Diana et al., 2024; En & Hui, 2023). This study also enriched the field with a systematic literature review that synthesized insights from 182 studies into five main themes: theories, characteristics, contexts, methods, and future recommendations for advancing SFTs adoption research (see Osrof et al., 2023).

Furthermore, this study adopted a value-centric perspective, largely overlooked in previous research, to examine the role of perceived value in the adoption process of SFTs. The importance of the value perspective was highlighted in several studies on SFTs adoption (e.g., de Witt et al., 2021; Ingram et al., 2022; Marshall et al., 2022; Moretti et al., 2023). Thus, this research adopted the Value-Based Adoption Model (VAM) as its core theoretical framework, focusing on the influence of value on technology adoption (Kim et al., 2007). Unlike the traditional unidimensional

approach to perceived value in VAM, this study integrates it with the Theory of Consumption Values (TCV) (Sheth et al., 1991), breaking down perceived value into functional, monetary, and conditional values. This integration offers a more nuanced understanding of the value in the context of SFTs adoption. In particular, the study conceptualizes Overall Perceived Value (OPV) as a second-order formative construct composed of these values, as recommended by previous reviews on perceived value (Tanrikulu, 2021; Zeithaml et al., 2020).

In addition, this research examines how various contextual drivers and barriers influence farmers' OPV and, eventually, their intentions to adopt SFTs. These factors represent the opportunities and challenges that smallholder farmers encounter in Malaysia (e.g., Ahmad et al., 2024; En & Hui, 2023; Hashim et al., 2024; MAFS, 2021; Zaman et al., 2023). While some factors (e.g., PE, PCO, and PCX) are integral to the original VAM, this study extends VAM's applicability by testing other variables like FIP and PUN for the first time in the SFTs adoption context (Mahmud et al., 2021).

This research also made a novel contribution by examining the moderating effect of Technology Readiness (TR) on the relationship between OPV and SFTs adoption, distinguishing between Motivators (optimism and innovativeness) and Inhibitors (discomfort and insecurity) (Blut & Wang, 2020; Parasuraman & Colby, 2015). Previous studies focused narrowly on farmers' readiness in terms of knowledge and skills (Haberli et al., 2017; Schukat & Heise, 2021), overlooking the broader concept of TR. By addressing TR as a moderating variable, this study offered new insights into how smallholder farmers' mixed views of technology can influence the relationship between OPV and their adoption intention of SFTs.

Finally, this study contributes methodologically by employing a hybrid PLS-SEM and ANN analytical approach. This dual technique addresses the limitations of

relying solely on traditional linear models (Leong et al., 2024). Adopting a bundle of SFTs is a complex decision, where numerous factors may interact non-linearly (Martin et al., 2022; Prakash et al., 2023). Thus, this approach leverages SEM's theory-testing strengths with ANN's capacity for recognizing complex patterns and non-linearities, offering a more robust and comprehensive understanding of farmers' subjective cognitions (Leong et al., 2024; Wang et al., 2024b).

1.8.2 Practical Significance

Malaysia's ambition to transform its agriculture sector through smart technologies is driven by urgent national priorities: sustainability, productivity, and food security (6Wresearch, 2024; MAFS, 2021). However, the low and fragmented adoption of SFTs, especially among smallholder paddy farmers, poses a significant obstacle to realizing this vision. By investigating the factors shaping farmers' intentions to adopt a bundle of SFTs, this study provides evidence-based insights that can guide multiple stakeholders, including policymakers, agricultural extension agencies, technology developers, and agribusinesses, in supporting more widespread and effective adoption of SFTs.

This study highlights several specific drivers and barriers that have practical significance for stakeholder action. Among the drivers, Perceived Efficiency (PE) emphasizes the importance of showcasing clear and tangible benefits, such as productivity gains, input savings, and operational improvements (Ravindran et al., 2024; Santoso et al., 2024). Policymakers and extension agencies can design demonstration programs to communicate these gains, while SFTs developers and agribusinesses should ensure that bundled offerings deliver demonstrable outcomes and highlight them in outreach efforts (Maffezzoli et al., 2022). Next, Facilitating Conditions (FC) highlight the role of rural infrastructure, technical support, and

training. Hence, investments in internet connectivity, access to advisory services, and peer-to-peer learning networks are crucial (Baharin et al., 2023; Hamid et al., 2024; Saili et al., 2024), with extension agents and farmer organizations acting as vital intermediaries in delivering practical, farmer-friendly guidance (Pawera et al., 2024; Tran et al., 2023). Moreover, the study emphasizes Financial Incentive Policy (FIP), calling for well-structured subsidies, grants, or low-interest loans to reduce upfront costs (Alam et al., 2023; Islam et al., 2024). Developers and agribusinesses can collaborate with government and financial institutions to create bundled financing options that enhance affordability and uptake.

Conversely, this study also identifies major barriers to adoption that must be addressed in tandem. Perceived Cost (PCO) remains a central obstacle, suggesting the need for cooperative purchasing schemes, leasing arrangements, or government-backed shared services to reduce financial burdens (Baharin et al., 2023; da Silveira et al., 2023). SFTs developers should prioritize scalable, cost-effective solutions, while agribusinesses can develop tailored return-on-investment (ROI) projections to strengthen farmers' confidence. Perceived Complexity (PCX) calls for intuitive, user-centered designs and interoperable systems that reduce operational friction (Geppert et al., 2024; Prakash et al., 2023), supported by hands-on training programs that build digital literacy and practical skills over time (Saili et al., 2024). Perceived Uncertainty (PUN) also reflects farmers' concerns about functionality, reliability, and their ability to respond to SFTs' continuous updates. Government agencies and research institutions should address these concerns by setting clear standards, supporting pilot projects, and fostering trust through transparency and demonstration farms (Klerkx et al., 2019). These barriers are interconnected, and tackling them is essential for overcoming adoption resistance.

Crucially, this study goes beyond identifying which drivers and barriers matter. It investigates how these factors shape farmers' Overall Perceived Value (OPV), which in turn mediates their influence on adoption intention. The detailed exploration of OPV, decomposed into Functional, Monetary, and Conditional Values, has meaningful implications. Policymakers, extension agents, and farmer organizations can prioritize the most salient value dimensions (e.g., the need for enabling infrastructure in CV, demand for economic returns in MV, or the appeal of efficiency in FV) to design more persuasive and targeted interventions (Ingram et al., 2022). SFTs developers and agribusinesses can tailor their communication strategies and value propositions to highlight how their offerings align with these farmer-prioritized values.

In addition, the study introduces Technology Readiness (TR) as a moderating variable that differentiates between technology-motivated and technology-inhibited farmers. This distinction has practical utility for segmentation strategies. TR-Motivated farmers, those with high optimism and innovativeness, can serve as early adopters, peer educators, or ambassadors to encourage broader uptake through social learning. In contrast, TR-Inhibited farmers, those experiencing insecurity or discomfort, may require tailored support, simplified interfaces, confidence-building tutorials, and access to low-risk trial programs (Taheri et al., 2020). Recognizing these psychological profiles enables stakeholders to deliver more targeted interventions that account for individual differences in technology attitudes.

Finally, this study adopts a hybrid PLS-SEM and Artificial Neural Network (ANN) approach to strengthen both the theoretical rigor and practical relevance of its findings (Leong et al., 2024). While PLS-SEM confirms causal relationships and moderation effects, ANN captures non-linearities in farmers' decision patterns that traditional methods may miss. This dual-stage model delivers richer, more predictive

insights, enabling policymakers and industry players to better prioritize interventions based on nuanced patterns of adoption behavior.

In sum, this study offers a robust, value-centered framework that explains not only which factors influence SFTs adoption but also how and why they do so. It equips stakeholders with a clearer blueprint for accelerating SFTs adoption, not through one-size-fits-all solutions, but through targeted, value-driven strategies grounded in farmers' real-world priorities. This, in turn, contributes to Malaysia's national food security goals, strengthens farmers' economic resilience, and supports broader global commitments such as the United Nations Sustainable Development Goals (SDGs) (Azlan et al., 2024b; MAFS, 2021; Sood et al., 2022).

1.9 Definition of Key Terms

This section delineates the contextual definition of the main terminologies used in this research:

Smart farming technologies (SFTs) refer to a bundle of advanced technologies that enhance and optimize in-field paddy cultivation operations. This study specifically considers SFTs that are currently relevant to Malaysian paddy farming, including smart automated planting and harvesting machinery (e.g., incorporating sensor-based data collection, GPS guidance, and precision capabilities), drones for advanced monitoring and targeted tasks, sensor devices for land levelling and inputs optimization, and mobile-based farm management information systems for decision support. This definition is drawn from concepts of Agriculture 4.0 and farm digitalization literature (e.g., da Silveira et al., 2021; Hashim et al., 2024; Javaid et al., 2022; Prakash et al., 2023), and also confirmed during field discussions with paddy farming entities in Malaysia (e.g., MARDI, MADA, and IADA).