Perspectives on data sharing by Southern African horticultural farmers

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Abstract:

This study examines the perceptions of data sharing among Southern African horticultural farmers utilising a Digital Agricultural Application (DAA). Employing a quantitative methodology, the study collected insights from farmers and agronomists, exploring the roles of digital trust, perceived risks, and perceived benefits in influencing their decisions to share farm data.

The findings indicated that, contrary to expectations, perceived risks and digital trust had a lesser impact on data sharing decisions, whereas perceived benefits significantly motivated farmers to share data. Factor and regression analyses challenged the initial assumptions, highlighting the complexity inherent in the decision-making processes of farmers. The research thus suggests that enhancing perceived benefits could be more effective in promoting data sharing than mitigating perceived risks.

The study's results have been contextualised within the broader academic discourse, explaining deviations from, and nuances of, established research. It discussed the implications of these findings for developers of DAA and agribusiness stakeholders, aiming to enhance technology adoption within agriculture. By integrating theoretical frameworks with practical applications, such as incorporating community feedback mechanisms like testimonial systems and discussion forums into DAA, visibility of benefits was enhanced and trust was established, thereby encouraging adoption through positive peer influence.

This analysis sheds light on the factors influencing data sharing among Southern African horticultural farmers and informs future technology and policy efforts to strengthen the digital agricultural ecosystem.

Key words:

Agribusiness, Horticultural Farming, Data Sharing, Trust, Risk, Benefits

Table of Contents

List of acronyms ix
1 Chapter 1 - Introduction 1
1.1 Statement of purpose 1
1.2 Background of the study 2
1.2.1 Research problem 4
1.2.2 Research questions: 6
1.3 Rationale 7
1.4 Delimitations of the study 8
1.5 Chapter outline 9
2 Chapter 2 – Narrative literature review and theoretical framework 10
2.1 Introduction 10
2.2 Definition of topic 10
2.3 Research Question 1: What factors of digital trust contribute to farmers deciding whether to share farm data on a digital agricultural application? 11
2.3.1 Digital trust and the impact of social influence 11
2.3.2 Digital trust and concerns over control and ownership 13
2.3.3 User experience and digital trust 14
2.3.4 Hypotheses for research question one 15
2.4 Research Question 2: To what extent does perceived risk impact farmer's view to share farm data on a digital agricultural application? 15
2.4.1 Perceived risk of privacy and security 15
2.4.2 Perceived risks and the technical challenge 16
2.4.3 Perceived risk of compatibility 17
2.4.4 Perceived financial risks 17
2.4.5 Hypothesis for research question two 18
2.5 Research Question 3: To what extent do perceived benefits impact farmer's decisions to share data on a digital agricultural application? 18
2.5.1 Hypothesis for research question three 20
2.6 Analytical framework 20
2.6.1 Theoretical and conceptual framework 20
2.6.2 Conceptual framework 21
2.7 Conclusion of literature review 22
3 Chapter 3 - Research Methodology 23

3.1 Research approach 24
3.2 Research design 24
3.3 Data collection methods 25
3.4 Population and sample 26
3.5 Research instrument 27
3.6 Procedure for data collection. 27
3.7 Data analysis strategies 28
3.8 Possible limitations 30
3.9 Quality assurance 30
3.9.1 External validity (generalisability) 30
3.9.2 Internal validity 31
3.9.3 Reliability 31
3.11 Conclusion 32
4 Chapter 4 - Data Analysis 34
4.1 Introduction 34
4.2 Data screening 35
4.3 Factor Analysis 38
4.4 Communalities 40
4.5 Eigenvalues and Rotated Sums of Squared Loading in Total Variance Explained 42
4.6 Pattern Matrix 44
4.7 Cronbach's Alpha 49
4.8 Descriptive Statistics 51
4.9 Descriptive statistics: Frequencies percentage of each survey question, grouped together per construct. 53
4.9.1 Perceived Benefit construct, survey question Frequency results (H5) 54
4.9.2 Digital Trust construct, survey question Frequency results (H2) 59
4.9.3 Perceived Risk construct, survey question Frequency results (H4) 64
4.9.4 Intention to Share Data construct, survey question Frequency results (H1) 68
4.10 Non-parametric correlations 73
4.11 Regression analysis 75
4.12 Summary of analysis of data for Hypotheses 1, 2, 3, 4, and 5 78
4.12.1 Hypothesis 1 - Digital Trust positively affects Intention to Share Farm Data on a DAA. 78

4.12.2 Hypothesis 2 - Digital Trust negatively affects farmers Perceived Risk of sharing farm data.. 80
4.12.3 Hypothesis 3 - Positive Intention to Share Data has a positive influence on actual sharing of farm data on a DAA. 81
4.12.4 Hypothesis 4 - Perceived Risk has an effect on Intention to Share Data.. 82
4.12.5 Hypothesis 5 - A farmer’s Perceived Benefits positively affects decisions to share farm data on a digital agricultural application... 83
4.13 Conclusion.. 85
5 Chapter 5 – Discussion 87
5.1 Introduction.. 87
5.2 Research question 1: What factors of digital trust contribute to farmers deciding whether to share farm data on a digital agricultural application? 88
5.2.1 H1: Digital trust positively affects intention to share farm data on a digital agricultural application. 89
5.2.2 H2: Digital trust negatively affects farmers perceived risk of sharing farm data on a digital agricultural application. 92
5.3 Research question 2: To what extent does perceived risk impact farmers’ decisions to share farm data on a digital agricultural application? 94
5.3.1 H4: A farmers perceived risk negatively affects intention to share farm data on a digital agricultural application. 94
5.4 Research question 3: To what extent do perceived benefits impact farmers’ decisions to share farm data on a digital agricultural application? 97
5.4.1 H5: A farmers perceived benefits positively affect decisions to share farm data on a digital agricultural application (PB) 97
6 Chapter 6: Recommendations and Conclusion 101
6.1 Theoretical contribution 101
6.2 Practical recommendations 102
6.2.1 Comprehensive communication, security and trust framework ... 102
6.2.2 User-centric design and positive experience 103
6.2.3 Peer influence, technical literacy, and community engagement .. 103
6.2.4 Software compatibility and educating on data sharing 104
6.2.5 Risk management and demonstrating benefits 104
6.2.6 Data legislators... 104
6.3 Limitations 106
6.3.1 Limitations of single-cross sectional research design.................. 106
6.3.2 Sample representation and generalisability................................ 106

6.3.3 Potential technological bias 106
6.3.4 Cultural and contextual factors 107
6.3.5 Limited knowledge of researcher 107
6.4 Factors not considered 107
6.4.1 Socio-economic status and farm size 107
6.4.2 Digital infrastructure and accessibility 108
6.4.3 Cultural attitudes and trust in technology 108
6.4.4 Education and digital literacy 108
6.4.5 Gender and age dynamics 108
6.5 Future research 108
6.5.1 Longitudinal studies on farmers' attitudes and behaviours 109
6.5.2 Exploring the impact of cultural and regional differences 109
6.5.3 Assessing the influence of emerging technologies and data legislation 109
6.6 Conclusion 110
References 111
Appendix A: Research questions and related hypothesis, with the literature references for each survey question. 117
Appendix B - Research questionnaire 122
Appendix C – Respondent consent form 126
Appendix D – Respondent participation form 129
Appendix E – Permission to research from business 131
Appendix F – Supervisor support letter 132
Appendix G – Ethics clearance certificate 133

List of tables

Table 1: Summary of the hypotheses 22
Table 2: PR Model (Kim et al., 2008) variables and relationships, inferred to the proposed conceptual model comparison table. 29
Table 3: Analysis of survey questions grouping to constructs 36
Table 4: Factor Analysis: KMO and Bartletts Test 39
Table 5: Communalities (Initial) 41
Table 6: Total Variance Explained 42
Table 7: Pattern Matrix using Principal Axis Factoring and Rotation Method: Oblimin with Kaiser Normalization. 44
Table 8: Revised grouping and ordering of initial survey questions by constructs and hypotheses 47
Table 9: Descriptive Statistics 51
Table 10: H1a Frequency table and histogram representation 54
Table 11: H1b Frequency table and histogram representation 55
Table 12: H5a Frequency table and histogram representation 56
Table 13: H5c Frequency table and histogram representation 57
Table 14: H5d Frequency table and histogram representation 58
Table 15: H1d Frequency table and histogram representation 59
Table 16: H1e Frequency table and histogram representation 60
Table 17: H1f Frequency table and histogram representation 61
Table 18: H2a Frequency table and histogram representation 62
Table 19: H4a Frequency table and histogram representation 63
Table 20: H1c Frequency table and histogram representation 64
Table 21: H3a Frequency table and histogram representation 65
Table 22: H4e Frequency table and histogram representation 66
Table 23: H5b Frequency table and histogram representation 67
Table 24: H2b Frequency table and histogram representation 68
Table 25: H4b Frequency table and histogram representation 69
Table 26: H4c Frequency table and histogram representation 70
Table 27: H4d Frequency table and histogram representation 71
Table 28: H5e Frequency table and histogram representation 72
Table 29: Non-parametric correlations 73
Table 30: Hypothesis 2 Test A 76
Table 31: Hypothesis 1,4 and 5 Test B 77

List of figures

Figure 1. Conceptual framework adapted from the trust-based consumer decision-making model in electronic commerce (Kim et al., 2008)..................... 1

Figure 2. A trust-based consumer decision-making model in electronic commerce (Kim et al., 2008)... 21

Figure 3. Conceptual framework adapted from the trust-based consumer decision-making model in electronic commerce.. 21

Figure 4: Updated model and hypotheses 85

List of acronyms

AI: Artificial Intelligence

ASOD: Actual Sharing of Data

DAA: Digital Agricultural Application

DT: Digital Trust

ITSD: Intention to Share Data

IOT: Internet of Things

IOT-A: Internet of Things and Artificial Intelligence

GPS: Global Positioning System

ML: Machine Learning

PB: Perceived Benefit

PR: Perceived Risk

ROI: Return on Investment

TAM: Technology Acceptance Model

1 Chapter 1 - Introduction

1.1 Statement of purpose

The purpose of this study was to investigate the risk perceptions of Southern African horticultural farmers when sharing their farm data on a digital agricultural application (DAA).

For the purpose of this study Southern African horticultural farmers are defined as cultivators of plants for food such as nut producing plants, tree crops, fruit trees, grapes and bananas and grow in open fields or controlled cultivation such as tunnel farming. The conceptual framework is built on the trust-based consumer decision-making model in electronic commerce (Kim et al., 2008) and has been extended to encompass trust across various forms of digital technology and online activity (Pietrzak & Takala, 2021).

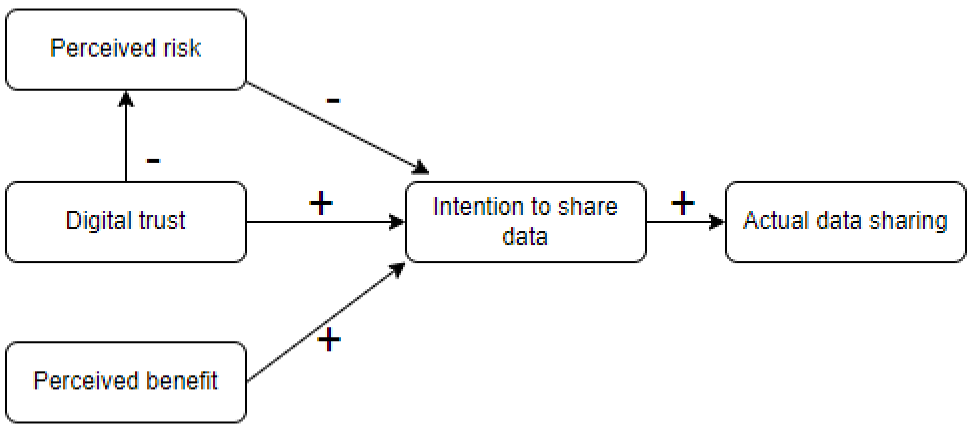


Figure 1. Conceptual framework adapted from the trust-based consumer decision-making model in electronic commerce (Kim et al., 2008).

The conceptual framework is an adaption of the trust-based consumer decision-making model in electronic commerce (Kim et al., 2008). For this study, trust has been expanded to digital trust and is seen as a broader concept that encompasses trust in all forms of digital technology and online activity (Pietrzak & Takala, 2021). In addition, the Intention to Purchase facets of the model have been changed to Intention to Share Data and Actual Data Sharing, respectively. As this study will explore the perceived risks of sharing data on digital applications, the e-commerce related constructs have been repurposed.

1.2 Background of the study

The proliferation of digital technologies since the turn of the century has increased the awareness of the potential risks of sharing personal and organisational data (OECD, 2019). A good example of a case study exploring lack of trust in sharing data was the Cambridge Analytica scandal in 2018. Cambridge Analytica was a political consulting firm that obtained data on millions of Facebook users without their consent, and used this data to create targeted political advertisements during the 2016 United States Presidential election (Hanna & Isaak, 2018).

The scandal highlighted the lack of transparency and control those individuals have over their personal data, and the potential for this data to be misused for political gain. It also revealed the lack of trust that many people have in companies and institutions to protect their personal data and use it responsibly plus opened a broader conversation about data privacy and regulation of the technical industry.

In 2017, South African citizens experienced a serious data breach where the personal data of over 24 million people and 793,749 businesses were leaked and made publicly available on the internet (Nieselow, 2018). The leaked data included information such as names, ID numbers, contact details, and employment history, which could be used for identity theft, financial fraud, and other types of malicious activity. The data breach was linked to a company called Jigsaw Holdings, which specialises in direct marketing and credit risk assessment and was accused of failing to secure the data of its clients (Nieselow, 2018).

Continuing the discussion on the risks and opportunities associated with the proliferation of digital technologies, it's clear that even the agricultural sector in Southern Africa is undergoing significant transformation (Aguera et al., 2020). According to Aguera et al. (2020) the integration of advanced technologies such as Machine Learning (ML), Artificial Intelligence (AI), and the Internet of Things (IoT) holds transformative potential for agriculture. Data management, analytical tools, IoT, ML, AI, drones and robotics all have the potential to enhance efficiency on farms by reducing costs, preserving resources, and increasing yields (Aguera et al., 2020).

There are 32 000 commercial farms in South Africa, of which around 7000 produce 80% of the output (International Trade Administration, 2021). Unfortunately, there remains limited evidence of how many farmers are using digital technology. However the South African government, through its “9 Point Plan” in the Adoption of the 2030 Agenda for Sustainable Development, highlights its support of digital technologies for water sustainability and enhanced agriculture efficiencies (United Nations, 2019).

In a ground-breaking study involving 1000 Australian farmers across 17 agricultural sectors, researchers analysed concerns to comprehend the perceived risks associated with sharing farm data, particularly in the context of absent legal or regulatory frameworks tailored for agricultural data. This study revealed that the act of being open to sharing data is inherently connected to trust (Wiseman et al., 2019).

Various legal frameworks around the world have been set up to regulate data sharing, and in South Africa the POPI Act has been legislated (POPIA, 2020) to protect personal data. While these controls are in place, monitoring and implementation are lagging, with reports of over 500 complaints received, yet no fines have been processed as a result (My Broadband, 2023) and an understanding of the ownership of farm data still remains vague (Aguera et al., 2020).

The need for these concerns to be understood is important for global adoption of precision farming to address global water sustainability, limited fertiliser resources and rising population growth (Delgado et al., 2011). According to reports from the United Nations, the global population will increase to 9.7 billion by 2050 (United Nations, 2022) which, together with water stress in a country like South Africa (farms facing increasing aridity and substantial warming in the next century impacting both surface water sources and groundwater recharge, exacerbating challenges for long-term water and food security in the face of drought and climate change), makes precision farming becomes increasingly critical (WWF, 2018).

Horticultural farmers in South Africa are primarily focused on addressing ways to enhance production levels and sustain a commercially viable business. Justin Chadwick, CEO of the Citrus Growers Association noted that citrus farmers suffered a difficult financial loss, with a decline of 5.7 million cartons in sales, with 2023 looking much the same (Chadwick, 2023). Load shedding, failing government enterprises and municipalities, labour costs, the unstable war in the Ukraine, have all impacted the production and costs of produce, resulting in a sharp decline of profits both locally and in the export market.

This study therefore examined the perspectives of horticultural farmers encompassing perceived risks, digital trust and perceived benefits of sharing farm data on a DAA.

1.2.1 Research problem

The extent of data sharing among Southern African horticultural farmers when utilising digital agricultural applications for precision farming is currently limited.

The current agricultural situation in South Africa has yielded a decrease in margins within the horticultural sector (Chadwick, 2023), prompting the need for precision farming techniques to decrease costs, increase yields, and ultimately boost profits (WWF, 2018). A DAA has been developed to assist in this effort, and the organisation behind it seeks to grow its user base. However, the perceived risks associated with sharing farm data among potential users could present a barrier to adoption (Wiseman et al., 2019). This study aims to investigate these perceived risks and provide insights on how the organisation could potentially address them to increase adoption of precision farming practices and enhance the sustainability of the horticultural sector in Southern Africa.

Previous research conducted in the agricultural sector of Australia has demonstrated that trust plays a significant role in farmers' willingness to share their data (Wiseman et al., 2019). Applying this insight to the Southern African context could potentially help alleviate concerns surrounding data sharing and promote digital adoption. However, at the time of this study, there was no empirical evidence on Southern African horticultural farmers' perceived risks associated with sharing their farm data.

Of particular interest to this study was the fact that the potential respondents are already using a DAA specific to the horticultural sector. Within this context, it could be deduced that respondents have already transitioned to the use of DAAs and an acceptance of sharing their agricultural data. At the time of this study, there was academic literature addressing farmers' perceived risks tied to the adoption of digital agricultural tools. Yet, there was a notable lack of empirical research focussing on farmers who are currently sharing their agricultural data through these platforms, an area that could yield further insights. The findings of this study could potentially be leveraged by agribusinesses to incorporate considerations in the design phase that address possible concerns and increase adoption rates, ultimately contributing to the sustainability of the horticultural industry.

This study proposes to fill the knowledge gap concerning the perceived risks that Southern African horticultural farmers associate with sharing their farm data. It also seeks to offer insights into how organisations could address these concerns to encourage the adoption of Digital Agricultural Assistants (DAA) in the agricultural sector.

A reflective review focusing on the perceived risks of data sharing amongst farmers revealed several possible constructs important to this research, unpacked under the following headings a) perceived risk b) perceived benefits c) digital trust d) intention to share farm data and e) actual sharing data behaviour.

Perceived risk of data sharing and the factors impacting digital trust are explored and incorporated into the conceptual framework adapted from the "Trust-based consumer decision-making model in electronic commerce (Kim et al., 2008). This is a trust model used to explore the relationship between perceived risk and trust towards using online e-commerce platforms. The model is based on e-commerce but could be used in relation to digital applications as they also involve online transactions and interactions. In addition, while there may be some differences in the context and specific features of these platforms, they share common elements detected in the research, related to user trust, such as data security, privacy, reliability, and user experience (Kim et al., 2008). By applying this model, the study hopes to understand what factors of digital trust, perceived risks and perceived benefits contribute to farmer's decisions to share their farm data on a DAA.

1.2.2 Research questions:

In order to foster data sharing and greater adoption of digital farming applications, it is necessary for empirical research to identify the specific perceived risks that farmers may have with regard to sharing their data. The following three research questions were therefore explored:

1. What factors of digital trust contribute to farmers deciding whether to share farm data on a digital agricultural application?
2. To what extent does perceived risk impact farmers' decisions to share farm data on a digital agricultural application?
3. To what extent do perceived benefits impact farmers' decisions to share farm data on a digital agricultural application?

1.3 Rationale

To promote the adoption of precision farming, which has been shown to increase yields, optimise fertiliser use and enhance water sustainability (Balasundram et al., 2023), it is crucial to ascertain the willingness of farmers in the horticultural sector of Southern Africa to share their farm data.

Proposed Contribution

The theoretical contribution of this research lies in its exploration of attitudes of horticultural farmers in Southern Africa regarding the perceived risks, perceived benefits and digital trust towards data sharing. By investigating this specific context, the study aims to shed light on farmers' attitudes, concerns, and barriers related to data sharing in the agricultural sector.

This study makes a novel theoretical contribution by adapting the original model (Kim et al., 2008) to the context of horticultural farmers in Southern Africa, an area that has been relatively underexplored. In doing so, it bridges the gap in existing knowledge and opens new avenues for future research. This adaptation underscores the importance of context in shaping farmers' attitudes towards data sharing, taking into account the factors inherent amongst Southern Africa's horticultural farmers who are already users of DAAs.

The adaptation also allows for a deeper understanding of the specific perceived risks, benefits, and trust issues related to data sharing in this context. This nuanced understanding could be an interesting development of theoretical models that could more accurately capture the realities faced by Southern African farmers.

The findings of this study could potentially have practical implications for various stakeholders, including DAA developers, agribusinesses and legal advisors. The identification of key factors influencing farmers' decisions to share data, and thus adoption of new technologies in the horticultural industry of Southern Africa, could help stakeholders tailor their strategies and interventions accordingly. It has the potential to inform the development and design of digital solutions centred on the user and appropriate legal frameworks to facilitate technology adoption and address farmers' concerns.

In summary, the study aims to contribute to understanding farmers' attitudes regarding data sharing risks, highlights potential benefits of digital applications; and provides potential insights for relevant stakeholders to promote technology adoption in the horticultural industry of Southern Africa.

1.4 Delimitations of the study

Firstly, the research is exclusively focused on one existing DAA that provides precision recommendations to 260 farmers in Southern Africa. Secondly, after post data cleaning, only 61 of these responses were considered valid for the study due to missing data resulting in a response rate of 23%.

Furthermore, the study only accounts for Southern African horticultural farmers (for the purpose of this study, horticultural farmers are defined as cultivators of plants for food such as nut producing plants, tree crops, fruit trees, grapes and bananas and grown in open fields or controlled cultivation such as tunnel farming), which may exhibit distinctive characteristics compared to other agricultural sectors, such as sugar farming.

Assumptions

The research report is based on the following assumptions:

I. Respondents are current users of the DAA for precision farming, and thus have experience with the technology and data sharing practices.
II. Respondents have a basic level of technology literacy and access to the necessary hardware and software to use the DAA.
III. Respondents have a range of horticultural farming operations, and their experiences with the digital agricultural application may vary.

1.5 Chapter outline

This chapter provided a foundation for an investigation of data concerning the perceived risks, perceived benefits and digital trust, experienced by Southern African horticultural farmers who utilise DAAs.

The upcoming literature review chapter delves into the findings of previous research that is relevant to perceived risks, perceived benefits and digital trust in agriculture data sharing. The perspectives of various authors in related studies will also be examined to fine-tune the focus of this research. By examining similar research, this study aims to identify pertinent questions to ask in the research instrument, which will be elaborated on in Chapter 3.

2 Chapter 2 – Narrative literature review and theoretical framework

2.1 Introduction

Since 2010, the adoption of digital applications in the agricultural sector has garnered significant attention. These technologies promise to enhance farm productivity, efficiency, and sustainability (Colizzi et al., 2020). However, farmers' willingness to share their farm data on DAAs is contingent upon their trust in these technologies, which is influenced by perceived risks and benefits associated with various aspects of digital trust (Durrant et al., 2021). Understanding the factors that contribute to farmers' perceived risks, perceived benefits and digital trust, and their impact on sharing farm data on DAAs is crucial for promoting the adoption of such technologies in the agricultural sector.

This narrative literature review aims to investigate the relationship between digital trust, perceived risks, and perceived benefits towards sharing data on DAAs in the horticultural sector of Southern Africa. The findings were then used to structure questions in an email quantitative survey questionnaire (created on Qualtrics) to address the research questions posed in Chapter 1.

By answering these research questions, this study sought to provide insights into the barriers and facilitators of sharing farm data in the horticultural agricultural sector of Southern Africa.

2.2 Definition of topic

The rapid expansion of digital technologies has heightened concerns over potential risks associated with sharing personal and organisational data, as evidenced by the Cambridge Analytica scandal and the 2017 Southern African data breach (Hanna & Isaak, 2018). Despite the increasing need for scientific recommendations and the potential benefits of digital technologies in the agricultural sector, concerns about data sharing, privacy and security regulations persist (Wiseman et al., 2019). In Southern Africa, where agriculture plays a significant role, understanding farmers' perceived risks of sharing farm data and their trust in digital applications is crucial for adopting precision farming practices, which could address global challenges like water sustainability and population growth (Smidt, 2021).

2.3 Research Question 1: What factors of digital trust contribute to farmers deciding whether to share farm data on a digital agricultural application?

2.3.1 Digital trust and the impact of social influence

Pietrzak and Takala (2021) observed that there is not yet a universally accepted definition of digital trust, a situation further complicated by the scarcity of academic research on the subject, which only began to increase in 2016. For the purposes of this study, digital trust is broadly defined as the trust in all forms of digital technology and online activities that involve the use of such technologies (Pietrzak & Takala, 2021).

Venkatesh et al. (2003) defines social influence as the extent to which a person 0believes that significant others think they should utilise a new system, which for the purposes of this study will incorporate the social influence on farmers when deciding to share their farm data on a DAA.

2.3.1.1 Concerns about reputation and image in relation to digital trust.

Regan (2019) examined risk perception among Irish farmers, uncovering their apprehensions regarding ethical dilemmas posed by various stakeholders about digital agricultural technology. An example given was the potential for consumer rejection of data-sharing and technologically-driven farming practices, which could deviate from their conventional and traditional perception of agricultural practices. This perspective was further supported by Durrant et al. (2021), who found that farmers exhibit reluctance to share data due to the commercial sensitivity of such data and the potential risks to their trustworthy image and reputation if competitors gain access to it. Furthermore, concerns about negative publicity that might stem from data-sharing practices were expressed. This would suggest that farmers rely on the recommendation of others, to determine the trustworthiness of the digital platform.

Regan (2019) further observed that the traditional narrative and visual portrayal of wholesome farming practices could be adversely affected by discussions surrounding data-sharing for digital solutions. This issue is compounded by farmers' apprehensions that an over-reliance on digital technology might erode the positive narrative of sound farming instincts and intuition (Regan, 2019). This suggests that there are possible concerns around data sharing and the use of digital technology for farm management negatively impacting the romanticised image of traditional farming.

Mani and Chouk (2018) highlighted the considerable influence that consumer self-image exerts on adoption behaviours towards innovative smart services. The research suggests that some consumers perceive a discrepancy between their self-image and the smart services they adopt, with the adoption decision depending on whether the service is perceived as an essential or just a luxury gadget. When comparing these findings in an agricultural context, research indicates that farmers express concerns about new innovative applications, worrying that they may be perceived as impractical "toys", thereby undermining their professional image of trustworthiness (Regan, 2019, p. 5).

2.3.1.2 The influence of peers on digital trust

Venkatesh et al. (2003) proposes that social influence plays a significant role in the adoption of technology. The study found that when peer endorsement towards the utilisation of novel IT system was perceived, the apprehension associated with its adoption decreased while digital trust increased. These findings where supported by Engotoit et al. (2016) who found that friends and family not only influence farmers but also inspire the adoption of mobile applications. Furthermore, Pillai and Sivathanu (2020) also noted that social interaction with other farmers regarding IoT-A, had a positive influence on them to adopt IoT technology in agriculture industry.

Similarly, Fox et al. (2021) found social influence to be a strong mediator of perceived performance and effort expectancy of non-users who had yet to adopt. Blasch et al. (2022) found that only 36.99% of non-adopting farmers did not know another adopter while 88.5% farmers who had already adopted precision farming knew at least one other adopter in their social environment. Furthermore, Pillai and Sivathanu (2020) also noted that positive social interaction with other farmers regarding IoT-A influenced them to adopt IoT technology in agriculture industry. This evidence underscores the significant impact that social networks have on technology adoption within farming communities. Sharing positive experiences about the benefits of data sharing can greatly influence and shape the trust perceptions of others in these communities.

2.3.2 Digital trust and concerns over control and ownership

Regan (2019) revealed Irish farmers' need for clarity regarding the nature of their data being shared, the parties gaining access to it, and the purposes for which their data would be utilised. This sentiment was echoed by Jakku et al. (2019) who found that Australian farmers expressed concerns about losing control over their own data, with issues of data ownership and access dominating their apprehensions. Additionally, their research further speculated that the level of digital trust in sharing farm data could potentially constrain the voluntary participation of agribusiness stakeholders (Jakku et al., 2019).

Similarly, Wiseman et al. (2019) raised concerns regarding the underrepresentation of agricultural data in academic research and questioned whether it should be classified as personal data. Van der Burg et al. (2019) echoed these apprehensions, arguing that it could be classed as business data and that the intermediaries that create the algorithm for interpretation are owners of computed data.

Furthermore, Van der Burg et al. (2019) argues the ethics around corporations' accessibility and control of data create an unfair advantage over farmers. Barrett and Rose (2022) supports these concerns and the subsequent influence that technology companies wield over farmers creating barriers to digital trust.

2.3.2.1 Ambiguous contracts impact on digital trust

In accordance with Wiseman et al. (2019), 70% of respondents are unaware of, or do not comprehend, the terms and conditions of contracts associated with service technology providers, primarily due to ambiguous contract language. Moreover, 52% of respondents express a lack of trust in these providers when it comes to the support, management, and maintenance of their contract. Similarly, Jakku et al. (2019) corroborates the concern among farmers regarding the transparency of data contracts and the potential for exploitation by large corporations. The issue of contract clarity is extensive and was also observed by Irish farmers, who expressed their apprehension about potential exploitation stemming from an imbalance of bargaining power when contracts are ambiguous (Regan, 2019). This perceived lack of transparency could decrease trust in sharing data.

2.3.3 User experience and digital trust

Navigation and design play a significant role in the ease of use, which contributes to increased overall confidence in the application. Positive feedback from fellow farmers about their experience, could reduce the perceived risk of sharing data, as farmers tend to trust their peers' observations (Shi et al., 2022). If a farmer perceives that an application poses a risk to their farming operation, they may find the application less user-friendly, even if it is technically simple to navigate (Barrett & Rose, 2022). This emphasises the importance of functionality in the user experience for DAAs, and the influence that sharing these positive user experiences has, in building confidence to share their own data. In line with this thinking, Rezaei-Moghaddam and Salehi (2010, p. 1194) showed that an "attitude of confidence has a direct effect on perceived ease of use of precision agriculture technologies", suggesting that by increasing the overall confidence in the application it could promote a wider sense of digital trust among users. If a DAA is easy to use, provides accurate results, and helps farmers achieve their goals (such as increasing crop yield or improving sustainability), it enhances the overall user experience. A positive experience could help to build confidence and trust in the application.

2.3.4 Hypotheses for research question one

The following hypotheses were derived to address the first research question:

1. Digital trust positively affects intention to share farm data on a digital agricultural application (H1).

2. Digital trust negatively affects farmers perceived risk of sharing farm data on a digital agricultural application (H2).

3. Positive intention to share farm data has a positive influence on actual sharing of farm data on a digital agricultural application (H3).

2.4 Research Question 2: To what extent does perceived risk impact farmer's view to share farm data on a digital agricultural application?

2.4.1 Perceived risk of privacy and security

In their study of trust-based decision-making in e-commerce, Kim et al. (2008) identified privacy and security as key influencers of perceived risk. This theme resonates in the agricultural context as well. Wiseman et al. (2019) found that the fear of security breaches and privacy infringements are among the leading concerns for farmers using DAAs. They discovered that a significant proportion of farmers, over 62%, indicated their unwillingness to share data with third parties, and 56% harboured scepticism towards technology providers securing their data privacy.

Further evidence of these apprehensions emerges from the research of Jakku et al. (2019), which highlighted farmers' reluctance to share data due to a perceived lack of a secure and trustworthy environment. They emphasised farmers' concerns about the absence of explicit legal measures established by the Australian government to deter security breaches. This sentiment aligns with the experiences of farmers in Bangladesh, as reported by Shi et al. (2022), who lamented their government's lack of legal governance to mitigate the risks they face. Moreover, Abrahams (2022) found that in Southern Africa, the act of sharing farm data remains a critical concern due to the country's weak governmental regulatory institutions.

Added to the concern of privacy of data is the risk of hacking and data breach which emerged as a significant concern with regard to consumer resistance and the adoption of digital applications (Mani & Chouk, 2018). Consumers expressed apprehension that their sensitive data could be exploited and used to their detriment. Similarly, Irish farmers raised concerns that supermarkets and large food corporations could acquire their sensitive data to make summations of the cost of production, thus exploiting farmers in the food chain (Regan, 2019).

The potential for cyber-attacks and hacking also influences farmers' willingness to share their data, as noted by Shi et al. (2022). Furthermore, the exploration of data to gain GPS locations of farmers poses a risk, and limits the adoption of IoT (Shi et al., 2022).

2.4.2 Perceived risks and the technical challenge

Training and support are crucial elements when transitioning to digitalisation to reduce perceived risk, as farmers' technology skills may be limited (Barrett & Rose, 2022). In a study conducted by Jakku et al. (2019) most respondents were unprepared for the new era of data-driven agriculture in terms of skills and resources, as data collection was not a customary aspect of their daily farming activities. They instead expressed greater concern regarding data transparency and ownership.

Ejdys (2018) emphasises that the ease of use and intuitiveness of a given software significantly diminishes the perceived risks associated with it. To ensure that farmers are comfortable sharing their data, it is crucial to develop user-friendly software. Smidt (2021) study indicates that many small-scale Southern African farmers grapple with low literacy levels, often compounded by insufficient training. Consequently, it was recommended that DAAs be designed in their native languages to overcome initial technical challenges.

Transitioning to DAAs, if not managed skilfully, could lead to unwarranted disruptions and loss of valuable time, as suggested by Regan (2019). This underscores the importance of ease of use in mitigating perceived risks. Shi et al. (2022) research further establishes a connection between farmers' user acceptance, perceived risk, and the technological challenges encountered in the field.

2.4.3 Perceived risk of compatibility

Incorporating digital applications into current farm management systems is perceived as a risk when sharing data (Jakku et al., 2019). This risk perception may be influenced by the relevance of the DAA to an individual farm's specific needs, as opposed to a one-size-fits-all solution (Regan, 2019). Tailoring digital solutions to cater to each farm's unique requirements could help mitigate these risks and encourage a higher level of adoption. Moreover, seamless integration with existing systems could reduce apprehension and build trust among farmers when sharing their data (Wiseman et al., 2019).

2.4.4 Perceived financial risks

The possibility of incurring expenses for digital applications without gaining valuable insights from shared data is a prevalent concern (Jakku et al., 2019). Furthermore, issues arising from the utilisation of data recommendations may have adverse effects on crop yields, thereby increasing financial risks (Barrett &

Rose, 2022). Smidt (2021) concurs, emphasising that small-scale farmers, who typically have lower income levels, cannot afford the risks associated with digital applications.

Additional evidence substantiates concerns regarding the significant financial risks associated with the adoption of digital technology in agriculture (Regan, 2019). Moreover, the study highlights the perception that the ROI and benefits derived from these technologies disproportionately favour larger farms, leaving small-scale farmers at a potential disadvantage. Shi et al. (2022) highlights the farmers’ needs for government policies to mitigate these financial risks. This is further evident in Southern Africa where a call for government support has been voiced, for business assistance to minimise risks (Abrahams, 2022).

Another factor influencing perceived financial risk according to Mani and Chouk (2018) is when an individual has an inherent predisposition to risk, particularly when significant costs are involved.

2.4.5 Hypothesis for research question two

The following hypothesis was derived from the second research question:

4. A farmer’s perceived risk negatively affects intention to share farm data on a digital agricultural application (H4).

2.5 Research Question 3: To what extent do perceived benefits impact farmer’s decisions to share data on a digital agricultural application?

Kim et al. (2008) revealed that perceived benefits could reduce risks and increase the intention to purchase. Pillai and Sivathanu (2020) supports this notion, suggesting that perceived usefulness is a key factor in technology adoption, as farmers primarily assess the usefulness of a technology before adopting it. However, Ejdys (2018) contradicts these findings, arguing that ease of use and intuitiveness of a given software form users' trust in technology, rather than its usefulness.

Jakku et al. (2019) contends that benefits are often difficult to perceive, as they may only materialise further down the line and, until then, users may face risks. Additionally, Barrett and Rose (2022) assert that there are limited tangible benefits and implementation examples, which increase risk and affect perceptions of usefulness. Recognising the benefits that outweigh the risks of using DAAs is crucial for successful adoption. One notable advantage is enhanced waste management, such as optimising plant nutrition and irrigation requirements (Barrett & Rose, 2022). By utilising digital tools, farmers could make more informed decisions, leading to more efficient resource use and waste reduction.

Regan (2019) observes that farmers aim to work smarter and achieve a better work-life balance. DAAs could support farmers in making more informed decisions, saving time, and automating tasks such as audits, budgeting and recommendations (Colizzi et al., 2020), thus mitigating the perceived risk of adopting digital technology (Wiseman et al., 2019). Pillai and Sivathanu (2020) adds that one of the reasons for adopting IoT-A is the perceived usefulness, as farmers primarily consider the usefulness of technology before adoption. Furthermore, social influence from other farmers' experiences and positive performance case studies could also reduce perceived risk of data sharing, thus increasing perceived benefits.

Another significant benefit is the customisation of crop norms to ensure optimal recommendations, thus reducing risks as feedback is tailored to individual farm needs (Vrchota et al., 2022). This customisation could help increase farm yields by providing targeted, data-driven insights into various aspects of farm management. By incorporating DAAs, farmers could access real-time information on factors such as soil health, weather patterns, and pest control, enabling them to make better-informed decisions (Vrchota et al., 2022).

Efficiently preparing for and excelling in agricultural audits within the sector could be a time-consuming process (Bland et al., 2023). Leveraging DAAs to centralise and organise data has the potential to streamline this process, allowing for fast access to information. The time benefits gained from using these digital tools may outweigh the risks associated with sharing data. Additionally, cost savings achieved through reduced labour and resource consumption are critical factors that contribute to meeting usefulness expectations in DAAs (Musa et al., 2019).

Consequently, successful implementation and demonstrable benefits from these digital tools possibly would foster trust and encourage wider adoption within the farming community (Blasch et al., 2022). Evidence of improved performance, as shared by peer farmers, could furthermore reinforce confidence in the technology and alleviate risks related to sharing sensitive data (Regan, 2019).

The perceived benefits of sharing data on a DAA, which include usefulness, ease of use, cost savings, improved decision-making and recommendations, increased efficiency, and enhanced productivity, underscore the transformative potential for farmers adopting these technologies.

2.5.1 Hypothesis for research question three

The following hypothesis was derived from the third research question:

5. A farmers' perceived benefits positively affects decisions to share farm data on a digital agricultural application (H5).

2.6 Analytical framework

2.6.1 Theoretical and conceptual framework

The trust-based consumer decision-making model in electronic commerce (Kim et al., 2008), focuses on trust, perceived risk and perceived benefits in consumer decision-making within e-commerce. Trust and perceived risk were found to be significant factors in purchasing decisions, with antecedents such as reputation, privacy and security concerns deemed helpful for this study's theoretical framework.

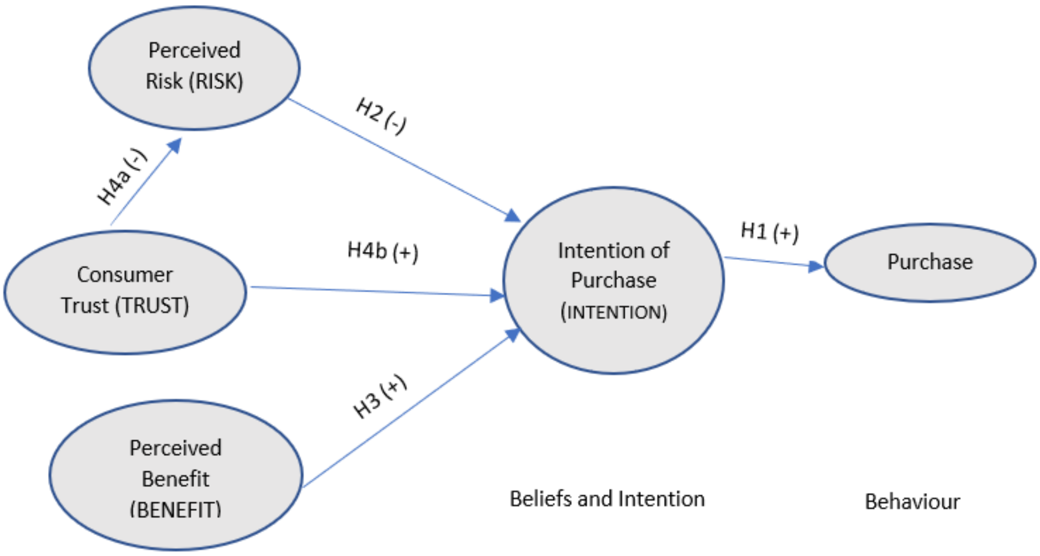


Figure 2. A trust-based consumer decision-making model in electronic commerce (Kim et al., 2008).

2.6.2 Conceptual framework

The following conceptual framework illustrates the relationships between perceived risks, perceived benefits and digital trust in digital applications. Trust was adapted to digital trust for this study, based on the definition provided by (Pietrzak & Takala, 2021).

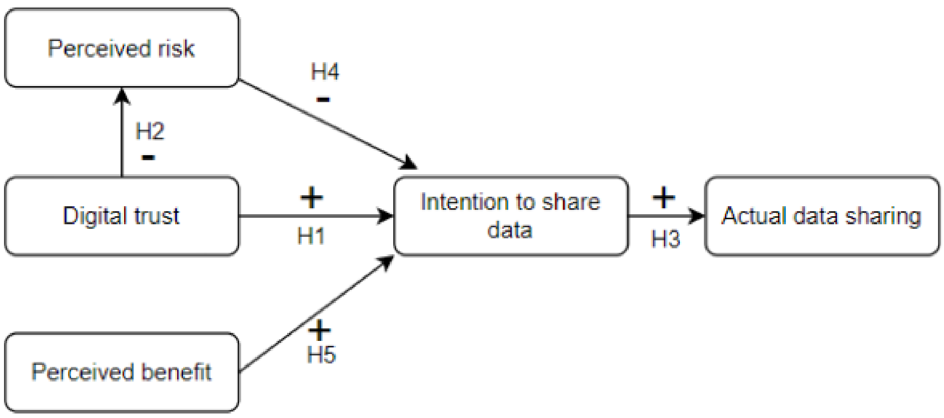


Figure 3. Conceptual framework adapted from the trust-based consumer decision-making model in electronic commerce.

2.7 Conclusion of literature review

In conclusion, it has been suggested that digital trust and willingness to share farm data on DAAs are potentially influenced by many factors. These included deviations from traditional values, peer influence, concerns regarding privacy and security, the potential for unauthorised access, control and ownership issues, ambiguous contracts and financial risks. These factors allegedly elevated perceived risks and adversely impacted farmers' digital trust. Conversely, sharing positive experiences, providing customised solutions and ensuring seamless integration with existing systems seemed to mitigate perceived risks and increase perceived benefits.

Table 1: Summary of the hypotheses

H1	Digital trust negatively affects farmers perceived risk of sharing farm data.
H2	Digital trust positively affects intention to share farm data on a digital agricultural application.
H3	Positive intention to share data has a positive influence on actual sharing of farm data on a digital agricultural application.
H4	A farmer’s perceived risk negatively affects intention to share farm data on a digital agricultural application.
H5	A farmer’s perceived benefits positively affects decisions to share farm data on a digital agricultural application.

The following chapter outlines the research methodology for the study, incorporating findings from the literature review to anchor the study in empirical and theoretical research.

3 Chapter 3 - Research Methodology

In Chapter 1 the perceived risks to data sharing among horticultural farmers in Southern Africa were introduced. A reflective review of the topic revealed the following statement of purpose:

To investigate perceptions of Southern African horticultural farmers in sharing their farm data on a digital agricultural application.

From this statement of purpose, research questions were identified as:

1. What factors of digital trust contribute to farmers deciding whether to share farm data on a digital agricultural application?
2. To what extent does perceived risk impact farmers' decisions to share farm data on a digital agricultural application?
3. To what extent do perceived benefits impact farmers' decisions to share farm data on a digital agricultural application?

Chapter 2 focused on the academic findings of various authors who conducted similar research to offer further insights into the research questions. Various themes were revealed which added a more in-depth understanding of the research question.

Chapter 3 contains the research method, research approach, research design and data collection methods, along with details of the population and sample, the research instrument, data analysis strategies and possible limitations of the study. Chapter 3 ends with a discussion about quality assurance and ethical considerations.

The majority of research analysed in the literature review, applied a quantitative research approach, using a Likert scale of 5 or 7. This method allows data to be transformed into measurable units using statistical analyses, as defined by Malhotra et al. (2017). The research instrument for this study has been influenced by the reviewed literature and their research design.

Data from the proposed study was analysed using a combination of descriptive and inferential statistical techniques. This approach facilitated the comprehension of relationships amongst differing variables by deploying illustrative tools such as graphs, tables and numerical statistical representations.

3.1 Research approach

This study employed a quantitative research approach due to the necessity to understand the nature of various variables and their interrelationships. Utilising descriptive statistical analysis and inferential statistical analysis facilitates the understanding of these relationships, as they present data in an easy-to-interpret format such as graphs, tables, and numerical statistics (McGivern, 2013). These methods are particularly advantageous when dealing with large samples such as the one in the study, as they allowed for efficient data analysis. Furthermore, a quantitative approach minimises bias since it involves limited researcher intervention (McGivern, 2013).

3.2 Research design

According to McGivern (2013) the purpose of the research design is to address the research problem in a robust manner to ensure credibility of your findings. Furthermore, the research data gathering tools, the sampling approach and data analysis must be guided by the chosen research method as validity of the findings hinges on how well the research, method and questions address the research problem.

The study adopted a quantitative research method as it required the collection and analysis of numerical and statistical data (McGivern, 2013) from a sample of 260 farmers and agronomists using a DAA. According to the Oxford Dictionary, an agronomist is a scientist who studies the relationship between crops and the environment. However, the constraints of quantitative research include challenges in uncovering deep motivations and emotions due to its structured and inflexible question design (Malhotra et al., 2017).

3.3 Data collection methods

Data collection was done via online survey questionnaire. The structured self-completion survey questionnaire, designed for quantitative analysis, will facilitate a statistical examination of the relationships among the different variables (Meadows, 2003).

According to Malhotra et al. (2017) high speed, low cost and perceived anonymity are some of the key benefits of an online quantitative research survey which marry the requirements of the current research, namely, limited time and money plus the confidentiality of respondents’ feedback. Furthermore, McGivern (2013) emphasises that they are relatively easy to set up, data is collected and captured automatically which saves time, plus you could monitor the response rate effortlessly due to the inherent digital nature of this method.

Unfortunately, the limitations include the challenge of delving deeper into answers as well as the need to account for potentially low response rates as respondents may either be too busy, or the emails could end up in their spam folders (McGivern, 2013). However, the convenience and speed of online surveys are contributing to their growing popularity. To mitigate this limitation, the email's subject line communicated the importance of the recipient's contribution to this brief, plus the time required for the survey. For example: Help Shape the Future of Data Privacy in SA Horticulture: Quick 5-Minute Survey.

Factors such as inaccurate mailing lists and computer security issues also need to be managed (Cooper & Schindler, 2014). Online surveys, according to Minnaar and Heystek (2013), might seem impersonal or even mistaken for spam. Moreover, without open-ended questions, there is a risk of not fully capturing the respondents' sentiments and experiences (Meadows, 2003). To address these issues, the accuracy of the mailing list was ensured by the users' regular logins to update their information. Additionally, the emails were designed to be perceived not as spam, but as a notification from the software that they use.

All three research questions required quantitative data, using the same data gathering tool. In the literature review, Likert rating scales were predominantly used.

The survey questionnaire was emailed to all respondents along with an informational cover letter. Prior to this a pilot study of three potential respondents completed the survey and provided feedback. Once changes were made, it was sent to all 260 users of the digital agricultural application with the covering letter explaining the process.

3.4 Population and sample

Population:

The population of this study was agronomists and farmers using a specific digital agricultural application for precision farming in Southern Africa. Since the entire population of 260 users was selected, it was a census approach. A census strives to gather data from every individual within a specific population that is of interest to the study, like university students in a specific class (Young, 2016). A census research approach sends information to all available members of an entire population (Schutt, 2022). Furthermore, a complete census eliminates the need for sampling but is often too resource-intensive for large populations (Schutt, 2022). However, the sample size of 260 was deemed manageable.

In this study, the sample encompassed the entire user population, so total population sampling is applicable. Lærd (2012) explains that total population sampling involves selecting an entire group with specific characteristics for a study. This method involves analysing the entire population with these traits. For this study, the census targeted all 260 horticultural farmers and agronomists in Southern Africa using the same DAA.

3.5 Research instrument

The research instrument was an online self-completion survey questionnaire consisting of 19 questions. Previous research was reviewed to enable structuring of research survey questions to ensure the study was based on evidence. Unfortunately, the average response rates for e-mail surveys is usually low (Malhotra et al., 2017) but could be increased if the survey was seen by the respondent as conducted by an academic institution and the topic was both relevant and significant. Furthermore, by limiting the number of questions, ensuring they are sequenced, clear and straightforward, plus avoiding ambiguity, could positively influence response rates. Also, appropriate questionnaire design could contribute to a higher response rate (Fan & Yan, 2010).

A table of research questions and related hypotheses, with the literature references for each survey question can be found in **Appendix A.**

All questions were based on a five-point Likert scale. Descriptive statistical analysis and inferential statistical analysis will then be applied using IBM SPSS version 28.0.1.0, in order to first describe the data collected in the study, then make broader conclusions or predictions based on that data (Young, 2016).

3.6 Procedure for data collection.

Survey questionnaires were distributed to all respondents via email. Initially, the owner of the DAA notified the respondents about the upcoming research survey, soliciting their participation and support. Following this, the potential respondents were sent a comprehensive email, explaining the aim of the research and its possible impact on data privacy laws and regulations in Southern Africa. Furthermore, they were assured that their anonymity will be preserved. The surveys were then securely stored in a password-protected file on the researcher's desktop to prevent any potential breaches.

The survey consisted of nineteen questions, offering options of 'agree', 'disagree', and 'neutral', among others. It was designed to be brief and straightforward, requiring a completion time of approximately ten minutes.

3.7 Data analysis strategies

McGivern (2013) states that the purpose of analysing data is to add value to the research, revealing reliable and valid information to help solve the research question. Furthermore, by employing descriptive and inferential statistical analyses, response levels could be viewed in an interpretable manner. Descriptive statistics allows for a summarised view of the data through measures such as mean, median, and mode (McGivern, 2013). The mean response could potentially show the average perceived risk of sharing data amongst respondents, while the mode could highlight the most common perception towards data sharing. Descriptive statistics also involve the use of visual tools like graphs, tables, and charts which could assist in revealing a representation of the responses.

In addition to descriptive statistics, the study also included inferential statistical analysis, a method which allows inference of characteristics from the sample data to a larger population, and is used for testing hypotheses (McGivern, 2013). This form of analysis could help to determine if the perceived risks (independent variable) significantly affect the likelihood of sharing data (dependent variable) in the selected target population (McGivern, 2013), which is all the horticultural farmers using the same DAA. The results could potentially be inferred to the whole sample as the census included all 260 farmers.

Correlation analysis then evaluated the strength and direction of the relationship between the constructs. A correlation could be positive (both variables increase together), negative (as one variable increases, the other decreases), or neutral (no relationship) (Hair et al., 2019).

Inferential analysis comprised of correlation analysis and regression analysis. Regression analysis assisted in the examination of the relationship between the dependent variable and the various independent variables identified in the study (Hair et al., 2019).

A key component of regression analysis included the use of 'R squared' value (McGivern, 2013), which indicates how much of the variance in the dependent variable (sharing data) could be explained by the independent variable (perceived risks) and gives an indication of the goodness of fit of the conceptual model. A goodness of fit is defined by Hair et al. (2019, p. 605) as a “measure indicating how well a specified model structure reproduces the covariance matrix among the indicator variables, alternatively, the accuracy of a proposed theory”.

The variables selected from Kim et al. (2008) consist of three main constructs and their relation on Intention to Purchase, which for the purpose of this study was adapted to Intention to Share Data.

Table 2 identifies the constructs and relationships inferred to the conceptual model, which have been derived from Kim et al. (2008). The five hypotheses for this study have been extrapolated from Kim et al. (2008) and in Chapter 5, the relationships will be compared to their findings.

Table 2: PR Model (Kim et al., 2008) variables and relationships, inferred to the proposed conceptual model comparison table.

PR Model (Kim et al., 2008)	Relationship	Construct	Conceptual Model	Relationship	Construct
Perceived **RISK**	-	**INTENTION** to purchase	Perceived **RISK**	-	**INTENTION** to share data
Consumer **TRUST**	+	**INTENTION** to purchase	Digital **TRUST**	+	**INTENTION** to share data
Perceived **BENEFIT**	+	**INTENTION** to purchase	Perceived **BENEFIT**	+	**INTENTION** to share data
Consumer **TRUST**	-	Perceived **RISK**	Digital **TRUST**	-	Perceived **RISK**
INTENTION to purchase	+	PURCHASE	**INTENTION** to share data	+	ACTUAL sharing of data

3.8 Possible limitations

Cooper and Schindler (2014) caution that any research report lacking stated limitations should invite scrutiny regarding its validity. Researchers should also consider the potential effects these limitations might have on their studies.

A drawback of a single-cross sectional research design is that it gathers data from a particular sample only once, instead of over a prolonged period as done in longitudinal studies. Consequently, this approach might not capture varying responses that could potentially arise at different times (Malhotra et al., 2017).

An additional significant constraint of the study lies in the respondents' concerns over data privacy (McGivern, 2013). This concern is notably intriguing given that the study is about understanding the perceived risks associated with sharing farm data on a DAA.

3.9 Quality assurance

3.9.1 External validity (generalisability)

Generalisability, as articulated by Malhotra et al. (2017), pertains to the extent to which findings from a specific sample could be extrapolated to the broader population. This study focused on a specific demographic: 260 farmers and agronomists using a DAA. All these individuals were selected as respondents in this survey. It is crucial to state, however, that the results and implications derived from this study are only generalisable within the confines of this sample group, which are horticultural farmers and agronomists operating within Southern Africa. This limitation is noteworthy when considering the application and broader relevance in the agricultural sector of the research findings.

3.9.2 Internal validity

Research validity (Cooper & Schindler, 2014, p. 257) pertains to the aptitude of the research "to accurately capture what it purports to measure". According to McGivern (2013), the concept of internal validity is concerned with the integrity of the measurement tool and the questions posed by the researcher. Furthermore, it questions whether the observed changes in the dependent variable (sharing data) are due to the manipulation of the independent variable (perceived risks), and not due to the influence of confounding variables.

The questions employed in this study were formulated based on previously validated constructs and outcomes of similar empirical studies. The research design thus enhanced construct validity. In addition, an analysis of the results from pretesting of the research instrument offered valuable insights into the viability of the research design and its measures, enhancing construct validity (McGivern, 2013).

3.9.3 Reliability

Cooper and Schindler (2014, p. 260) argue that the reliability of a research design is evaluated based on its capacity to yield consistent results. Large sample sizes obtained through a quantitative research methodology typically offer controlled, consistent responses, hence increasing reliability (McGivern, 2013). As the data collection instrument used in the research was a quantitative questionnaire survey delivered with predetermined answers using SPSS software, the responses were standardised, and captured automatically, thereby enhancing research reliability.

However, the reliability of the research may be compromised if the predetermined responses in the questionnaire do not align with the research questions (Hair et al., 2019) or if the respondents do not comprehend them (McGivern, 2013). To address these potential issues, a pilot test was carried out with three potential respondents from the sample group, who did not form part of the final data collection. This approach allowed for any required modifications to be made to both the questions and the established responses.

3.10 Ethical considerations

Informed consent was acknowledged online, before respondents began the questionnaire. The data provided by all respondents in this study will be kept confidential. Personal identifiers will be anonymised. Data will be stored in a password-protected electronic format on researcher’s desktop. There were no known risks to participating in this study. Responses were anonymous and cannot be linked back to respondents. Also, in respect of their contribution, and to improve transparency, results will be shared with respondents but in a way that does not breach privacy or confidentiality. Additionally, the researcher applied for ethical clearance with the University of Witwatersrand and was granted permission to collect data for the study.

3.11 Conclusion

In Chapter 3, the methodology employed to study the perceptions of Southern African horticultural farmers regarding the sharing of their farm data through a digital agricultural application (DAA) was outlined. This chapter delved into the quantitative research approach, the design, and various data collection methods that had been systematically chosen to ensure the credibility and reliability of the findings. By leveraging a structured online survey questionnaire, which was influenced by prior academic works and designed to extract measurable data, the study aimed to uncover the various factors that influenced farmers' decisions to share data. The analysis of the data through descriptive and inferential statistical techniques enabled an examination of the extent to which perceived risks, benefits, and digital trust affected these decisions. Moreover, the chapter detailed the research's scope by clarifying the population and sample size, consisting entirely of the user base of the DAA, thus allowing for a detailed census approach within this specific demographic.

4 Chapter 4 - Data Analysis

4.1 Introduction

In this chapter, the results obtained from the data analyses are presented, with a focus on the topic of perspectives of South African horticulture farmers using a DAA. The core of the study centres on understanding these farmers' perceptions and reservations about sharing their farm data on this particular platform.

The logic and flow of the analysis was as follows:

- Data Screening: involved preliminary analysis to ensure data quality. This included checking for missing values, outliers and ensuring that data meets the assumptions necessary for further analysis (McGivern, 2013). This step provided the foundation for all subsequent analyses.
- Factor Analysis: After ensuring the data was clean, factor analysis was performed to explore the underlying structure of the data. This involved identifying latent variables (factors) that explain the patterns of correlations within the set of variables. This step was crucial for reducing data complexity and identifying construct validity (Field, 2018).
- Communalities: examines how much of each variable's variance is explained by the extracted factors from the factor analysis (Field, 2018). It follows after factor analysis, to help understand the contribution of each variable to the identified factors.
- Pattern Matrix: A key output of factor analysis. It shows the correlations (loadings) of each variable on the extracted factors to understand how variables contribute to, or are influenced by, different factors (Malhotra et al., 2017). It follows on from communalities, focusing more on the relationships between variables and factors.
- Cronbach’s Alpha: Examines the internal consistency of the scales/factors identified. Cronbach's Alpha is a measure of reliability, or how closely related a set of items are as a group. It follows on from factor analysis to ensure the factors or scales used in research are reliable (Field, 2018).

- Non-parametric correlations: After establishing the reliability of the constructs, the relationships between the constructs were explored using non-parametric correlations. This step helps in understanding the strength and direction of associations between your variables (Malhotra et al., 2017).
- Regression Analysis: to understand how variables predict or are associated with each other. This is where the hypotheses were tested, examining the impact of independent variables on dependent variables, controlling for other factors (Malhotra et al., 2017).
- Finally, a summary of the findings per hypotheses is presented.

4.2 Data screening

From the total sample of 260 users of the digital agricultural app, 89 responses were received (34%). Post data cleaning, only 61 of these responses were considered valid for the study due to missing data. A 23% response rate was achieved in this study, surpassing the typical response rate of 10% or less for online survey questionnaires, as noted by McGivern (2013). Furthermore, Malhotra et al. (2017, p. 283) had observed that “online surveys can have very poor response rates – very frequently under 10%”. Brtnikova et al. (2018) found that online surveys typically generated less than a 30% response when incentives were not provided, which was the case with this study. Daikeler (2020) discovered a consistent discrepancy in response rates between online web surveys and traditional methods, with a mean response rate difference of 12 percentage points. Additionally, Han et al. (2019) noted that the mode of data collection was a significant factor, with the lowest response rates for online surveys being 24%. Thus, the 23% response rate obtained after data cleaning was considered acceptable for this research.

All 260 users of the DAA were given an equal opportunity to respond. Due to the anonymity of the farmers, no specific demographic details about the respondents were explored in this study.

The initial conceptual framework was built around five core constructs: Perceived Risk (PR), Perceived Benefit (PB), Digital Trust (DT), Intention to Share Data (ITSD), and Actual Sharing of Data (ASOD). To confirm the validity of these constructs and the classification of survey questions within the study, a Factor Analysis was performed. The initial version of Table 3 aligns the survey questions with various constructs based on insight from a literature review. Further in the chapter, the study will explore the 'Grouping after Factor Analysis' column. This section reveals misalignments in how survey questions were originally associated with each construct.

Table 3: Analysis of survey questions grouping to constructs

SQ	**SQ and Hypothesis Initial Grouping**	**Factor Analysis: Grouping**				
	CONSTRUCTS:	PB	DT	PR	ITSD	ASOD
H1	**Hypothesis 1: Digital trust positively affects intention to share farm data on a digital agricultural application.**					
1	H1a - If other farmers in the community recommend using the digital agricultural app, I would be more likely to share my farm data.					
2	H1b - The experiences of other farmers using the digital agricultural app influence my decisions to share my farm data.					
3	H1c - The reputation of the digital agricultural app service provider plays a significant role in my decision to share my farm data.					
4	H1d - When considering sharing my farm data it is important that the digital agricultural app clearly communicates its data privacy policies and ownership.					
5	H1e - When considering sharing my farm data on the digital agricultural app, it is important that I have control over my farm data.					
6	H1f - Having a positive experience using the digital agricultural app is important in deciding whether I should share my farm data.					
H2	**Hypothesis 2: Digital trust negatively affects famers perceived risk of sharing farm data on a digital agricultural application.**					
7	H2a - The attitude of my peers towards sharing my farm data in precision farming is an important factor.					

8	H2b - The attitude of the end consumer towards my decision to share my farm data for precision farming is an important consideration.					
H3	**Hypothesis 3: Positive intention to share farm data has a positive influence on actual sharing of farm data on a digital agricultural app.**					
9	H3a - Positive interaction with the current digital agricultural app will encourage me to continue using it for the next crop season.					
H4	**Hypothesis 4: A farmers perceived risk negatively affects intention to share farm data on a digital agricultural application.**					
10	H4a - The digital agricultural app's data security measures are critical when deciding whether to share my farm data.					
11	H4b - I will still share my farm data on the digital agricultural app if it is shared with third parties.					
12	H4c - If I felt more confident in my ability to navigate technical issues with the digital agricultural app, I would be more willing to share my farm data.					
13	H4d - The risk of software compatibility on the digital agricultural app to my current IT infrastructure plays a significant role in my decision to share my farm data.					
14	Reversed: H4e - I worry that sharing my farm data on the digital agricultural app could make me vulnerable to financial loss.					
H5	**Hypothesis 5: A farmers perceived benefits positively affect decisions to share farm data on a digital agricultural application.**					
15	H5a - The perceived benefits I gain from using the digital agricultural app increase my willingness to share my farm data.					
16	H5b - The improved farm management decision making benefits I gain from using the digital agricultural app increase my willingness to share my farm data.					
17	H5c - If I believed that sharing more of my farm data would enhance irrigation and fertiliser optimisation, I would be more inclined to share additional sensitive data on the digital agricultural app.					
18	H5d - Positive feedback on the benefits of using the digital agricultural app, from other farmers, will encourage me to share my farm data.					
19	H5e - The benefits of ease of use impact my decision to share my farm data on the digital agricultural app.					

The initial alignment of survey questions with the constructs of the conceptual framework was found to be inappropriate for this study. Furthermore, later in this chapter, it is revealed through Factor Analysis that the fifth construct, Actual Sharing of Data, was not a valid construct for this research. Consequently, the survey questions needed to be reorganised according to the grey blocks on the right side of Table 3 in relation to each construct.

4.3 Factor Analysis

Factor analysis is a method that aims to simplify a large amount of data. It does this by finding the smallest number of key concepts (called variables or factors) that could explain most of the shared differences (common variance) seen when different items are compared. They work together to validate the structure of the factors and ensure that the data is suitable for analysis (Field, 2018).

The following tests were used in the Factor Analysis for this study:

- KMO (Kaiser-Meyer-Olkin) and Bartlett's© Test
- Principal Axis Factoring (PAF)
- Communalities
- Eigenvalues and Rotation Sums of Squared Loadings
- Pattern Matrix using Principal Axis Factoring and Rotation Method

Table 4: Factor Analysis: KMO and Bartletts Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,827
Bartlett's Test of Sphericity	Approx. Chi-Square	540,513
	Df	171
	Sig.	0,000

IBM SPSS Factor Analysis KMO and Bartletts Test

The Kaiser-Meyer-Olkin (KMO) index assesses the suitability of data for factor analysis (Field, 2018). Furthermore, it is suggested that Kaiser's criterion tends to be reliable when there are fewer than 30 variables and the communalities (values derived after extraction) exceed 0.7. This indicates that under these specific conditions, Kaiser's method for factor analysis could be considered accurate.

A KMO value closer to 0 suggests a large proportion of partial correlations relative to the total correlations, implying a dispersed correlation pattern that typically renders factor analysis inadvisable. Conversely, a KMO value nearing 1 suggests more pronounced correlation patterns, indicating that factor analysis is likely to identify clear and reliable factors. The KMO value was 0.827, suggesting that the dataset was “Meritorious” for factor analysis (Field, 2018, p. 1014).

Bartlett’s Test of Sphericity checks if the variance-covariance matrix resembles an identity matrix, which means it assesses if the covariances among variables are essentially zero and if the variances (the values on the matrix's diagonal) are approximately the same. A significant test (i.e., a low level of significance), indicates that the observed correlation matrix is not an identity matrix (Field, 2018). The significance (Sig.) level is 0.000. This is less than the typical threshold of 0.05, indicating that the test is significant. This means that there were some relationships between the variables, and it was acceptable to proceed with the factor analysis.

A Chi-Square statistic needs to be evaluated in the context of its degrees of freedom to determine the statistical significance of the observed association (Field, 2018). By comparing the calculated Chi-Square statistic to a critical value from the Chi-Square distribution for 171 degrees of freedom, “the degrees of freedom relate to the number of observations that are free to vary” (Field, 2018, p. 106), it will reveal whether the association observed could be due to chance or if it is statistically significant. The Chi-Square statistic for this test was 540,513 with 171 degrees of freedom which is likely to be significant, indicating a very low probability that the observed distribution is due to random chance. This typically leads to a rejection of the null hypothesis, which usually states that there is no association between the variables under investigation.

In summary, Table 4 suggests that the dataset was appropriate for factor analysis based on the KMO measure and the significant Bartlett's Test of Sphericity.

4.4 Communalities

Table 5 below offers an understanding of the degree to which each statement (survey question) corresponds with the underlying constructs or factors that have been uncovered through Principal Axis Factoring. According to Field (2018), statements that possess communalities greater than 0.3 align more effectively with the factors that have been identified, indicating a stronger connection with the central themes or patterns present in the data. Conversely, statements that exhibit communalities less than 0.3 may not integrate as well with these foundational themes or constructs.

All statements had communalities exceeding the 0.3 threshold, and were therefore considered appropriate for the analysis.

Table 5: Communalities (Initial)

H1b - The experiences of other farmers using the digital agricultural app influence my decisions to share my farm data.	0,403
H1c - The reputation of the digital agricultural app service provider plays a significant role in my decision to share my farm data.	0,532
H1d - When considering sharing my farm data it is important that the digital agricultural app clearly communicates its data privacy policies and ownership.	0,508
H1e - When considering sharing my farm data on the digital agricultural app, it is important that I have control over my farm data.	0,591
H1f - Having a positive experience using the digital agricultural app is important in deciding whether I should share my farm data.	0,549
H2a - The attitude of my peers towards sharing my farm data in precision farming is an important factor.	0,564
H2b - The attitude of the end consumer towards my decision to share my farm data for precision farming is an important consideration.	0,529
H3a - Positive interaction with the current digital agricultural app will encourage me to continue using it for the next crop season.	0,629
H4a - The digital agricultural app's data security measures are critical when deciding whether to share my farm data.	0,630
H4b - I will still share my farm data on the digital agricultural app if it is shared with third parties.	0,381
H4c - If I felt more confident in my ability to navigate technical issues with the digital agricultural app, I would be more willing to share my farm data.	0,604
H4d - The risk of software compatibility on the digital agricultural app to my current IT infrastructure plays a significant role in my decision to share my farm data.	0,383
H4e - I worry that sharing my farm data on the digital agricultural app could make me vulnerable to financial loss.	0,397
H5a - The perceived benefits I gain from using the digital agricultural app increase my willingness to share my farm data.	0,666
H5b - The improved farm management decision making benefits I gain from using the digital agricultural app increase my willingness to share my farm data.	0,632
H5c - If I believed that sharing more of my farm data would enhance irrigation and fertiliser optimisation, I would be more inclined to share additional sensitive data on the digital agricultural app.	0,617

H5d - Positive feedback on the benefits of using the digital agricultural app, from other farmers, will encourage me to share my farm data.	0,684
H5e - The benefits of ease of use impact my decision to share my farm data on the digital agricultural app.	0,706
H1a - If other farmers in the community recommend using the digital agricultural app, I would be more likely to share my farm data.	0,647

IBM SPSS Extraction Method: Principal Axis Factoring.

4.5 Eigenvalues and Rotated Sums of Squared Loading in Total Variance Explained

Table 6: Total Variance Explained

Total Variance Explained				
	Initial Eigenvalues			Rotation Sums of Squared Loadings[a]
Factor	Total	% of Variance	Cumulative %	Total
1	6,340	33,367	33,367	4,387
2	2,788	14,674	48,040	3,144
3	1,803	9,489	57,530	2,675
4	1,309	6,888	64,418	3,156
5	0,883	4,650	69,068	
6	0,846	4,453	73,520	
7	0,693	3,650	77,170	
8	0,646	3,402	80,572	
9	0,597	3,141	83,713	
10	0,477	2,510	86,223	
11	0,454	2,392	88,616	
12	0,402	2,118	90,733	
13	0,382	2,013	92,746	
14	0,299	1,571	94,318	
15	0,259	1,361	95,679	
16	0,252	1,324	97,003	
17	0,217	1,143	98,146	
18	0,194	1,019	99,165	
19	0,159	0,835	100,000	

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

The results in Table 6 reveal that the first four factors had eigen values exceeding one, signifying that they account for a substantial portion of the variance within the dataset. The subsequent factors demonstrated overlapping variances. An eigenvalue represents the total variance explained by each factor. It helps in determining the number of factors to retain. A common criterion for retaining a factor is that its eigenvalue should be greater than one (Malhotra et al., 2017). This is a process that simplifies the interpretation of the factors after extraction. It redistributes the variance associated with the original factors to make the structure easier to interpret

The first four factors accounted for a substantial portion of the variance within the dataset showing strong and meaningful constructs in the context of this study. The subsequent factors demonstrated overlapping variances which may not be measuring distinct constructs thus the additional factors did not contribute unique or significant insight into the data structure. Further exploration of the overlapping variances among the subsequent factors may therefore have been necessary, by reviewing the variables allocated to the constructs.

4.6 Pattern Matrix

The following pattern matrix table reveals the grouping of the survey questions to constructs in this research after applying Principal Axis Factoring (PAF) and Oblimin with Kaiser Normalization Rotation Method.

Table 7: Pattern Matrix using Principal Axis Factoring and Rotation Method: Oblimin with Kaiser Normalization.

Pattern Matrix[a]

Survey Question	Factor			
	PB	DT	PR	ITSD
H5d - Positive feedback on the benefits of using the digital agricultural app, from other farmers, will encourage me to share my farm data.	0,702			
H1a - If other farmers in the community recommend using the digital agricultural app, I would be more likely to share my farm data.	0,680			
H5c - If I believed that sharing more of my farm data would enhance irrigation and fertiliser optimisation, I would be more inclined to share additional sensitive data on the digital agricultural app.	0,602		-0,402	
H5a - The perceived benefits I gain from using the digital agricultural app increase my willingness to share my farm data.	0,565			
H1b - The experiences of other farmers using the digital agricultural app influence my decisions to share my farm data.	0,540			
H1e - When considering sharing my farm data on the digital agricultural app, it is important that I have control over my farm data.		0,744		
H1d - When considering sharing my farm data it is important that the digital agricultural app clearly communicates its data privacy policies and ownership.		0,720		
H4a - The digital agricultural app's data security measures are critical when deciding whether to share my farm data.		0,681		
H2a - The attitude of my peers towards sharing my farm data in precision farming is an important factor.		0,590		
H1f - Having a positive experience using the digital agricultural app is important in deciding whether I should share my farm data.		0,461		
H3a - Positive interaction with the current digital agricultural app will encourage me to continue using it for the next crop season.			-0,665	
H1c - The reputation of the digital agricultural app service provider plays a significant role in my decision to share my farm data.			-0,654	

H5b - The improved farm management decision making benefits I gain from using the digital agricultural app increase my willingness to share my farm data.			-0,518	
Reversed: H4e - I worry that sharing my farm data on the digital agricultural app could make me vulnerable to financial loss.			-0,430	
H2b - The attitude of the end consumer towards my decision to share my farm data for precision farming is an important consideration.				-0,688
H4c - If I felt more confident in my ability to navigate technical issues with the digital agricultural app, I would be more willing to share my farm data.				-0,679
H5e - The benefits of ease of use impact my decision to share my farm data on the digital agricultural app.	0,421			-0,535
H4d - The risk of software compatibility on the digital agricultural app to my current IT infrastructure plays a significant role in my decision to share my farm data.				-0,526
H4b - I will still share my farm data on the digital agricultural app if it is shared with third parties.				-0,418
Cronbach's Alpha	**0.806**	**0.815**	**0.661**	**0.748**

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 23 iterations.

The original groupings underwent significant changes regarding the survey and its constructs. Notably, the construct of ASOD was not deemed valid for this study. The test results indicated that the survey questions initially linked to this construct were more relevant to the Perceived Risk construct, leading to the conclusion that Actual Sharing of Data did not constitute a valid construct in this context. Thus, construct ASOD, which was evaluated through survey question H3a and initially included in Hypothesis 3, was unnecessary for the scope of this study. Consequently, the analysis was streamlined to include only four constructs and four corresponding hypotheses.

The Pattern Matrix results were used to decipher the factors of each survey question and pertinent constructs (Field, 2018). The results identified four key components: Perceived Benefits (PB), Perceived Risk (PR), Digital Trust (DT), and the Intention to Share Data (ITSD).

In Table 7 the variables observed, and their correlations to the four factors, are represented in the columns titled 'PB', 'DT', 'PR', and 'ITSD’.

The rows list various statements (e.g., H5d, H1a) about farmers' decisions to share their farm data on a DAA.

The numbers in the table are factor loadings, which are correlations between the statements and the factors. These loadings help determine the extent to which each statement "belongs" to each factor. A high absolute value (close to 1 or -1) means that the statement strongly relates to that factor. Positive loadings indicate a direct relationship, while negative loadings suggest an inverse relationship (Malhotra et al., 2017).

The range for Perceived Benefit (PB) was 0.702 to 0.540, with the strongest correlation identified in H5d (loading of 0.702). This indicates that positive feedback from other farmers regarding the benefits of the application was highly associated with this factor. Conversely, H1b exhibited the lowest correlation, implying a less significant link between PB and how other farmers' positive experiences influence the decision to share farm data.

For Digital Trust (DT), the range was 0.744 to 0.461. The strongest correlation was found in H1e (loading of 0.744), suggesting that farmers' ability to control their farm data was closely related to Digital Trust. On the other hand, H1f had the lowest correlation, indicating a weaker association between DT and how positive experiences impact the sharing of farm data.

The range for Perceived Risk (PR) was 0.665 to 0.430, with the highest correlation in H3a (loading of 0.665). This suggests that positive interactions with the current digital application reduce PR and encourage farmers to share their crop data for the upcoming season. H4e showed the weakest link to PR, relating to the vulnerability to financial loss when sharing farm data. This survey question was also reverse-scored due to its negative phrasing as per survey question in Kim et al. (2008) to align with other survey questions in this study.

Lastly, the range for Intention to Share Data (ITSD) was -0.688 to -0.418 (inverse relationships). The strongest correlation was with H2b (loading of 0.688), indicating that consumer attitudes towards farmers sharing their data impact their intention to share data. Conversely, H4b presented the lowest correlation, suggesting a weaker relationship between ITSD and the sharing of data with third parties.

Table 8: Revised grouping and ordering of initial survey questions by constructs and hypotheses.

SQ	SQ and Hypothesis Grouping After Factor Analysis	Grouping after Factor Analysis				
	CONSTRUCTS:	PB	DT	PR	ITSD	~~ASOD~~
	Hypothesis 1: Digital trust positively affects intention to share farm data on a digital agricultural application. (ITSD)					
8	H2b - The attitude of the end consumer towards my decision to share my farm data for precision farming is an important consideration.					
11	H4b - I will still share my farm data on the digital agricultural app if it is shared with third parties.					
12	H4c - If I felt more confident in my ability to navigate technical issues with the digital agricultural app, I would be more willing to share my farm data.					
13	H4d - The risk of software compatibility on the digital agricultural app to my current IT infrastructure plays a significant role in my decision to share my farm data.					
19	H5e - The benefits of ease of use impact my decision to share my farm data on the digital agricultural app.					
	Hypothesis 2: Digital trust negatively affects famers perceived risk of sharing farm data on a digital agricultural application. (DT)					
7	H2a - The attitude of my peers towards sharing my farm data in precision farming is an important factor.					
10	H4a - The digital agricultural app's data security measures are critical when deciding whether to share my farm data.					
4	H1d - When considering sharing my farm data it is important that the digital agricultural app clearly communicates its data privacy policies and ownership.					
5	H1e - When considering sharing my farm data on the digital agricultural app, it is important that I have control over my farm data.					
6	H1f - Having a positive experience using the digital agricultural app is important in deciding whether I should share my farm data.					

	~~**Hypothesis 3: Positive intention to share farm data has a positive influence on actual sharing of farm data on a digital agricultural app.**~~					
	Hypothesis 4: A farmers perceived risk negatively affects intention to share farm data on a digital agricultural application. (PR)					
3	H1c - The reputation of the digital agricultural app service provider plays a significant role in my decision to share my farm data.					
9	H3a - Positive interaction with the current digital agricultural app will encourage me to continue using it for the next crop season.					
14	Reversed: H4e - I worry that sharing my farm data on the digital agricultural app could make me vulnerable to financial loss.					
16	H5b - The improved farm management decision making benefits I gain from using the digital agricultural app increase my willingness to share my farm data.					
	Hypothesis 5: A farmers perceived benefits positively affect decisions to share farm data on a digital agricultural application. (PB)					
1	H1a - If other farmers in the community recommend using the digital agricultural app, I would be more likely to share my farm data.					
2	H1b - The experiences of other farmers using the digital agricultural app influence my decisions to share my farm data.					
15	H5a - The perceived benefits I gain from using the digital agricultural app increase my willingness to share my farm data.					
17	H5c - If I believed that sharing more of my farm data would enhance irrigation and fertiliser optimisation, I would be more inclined to share additional sensitive data on the digital agricultural app.					
18	H5d - Positive feedback on the benefits of using the digital agricultural app, from other farmers, will encourage me to share my farm data.					

Table 8 demonstrates the adjustments made to the initial selection and alignment of survey questions with hypotheses, which were guided by insights from the literature review and the theoretical model (Kim et al., 2008). The need for these modifications may be attributed to several unique aspects of the study's context. Firstly, the study is set in Southern Africa in 2023 and focuses on farmers, whereas the theoretical model was based on consumers perceived risks of shopping online in Singapore 2008 (468 respondents of active online consumers that purchased products at least once online in twelve months, and their average self-rated internet experience was 5.52 on a 7 point Likert scale, 7 being expert) (Kim et al., 2008). Secondly, the respondents for this study were already daily users of a specific DAA, indicating their adoption of the technology. Kim et al. (2008) respondents were selected based on internet use within twelve-months. Lastly, the researcher's limited experience in constructing questionnaires and ensuring their accurate alignment with survey questions, constructs, and hypotheses from the beginning to the end of the research, may have contributed to the need for these adjustments.

4.7 Cronbach’s Alpha

Cronbach’s Alpha measures how closely related a set of items are as a group which is the most common measure of scale reliability (Field, 2018).

It ranges from 0 to 1, with higher values indicating greater reliability. Cronbach's Alpha of 0.7 or above is considered acceptable (Field, 2018).

Testing the Reliability for each construct explanation

The following results have been placed in block format for ease of use.

PB Reliability Statistics

Cronbach's Alpha	N of Items
.806	5

PB: An alpha of 0.806 suggests a good level of reliability. Thus, the five variables had a good level of internal consistency, making it a relatively reliable measure for PB.

DT Reliability Statistics

Cronbach's Alpha	N of Items
.815	5

DT: An alpha of 0.815 suggests a good level of reliability. Thus, the five variables had a good level of internal consistency, making it a relatively reliable measure for DT.

PR Reliability Statistics

Cronbach's Alpha	N of Items
.661	4

PR: An alpha of 0.661 suggests moderate reliability. Thus the 4 variables have a moderate level of internal consistency, making it somewhat related to each other but not be fully capturing the same underlying construct.

ITSD Reliability Statistics

Cronbach's Alpha	N of Items
.748	5

ITSD: An alpha of 0.748 suggests a good level of reliability. Thus, the five variables had a good level of internal consistency, making it a relatively reliable measure for ITSD.

4.8 Descriptive Statistics

Table 9: Descriptive Statistics

	N	Std. Deviation	Skewness	Kurtosis
Perceived Benefit	61	.92867751	-.723	1.059
Digital Trust	61	.92681937	.751	.515
Perceived Risk	61	.89592722	.304	-.335
Intention to Share Data	61	.90915431	-1.039	1.520
Valid N (listwise)	61			

Table 9 above presents various statistical measures for four different variables: Perceived Benefit, Digital Trust, Perceived Risk, and Intention to Share Data. These measures help in understanding the distribution and characteristics of the data collected for each variable (Field, 2018). The variables show standard deviations are around 0.9, indicating that the responses vary around the mean (average).

To evaluate whether the distribution of scores aligns with a normal distribution, it is essential to consider the skewness and kurtosis values (Field, 2018).

Skewness refers to the asymmetry in the distribution of scores. When skewness is positive, it implies an excess of lower scores in the distribution, whereas a negative skewness indicates a concentration of higher scores (Field, 2018).

Kurtosis, on the other hand, is a measure of the tailenders of the distribution. A positive kurtosis value suggests that the distribution has heavier tails, indicating more outliers than a normal distribution. Conversely, a negative kurtosis signifies a distribution with lighter tails, indicating fewer outliers (Field, 2018).

The degree to which these values deviate from zero is indicative of the likelihood that the data deviate from a normal distribution. Larger absolute values of skewness and kurtosis suggest a greater departure from normality.

The data for "Intention to Share Data" demonstrates significant positive skewness and high kurtosis. This suggests that the distribution is likely more dispersed, with a lengthier tail extending to the right and potential outliers (Field, 2018). In contrast, "Perceived Benefit" and "Digital Trust" exhibit moderate skewness and kurtosis, indicating slight deviations from a normal distribution, though these are less pronounced compared to "Intention to Share Data". Among the four variables, "Perceived Risk" shows the closest resemblance to a normal distribution, being symmetrical and not excessively peaked, as inferred from its skewness and kurtosis values.

Perceived Benefit (PB):

Standard Deviation: 0.92867751 suggests a moderate dispersion around the mean.

Skewness: -0.723 indicates a distribution that is moderately skewed to the left, meaning there are more high scores than low scores.

Kurtosis: 1.059 suggests a slightly heavy-tailed distribution compared to a normal distribution, indicating a presence of outliers.

Digital Trust (DT):

Standard Deviation: 0.92681937 also shows a moderate dispersion around the mean.

Skewness: 0.751 suggests a moderate right skew, meaning there are more low scores than high scores.

Kurtosis: 0.515 indicates a distribution that is very close to normal in terms of its tails, but slightly heavy-tailed, suggesting a few outliers.

Perceived Risk (PR):

Standard Deviation: 0.89592722 indicates a moderate dispersion around the mean.

Skewness: 0.304 shows a slight skew to the right, with a minor excess of low scores.

Kurtosis: -0.335 suggests a distribution with slightly lighter tails than a normal distribution, which means fewer outliers.

Intention to Share Data (ITSD):

Standard Deviation: 0.90915431 indicates a moderate level of dispersion around the mean.

Skewness: -1.039 shows a distribution that is significantly skewed to the left, with a notable concentration of higher scores.

Kurtosis: 1.520 suggests a distribution with very heavy tails, pointing to a significant number of outliers.

4.9 Descriptive statistics: Frequencies percentage of each survey question, grouped together per construct.

The histogram and accompanying frequency tables illustrate the distribution of responses for various survey questions, categorised according to different constructs. Each histogram is divided into bars that represent the range of responses on a 5-point Likert scale, from strongly disagree to strongly agree. The height of each bar corresponds to the count of responses within that particular range. The visual representation of the bars on the histogram provides insight into the response pattern: a symmetrical bell-shaped distribution signifies a normal distribution, centred around the mean value. This symmetry is further emphasised by the line overlaying the histogram, which depicts the idealised bell curve, characteristic of a normally distributed set of data. Such a configuration allows for easy interpretation of the central tendency and the dispersion of responses among the survey respondents.

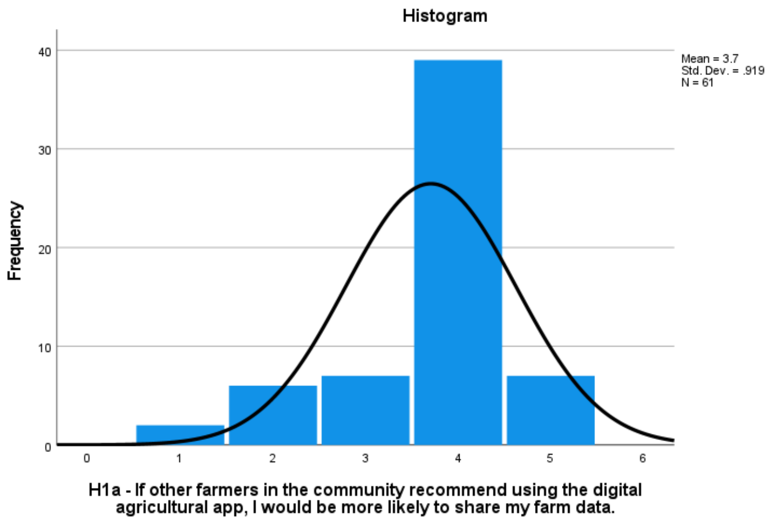
The survey question findings are organised based on the Factor Analysis and Pattern Matrix results. Each construct is aligned with its corresponding hypothesis, as detailed below. This reorganisation accounts for the change in order from the initial presentation of the survey questions and hypotheses.

4.9.1 Perceived Benefit construct, survey question Frequency results (H5)

Table 10: H1a Frequency table and histogram representation

H1a - If other farmers in the community recommend using the digital agricultural app, I would be more likely to share my farm data.

		Frequency	Percent
Valid	Strongly disagree	2	3,3
	Disagree	6	9,8
	Don't know	7	11,5
	Agree	39	63,9
	Strongly agree	7	11,5
	Total	61	100,0



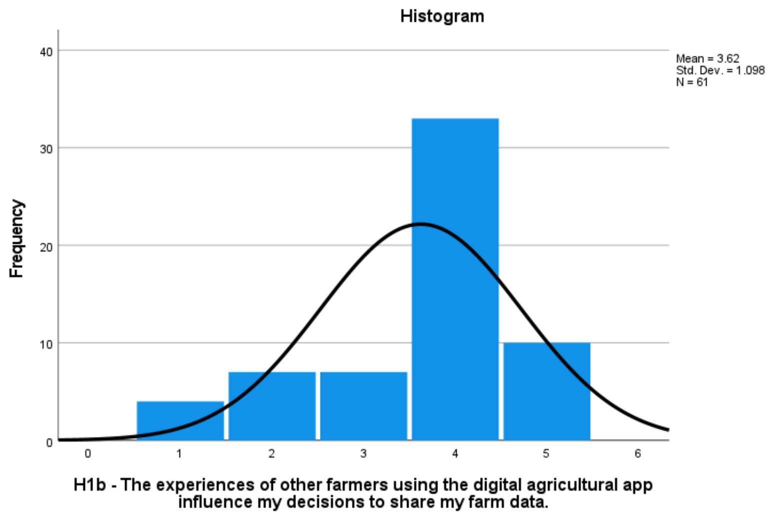
H1a Results:

Table 10 (survey question H1a) notes that over 54% strongly agree and presents a positive likelihood of sharing their farm data contingent upon recommendations from other farmers in the community regarding a DAA. The data clusters towards the upper end of the response scale, with the mode falling in the '4' category of the 5-point Likert scale. This suggests a general propensity among respondents to consider community advice positively in their decisions to share data. With a mean score of 3.7, the central tendency of the dataset supports this inclination, albeit with a standard deviation of 0.919, indicating a modest spread of opinions. Given the sample size of 61, it is evident that peer endorsement is a significant factor for the farmers surveyed.

Table 11: H1b Frequency table and histogram representation

H1b - The experiences of other farmers using the digital agricultural app influence my decisions to share my farm data.

		Frequency	Percent
Valid	Strongly disagree	4	6,6
	Disagree	7	11,5
	Don't know	7	11,5
	Agree	33	54,1
	Strongly agree	10	16,4
	Total	61	100,0



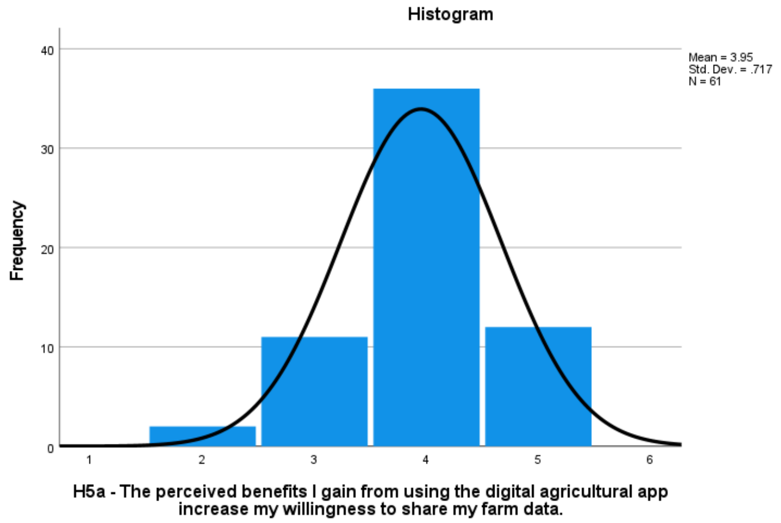
H1b Results

The histogram associated with survey question H1b portrays the responses from farmers on how the experiences of their peers using a DAA might affect their own data-sharing decisions. The mode of the distribution is seen at the response level of 4, which shows a trend towards agreement, indicating that many farmers are positively influenced by their peers' experiences. The mean response is calculated at 3.62, which supports the observation that there is a generally favourable attitude towards the influence of peer experiences on data-sharing decisions. However, the standard deviation of 1.098 suggests a wider range of responses, signifying a more varied opinion among the respondents.

Table 12: H5a Frequency table and histogram representation

H5a - The perceived benefits I gain from using the digital agricultural app increase my willingness to share my farm data.

		Frequency	Percent
Valid	Disagree	2	3,3
	Don't know	11	18,0
	Agree	36	59,0
	Strongly agree	12	19,7
	Total	61	100,0



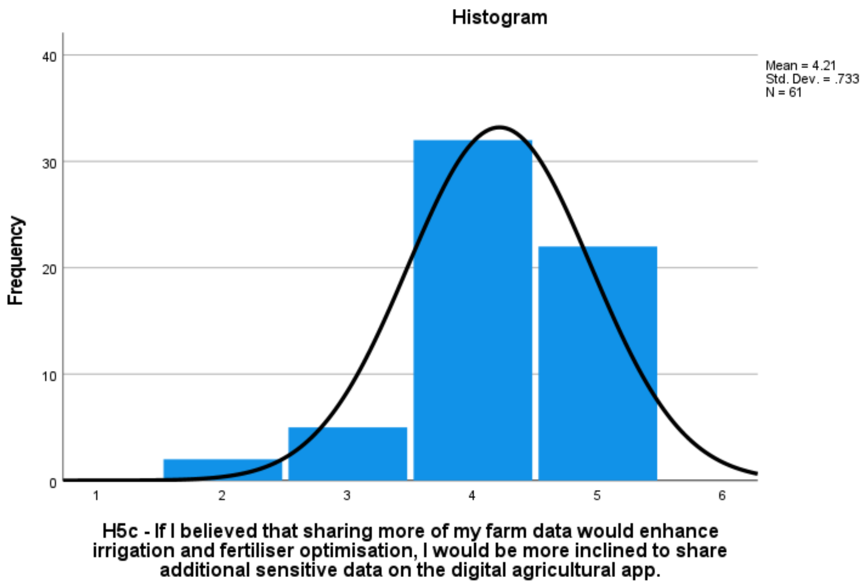
H5a Results

The histogram for survey question H5a reveals the distribution of farmer responses regarding how perceived benefits from using a DAA might affect their willingness to share farm data. The distribution peaks at a rating of 4 on the 5-point Likert scale, indicating a strong agreement that benefits from the application correlate with a greater willingness to share data. A mean score of 3.95 closely aligns with this peak, suggesting overall positive sentiments toward data sharing when benefits are evident. The standard deviation of 0.717 points to a moderately narrow spread in responses, reflecting a consistent view among the 61 respondents.

Table 13: H5c Frequency table and histogram representation

H5c - If I believed that sharing more of my farm data would enhance irrigation and fertiliser optimisation, I would be more inclined to share additional sensitive data on the digital agricultural app.

		Frequency	Percent
Valid	Disagree	2	3,3
	Don't know	5	8,2
	Agree	32	52,5
	Strongly agree	22	36,1
	Total	61	100,0



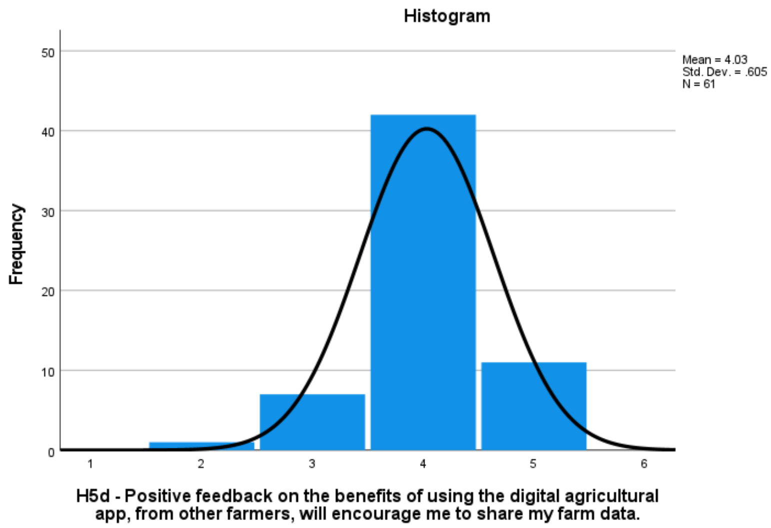
H5c Results:

The findings suggest a somewhat normally distributed set of data, where the majority of the responses are concentrated around the mean value of 4.21. This average signifies a general agreement among the respondents, who show a willingness to share their farm data if it leads to improvements in irrigation and fertiliser optimisation. The standard deviation of 0.733 points to a relatively tight clustering of responses near this mean, indicating that there's not a wide spread of opinions and the responses are not highly polarised. In essence, the data reflects a consensus towards the positive benefits of data sharing in digital agriculture, with most respondents leaning towards agreement rather than extremes of disagreement or strong agreement.

Table 14: H5d Frequency table and histogram representation

H5d - Positive feedback on the benefits of using the digital agricultural app, from other farmers, will encourage me to share my farm data.

		Frequency	Percent
Valid	Disagree	1	1,6
	Don't know	7	11,5
	Agree	42	68,9
	Strongly agree	11	18,0
	Total	61	100,0



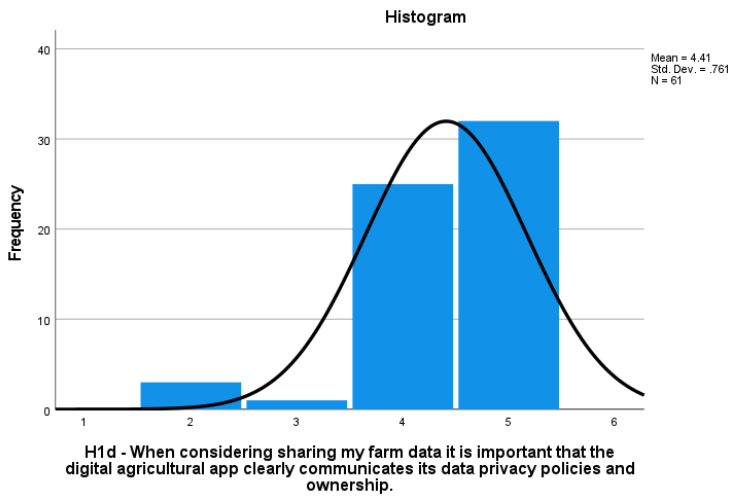
The histogram for survey question H5d illustrates the distribution of responses concerning how positive feedback on the benefits of a DAA influences farmers' willingness to share their farm data. The data peaks at the 4 mark on the 5-point Likert scale, indicating that a significant number of respondents are inclined to share their data when they receive positive feedback. With a mean score of 4.03, the results lean towards the higher end of the scale, suggesting an overall positive response. The standard deviation of 0.605 implies a fairly concentrated consensus around this positive sentiment among the 61 surveyed farmers.

4.9.2 Digital Trust construct, survey question Frequency results (H2)

Table 15: H1d Frequency table and histogram representation

H1d - When considering sharing my farm data it is important that the digital agricultural app clearly communicates its data privacy policies and ownership.

		Frequency	Percent
Valid	Disagree	3	4,9
	Don't know	1	1,6
	Agree	25	41,0
	Strongly agree	32	52,5
	Total	61	100,0



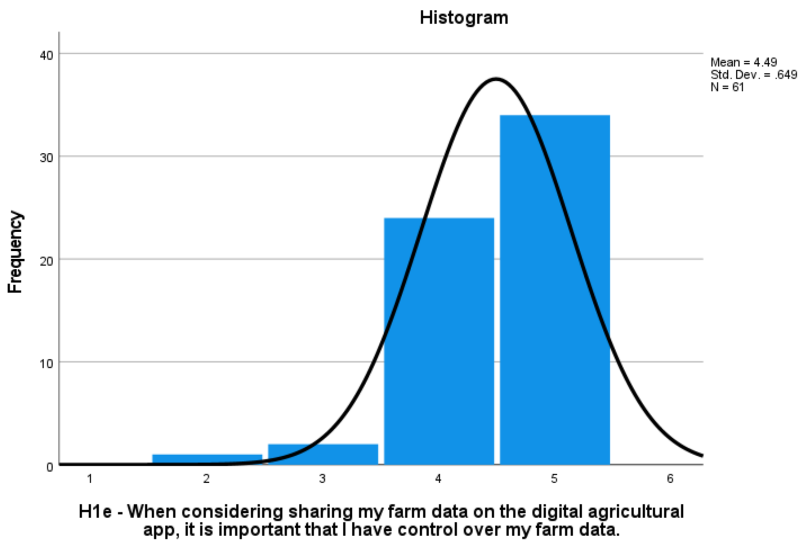
H1d Results

The histogram related to survey question H1d represents farmers' perspectives on the importance of a DAA's communication of its data privacy policies and ownership when they consider sharing their farm data. The most responses are concentrated at the higher end of the Likert scale, with a peak at level 5, showing a strong consensus on the significance of clear communication regarding data privacy. The mean score of 4.41 further emphasises the importance farmers place on this aspect. With a standard deviation of 0.761, there is some variation in the responses, yet the overall trend leans heavily towards the need for transparency in data privacy policies.

Table 16: H1e Frequency table and histogram representation

H1e - When considering sharing my farm data on the digital agricultural app, it is important that I have control over my farm data.

		Frequency	Percent
Valid	Disagree	1	1,6
	Don't know	2	3,3
	Agree	24	39,3
	Strongly agree	34	55,7
	Total	61	100,0



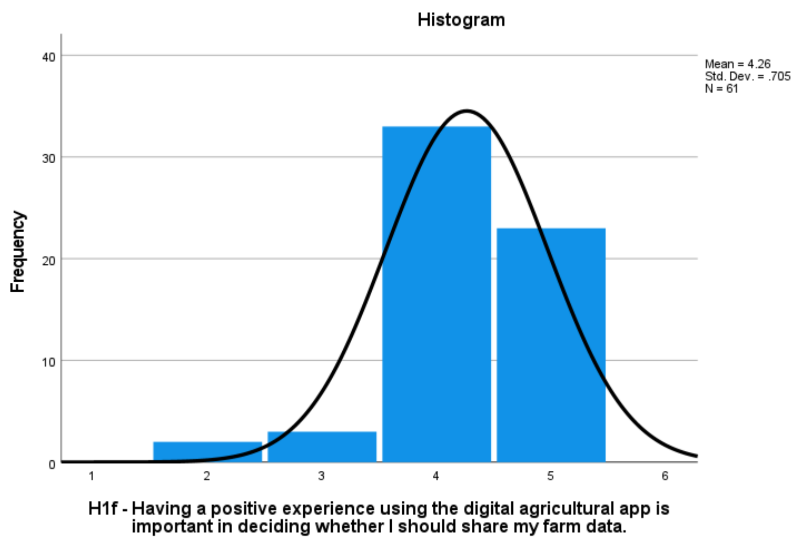
H1e Results

The histogram for survey question H1e details the responses of farmers on the importance of having control over their farm data when considering sharing it on a DAA. The most frequent response is at level 5 on the 5-point Likert scale, which strongly indicates that farmers place high importance on data control. The mean response of 4.49 is high, corroborating a strong overall agreement with the statement. Additionally, the standard deviation of 0.649 suggests a moderate agreement across the sample of 61 respondents, pointing to a common concern for data control among them.

Table 17: H1f Frequency table and histogram representation

H1f - Having a positive experience using the digital agricultural app is important in deciding whether I should share my farm data.

		Frequency	Percent
Valid	Disagree	2	3,3
	Don't know	3	4,9
	Agree	33	54,1
	Strongly agree	23	37,7
	Total	61	100,0



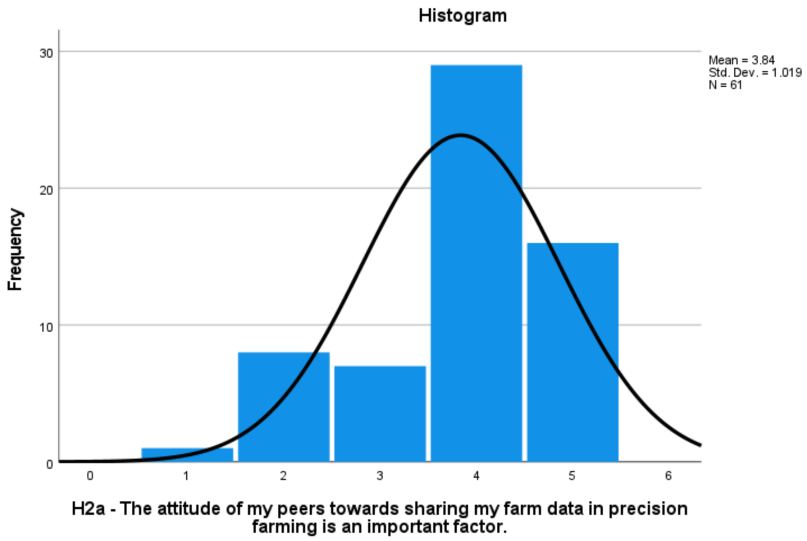
H1f Results

The histogram for question H1f in the shows the farmers' responses regarding the importance of having a positive experience with the DAA when deciding to share their farm data. A significant number of responses are at the high end of the scale, particularly around the 4 mark, suggesting that positive experiences with the app are indeed an important consideration for the respondents. The mean score is 4.26, further indicating a strong agreement across the sample. The standard deviation of 0.705 points to a relatively homogenous set of responses, meaning most respondents feel similarly about the importance of a positive app experience.

Table 18: H2a Frequency table and histogram representation

H2a - The attitude of my peers towards sharing my farm data in precision farming is an important factor.

		Frequency	Percent
Valid	Strongly disagree	1	1,6
	Disagree	8	13,1
	Don't know	7	11,5
	Agree	29	47,5
	Strongly agree	16	26,2
	Total	61	100,0



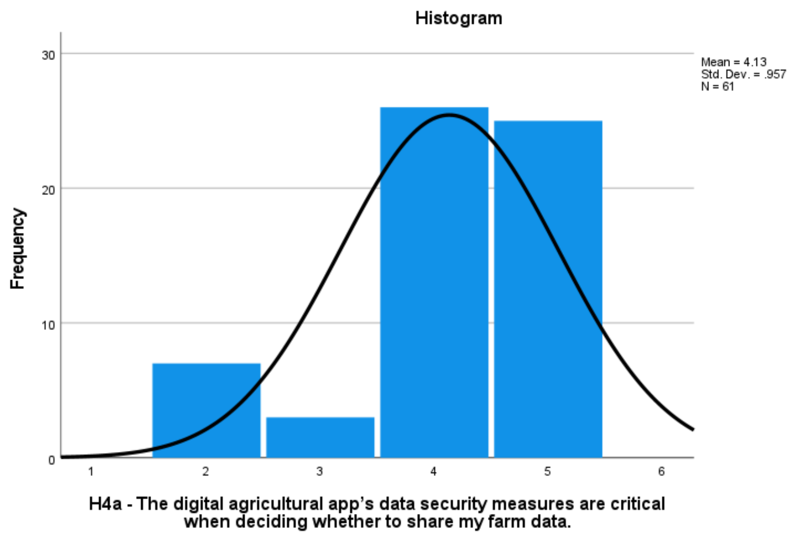
H2a Results

The histogram for survey question H2a displays how farmers rate the importance of their peers' attitudes towards sharing farm data in the context of precision farming. The distribution shows a concentration of responses at level 4 on the Likert scale, indicating that many farmers view peer attitudes as an important factor. The mean response rate of 3.84 suggests a general agreement with the statement, although not as strong as some other factors might be. The standard deviation of 1.019, which is relatively higher than in some other surveyed areas, indicates a wider range of opinions on this matter. Nonetheless, it is clear that peer attitudes hold significant weight for many farmers when it comes to decisions about sharing data in precision farming practices**.**

Table 19: H4a Frequency table and histogram representation

H4a - The digital agricultural app's data security measures are critical when deciding whether to share my farm data.

		Frequency	Percent
Valid	Disagree	7	11,5
	Don't know	3	4,9
	Agree	26	42,6
	Strongly agree	25	41,0
	Total	61	100,0



H4a Results

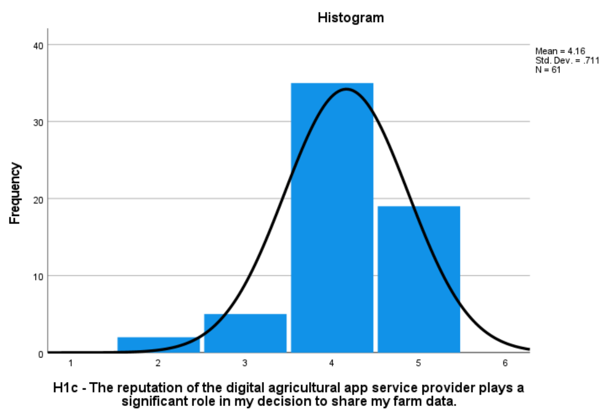
The histogram for question H4a captures the farmers' attitudes towards the importance of data security measures in a DAA when making decisions about sharing their farm data. The distribution of responses is heavily skewed towards the higher end of the Likert scale, with a substantial concentration of responses at level 4. This indicates that data security measures are considered critical by the respondents. The mean of the responses is 4.13, which underscores the importance placed on security measures by the farmers. The standard deviation of 0.957 reflects some variability but generally a high level of agreement.

4.9.3 Perceived Risk construct, survey question Frequency results (H4)

Table 20: H1c Frequency table and histogram representation

H1c - The reputation of the digital agricultural app service provider plays a significant role in my decision to share my farm data.

		Frequency	Percent
Valid	Disagree	2	3,3
	Don't know	5	8,2
	Agree	35	57,4
	Strongly agree	19	31,1
	Total	61	100,0



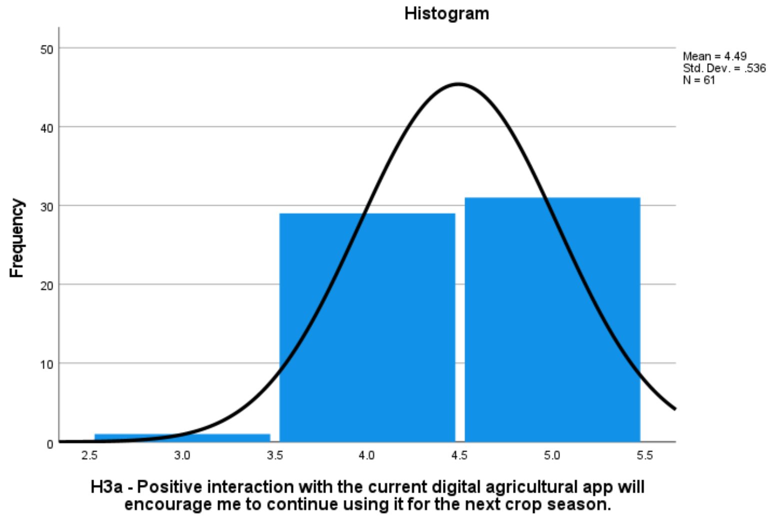
H1c Results

The histogram for survey question H1c shows the distribution of farmers' opinions on how the reputation of the DAA's service provider influences their decision to share data. The bulk of the responses are skewed towards the higher end of the scale, with the majority of farmers selecting '4', indicating that the reputation of the service provider is deemed a significant factor in their decision-making process. The mean response of 4.16 reinforces the strong influence that the service provider's reputation has on these decisions. Meanwhile, a standard deviation of 0.711 suggests that while there is some variation in responses, there is a general consensus among the respondents.

Table 21: H3a Frequency table and histogram representation

H3a - Positive interaction with the current digital agricultural app will encourage me to continue using it for the next crop season.

		Frequency	Percent
Valid	Don't know	1	1,6
	Agree	29	47,5
	Strongly agree	31	50,8
	Total	61	100,0



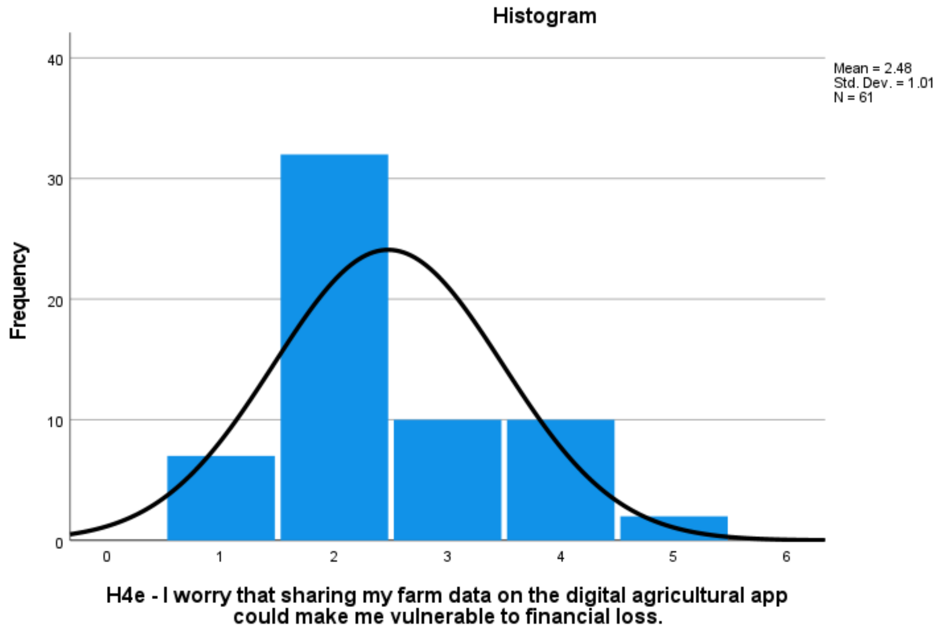
H3a Results

The histogram for survey question H3a reflects the farmers' responses about the influence of positive interactions with a DAA on their decision to continue using it for the next crop season. The data clusters around the higher end of the scale, with a peak at the 4.5 to 5.0 range, which indicates a strong agreement that positive interactions are a motivator for continued use. The mean value of 4.49 echoes this strong agreement, while a standard deviation of 0.536 points to a relatively close agreement among the respondents on this matter.

Table 22: H4e Frequency table and histogram representation

H4e - I worry that sharing my farm data on the digital agricultural app could make me vulnerable to financial loss.

		Frequency	Percent
Valid	Strongly disagree	7	11,5
	Disagree	32	52,5
	Don't know	10	16,4
	Agree	10	16,4
	Strongly agree	2	3,3
	Total	61	100,0



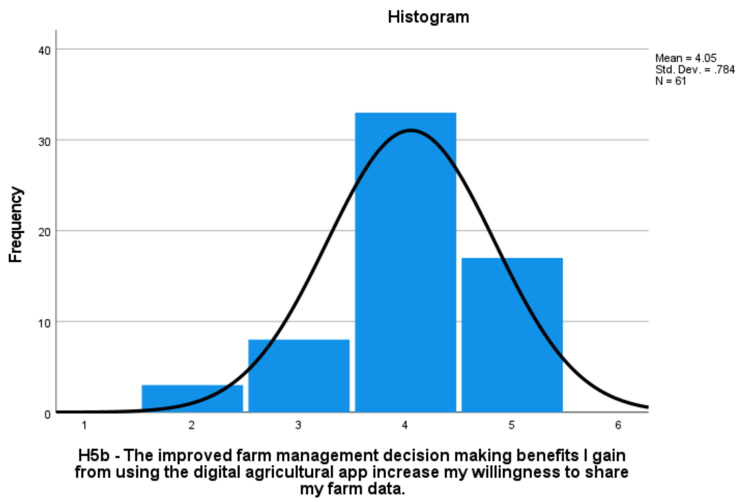
H4e Results

The histogram for survey question H4e shows the distribution of farmers' concerns regarding the potential financial risk associated with DT and sharing farm data on a DAA. The responses are concentrated around the lower end of the scale, with the most common response being 2, indicating a general disagreement with the statement that sharing data could lead to financial loss. The mean response is relatively low at 2.48, reinforcing the trend that most farmers do not associate significant financial risk with sharing their data through the app. A standard deviation of 1.01 reflects some diversity in opinion, but the overall pattern indicates that concerns about financial vulnerability are not predominant among the 61 farmers surveyed.

Table 23: H5b Frequency table and histogram representation

H5b - The improved farm management decision making benefits I gain from using the digital agricultural app increase my willingness to share my farm data.

		Frequency	Percent
Valid	Disagree	3	4,9
	Don't know	8	13,1
	Agree	33	54,1
	Strongly agree	17	27,9
	Total	61	100,0



H5b Results

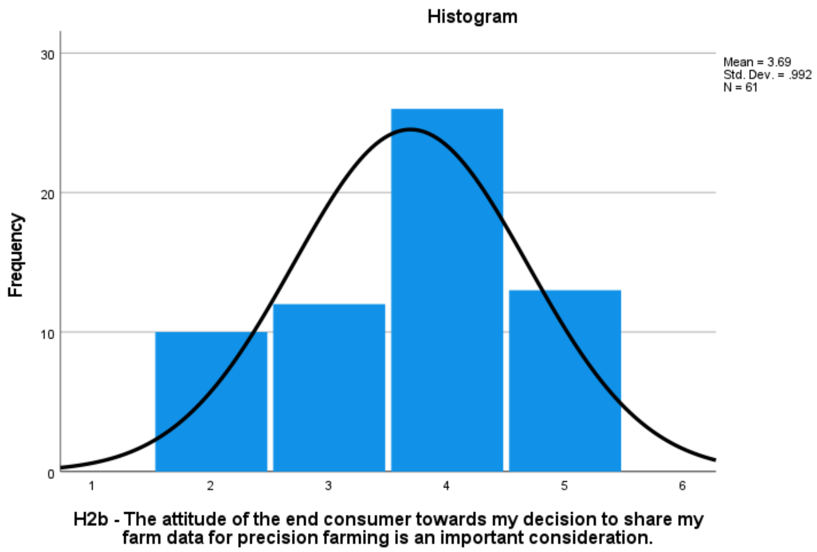
The histogram for survey question H5b displays the responses from farmers on whether the improved farm management decision-making benefits obtained from using the DAA have increased DT and thus minimising PR. The mean score of 4.05 suggests a strong agreement overall with the statement. Furthermore, the standard deviation of 0.784 shows a moderate level of agreement among the 61 respondents.

4.9.4 Intention to Share Data construct, survey question Frequency results (H1)

Table 24: H2b Frequency table and histogram representation

H2b - The attitude of the end consumer towards my decision to share my farm data for precision farming is an important consideration.

		Frequency	Percent
Valid	Disagree	10	16,4
	Don't know	12	19,7
	Agree	26	42,6
	Stronglyagree	13	21,3
	Total	61	100,0



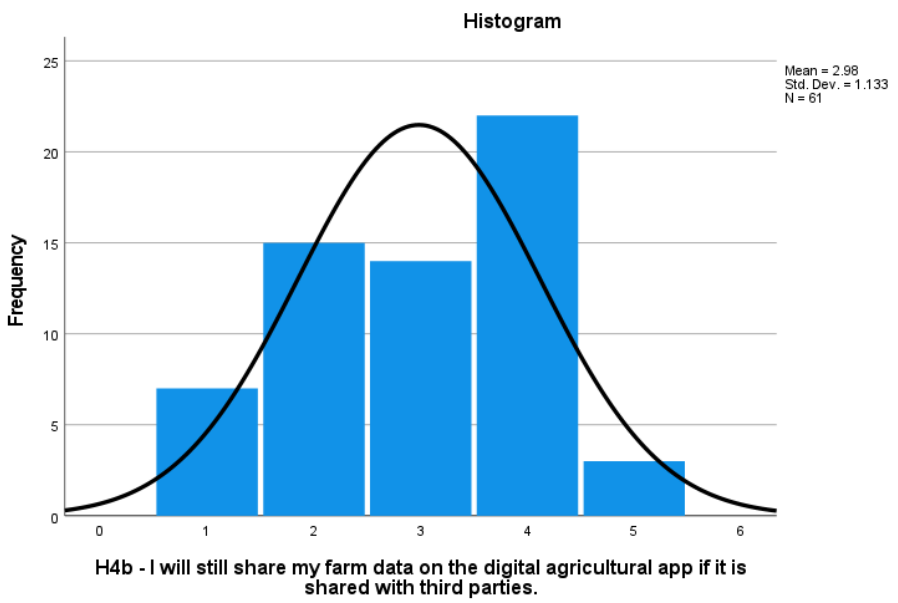
H2b Results

The histogram for survey question H2b depicts the distribution of farmers' views on how the attitudes of end consumers affect their decision to share farm data for precision farming. The responses show a notable peak at the '4' mark on the Likert scale, suggesting that end-consumer attitudes are considered an important factor by many of the farmers. The mean value of 3.69 reflects a general, but not unanimous agreement with the sentiment. With a standard deviation of 0.992, the responses exhibit a wide range of opinions, indicating some variability in how much farmers weigh consumer attitudes in their decision-making.

Table 25: H4b Frequency table and histogram representation

H4b - I will still share my farm data on the digital agricultural app if it is shared with third parties.

		Frequency	Percent
Valid	Strongly disagree	7	11,5
	Disagree	15	24,6
	Don't know	14	23,0
	Agree	22	36,1
	Strongly agree	3	4,9
	Total	61	100,0



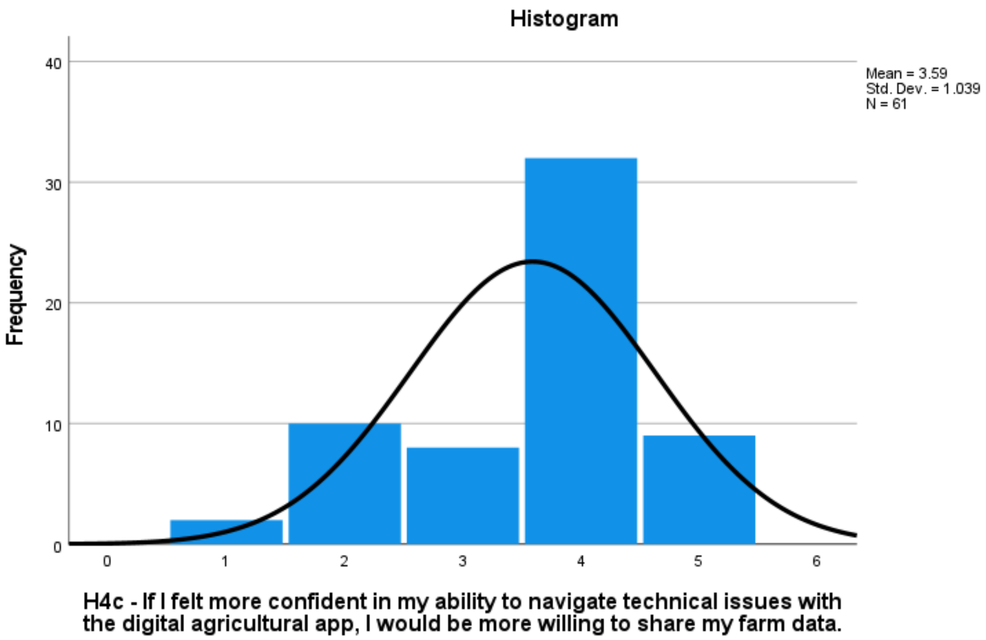
H4b Results

The histogram for survey question H4b illustrates the farmers' willingness to share their farm data on a DAA even if the data is shared with third parties. The data is spread across the scale with a mode at the '4' point, but there's no strong skew towards either end. The mean response of 2.98 is close to the midpoint of the scale, indicating a balanced spread of opinions on this issue. With a standard deviation of 1.133, there is significant variability in the responses, suggesting diverse views among the 61 farmers surveyed.

Table 26: H4c Frequency table and histogram representation

H4c - If I felt more confident in my ability to navigate technical issues with the digital agricultural app, I would be more willing to share my farm data.

		Frequency	Percent
Valid	Strongly disagree	2	3,3
	Disagree	10	16,4
	Don't know	8	13,1
	Agree	32	52,5
	Strongly agree	9	14,8
	Total	61	100,0



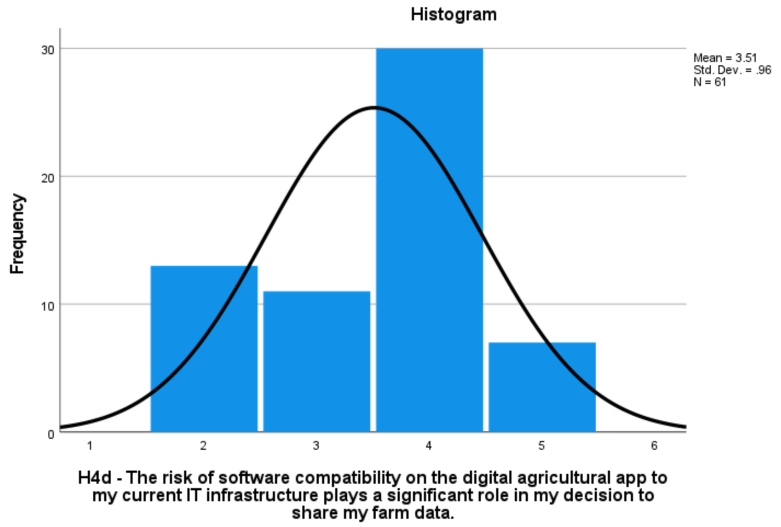
H4c Results

The histogram for survey question H4c shows the farmers' responses on how their confidence in navigating technical issues with the DAA affects their willingness to share farm data. The responses mostly concentrate around the '4' mark on the Likert scale, suggesting that greater technical confidence correlates with an increased willingness to share data. The mean of the distribution is 3.59, which indicates a positive inclination towards data sharing with increased technical confidence, although it's not a strong consensus. A standard deviation of 1.039 reflects a varied range of opinions, indicating that while technical confidence is an important factor for many farmers, it is not universally so.

Table 27: H4d Frequency table and histogram representation

H4d - The risk of software compatibility on the digital agricultural app to my current IT infrastructure plays a significant role in my decision to share my farm data.

		Frequency	Percent
Valid	Disagree	13	21,3
	Don't know	11	18,0
	Agree	30	49,2
	Strongly agree	7	11,5
	Total	61	100,0



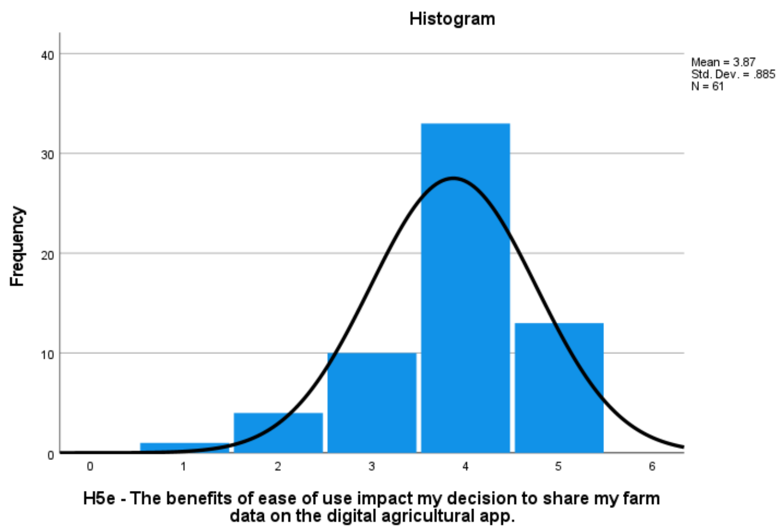
H4d Results

The histogram for survey question H4d assesses farmers' concerns about software compatibility issues with the DAA and their current IT infrastructure, and its influence on their decision to share farm data. The distribution peaks at the '4' mark on the scale, indicating a recognition of compatibility risks as a notable factor in decision-making. The mean score sits at 3.51, leaning towards the higher end of the scale, which suggests a moderate level of concern among the respondents about software compatibility. The standard deviation of 0.96 denotes a reasonable spread in the data, reflecting a range of opinions on this issue.

Table 28: H5e Frequency table and histogram representation

H5e - The benefits of ease of use impact my decision to share my farm data on the digital agricultural app.

		Frequency	Percent
Valid	Strongly disagree	1	1,6
	Disagree	4	6,6
	Don't know	10	16,4
	Agree	33	54,1
	Strongly agree	13	21,3
	Total	61	100,0



H5e Results

Table 28 (for survey question H5e) presents the farmers' ratings on how the ease of use of the DAA influences their decision to share farm data. There is a clear leaning towards the higher end of the scale, with the most responses at the '4' mark, suggesting that usability is a positive influence on their decision to share data. The mean of the responses is 3.87, which supports the view that ease of use is an important factor for the respondents. The standard deviation of 0.885 indicates a moderate spread of responses, signifying that while ease of use is generally important, there are varying levels of agreement among the 61 farmers surveyed.

4.10 Non-parametric correlations

Table 29: Non-parametric correlations

	Perceived Benefit	Digital Trust	Perceived Risk	Intention to Share Data
Perceived Benefit	--			
Digital Trust	-.245	--		
Perceived Risk	-.438**	.120	--	
Intention to Share Data	.347**	-.094	-.302*	--

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Extraction IBM SPSS: Spearman’s Rank Order

Non-parametric correlations measure the strength and direction of the relationship between two variables without assuming that the data follows any specific parametric distribution such as the normal distribution (McGivern, 2013). Non-parametric correlations are advantageous because they are less sensitive to outliers and could be used with data that is not normally distributed (Field, 2018). Therefore, in this study, non-parametric correlation methods were employed due to the kurtosis value indicating the presence of outliers in the distribution, which deviated from the bell curve distribution.

The table represent the results of non-parametric correlation analysis between four constructs: Perceived Benefit, Digital Trust, Perceived Risk and Intention to Share Data and is useful for understanding how these variables are correlated to each other (Malhotra et al., 2017).

The Diagonal (--):is not filled because it would represent the correlation of a variable with itself, which is not meaningful in this context (Malhotra et al., 2017).

Correlation Coefficients: The values in the table are correlation coefficients, which measure the strength and direction of the relationship between two variables. These coefficients range from -1 to 1, where: 1 indicates a perfect positive correlation. **0** indicates no correlation. **-1** indicates a perfect negative correlation (Malhotra et al., 2017).

Significant Correlations:

A double asterisk (**) next to a coefficient indicates a statistically significant correlation at the 0.01 level (99% confidence that the correlation is not due to random chance).

A single asterisk (*) indicates a statistically significant correlation at the 0.05 level (95% confidence).

Looking at the specific coefficients:

- **Perceived Benefit and Digital Trust**: A coefficient of -0.245 suggests a weak negative correlation between these variables, which is not statistically significant.
- **Perceived Benefit and Perceived Risk**: The coefficient of -0.438 indicates a moderate negative correlation, significant at the 0.01 level, suggesting that high values of Perceived Benefit are associated with low values of Perceived risk.
- **Perceived Benefit and Intention to Share Data**: A coefficient of 0.347 suggests a moderate positive correlation, significant at the 0.01 level, indicating that high values of Perceived Benefit are associated with high values of Intention to Share Data.
- **Digital Trust and Perceived Risk**: The positive coefficient of 0.120 indicates a slight, non-significant positive correlation, suggesting a weak relationship between these two variables.
- **Digital Trust and Intention to Share Data**: A coefficient of -0.094 indicates a very weak negative correlation, which is not statistically significant.
- **Perceived Risk and Intention to Share** Data: The coefficient of -0.302 represents a moderate negative correlation, significant at the 0.05 level, suggesting that high values of Perceived Risk are associated with low values of Intention to Share Data.

4.11 Regression analysis

Regression analysis serves as a statistical method used to explore and model the relationship between a dependent variable, which is measured on a continuous scale, and one or more independent variables (Malhotra et al., 2017).

The relationship between ITSD and the three dependent variables: DT, PR, PB is different to the independent variable DT and the dependent variable PR as seen in Hypothesis Test A and Test B below.

Table 30: Hypothesis 2 Test A

Dependent variable = Perceived risk

Independent variable = Digital trust

<table>
<tr><td colspan="2" rowspan="2"><u>Test A</u></td><td colspan="2">Unstandardized Coefficients</td><td>Standardized Coefficients</td><td rowspan="2">t</td><td rowspan="2">Sig.</td><td colspan="2">Test Summary</td></tr>
<tr><td>B</td><td>Std. Error</td><td>Beta</td><td>F</td><td>Sig</td></tr>
<tr><td colspan="2">Constant</td><td>1.963E-16</td><td>0.115</td><td></td><td>0.000</td><td>1.000</td><td>0.467</td><td>0.497</td></tr>
<tr><td>H2</td><td>Digital Trust</td><td>0.086</td><td>0.125</td><td>0.089</td><td>0.683</td><td>0.497</td><td></td><td></td></tr>
</table>

IBM SPSS: The regression model is not significant: F=0.467, p=0.497

<u>Results pertaining to Hypothesis 2</u>

H2: Digital trust has an effect on Perceived risk

This hypothesis is not supported, and not significant (β=0.086, p >0.05).

Table 31: Hypothesis 1,4 and 5 Test B

Dependent variable = ITSD

Independent variable = DT, PB, PR

Test B		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Test Summary	
		B	Std. Error	Beta			F	0.006
H5	Perceived Benefit	**0.405**	0.131	0.414	3.094	**0.003**	4.556	
H1	Digital Trust	**0.073**	0.121	0.074	0.601	**0.550**		
H4	Perceived Risk	**-0.083**	0.130	-0.082	-0.636	**0.527**		

Regression Model B is significant with F=4.556 and p=0.006

Results pertaining to Hypothesis 1

H1: Digital trust has an effect on Intention to Share Data.

The hypothesis is not strongly supported (β=0.073, p >0.05) and is not statistically significant. Therefore, changes in digital trust may not be associated with changes in Intention to Share Data.

Results pertaining to Hypothesis 3

H3: This hypothesis was eliminated and the relevant survey question was correlated to Hypothesis 4.

Results pertaining to Hypothesis 4

H4: Perceived risk has an effect on Intention to Share Data.

This hypothesis is not supported and not significant (β=-0.083, p >0.05).

Results pertaining to Hypothesis 5

H5: Perceived benefit has an effect on Intention to Share Data

The hypothesis is supported and significant ($\beta=0.405$, $p < 0.05$). Perceived benefit has a positive effect on Intention to Share Data (as PB increase, ITSD also tends to increase).

4.12 Summary of analysis of data for Hypotheses 1, 2, 3, 4, and 5

4.12.1 Hypothesis 1 - Digital Trust positively affects Intention to Share Farm Data on a DAA.

- **Finding:** Hypothesis 1 (H1) is not supported, with no significant influence ($\beta=0.073$, $p > 0.05$).

Reliability and Pattern Matrix Analysis:

- **ITSD Reliability:** An alpha of 0.748 indicates good reliability, with consistent internal consistency among the five variables.

- **Pattern Matrix Analysis:** Correlation range for ITSD was -0.688 to -0.418, showing inverse relationships. The strongest correlation was with H2b (loading of 0.688), linking consumer attitudes towards data sharing with farmers' intentions. H4b had the lowest correlation, indicating a weaker relationship between ITSD and sharing data with third parties.

Descriptive statistics

- Intention to Share Data:
  - Standard Deviation: 0.90915431 indicates a moderate level of dispersion around the mean.
  - Skewness: -1.039 shows a distribution that is significantly skewed to the left, with a notable concentration of higher scores.

    - Kurtosis: 1.520 suggests a distribution with very heavy tails, pointing to a significant number of outliers.

Non-parametric analysis:

- **Digital Trust and Intention to Share Data:** A coefficient of -0.094 suggests a very weak, non-significant negative correlation.

Frequency results for ITSD construct:

- **H2b:** 21.3% Strongly Agree, 42.6% Agree; mean of 3.69 and standard deviation of 0.992 indicate general agreement on the importance of end-consumer attitudes.

- **H4b:** 11.5% Strongly Disagree, 24.6% Disagree, 23% Don't Know; mean of 2.98 and standard deviation of 1.133 show diverse views on sharing data with third parties.

- **H4c:** 14.8% Strongly Agree, 52.5% Agree; standard deviation of 1.039, reflecting varied opinions on the influence of technical confidence.

- **H4d:** 11.5% Strongly Agree, 49.2% Agree; mean of 3.51 and standard deviation of 0.96 indicate moderate concern about software compatibility.

- **H4e:** 21.3% Strongly Agree, 54.1% Agree; mean of 3.87 and standard deviation of 0.885 show moderate agreement on usability as a positive influence.

Survey Question Revisions:

- **Initial survey questions for H1:** H1a, H1b, H1c, H1d, H1e, and H1f.

- **Updated survey questions Post-Factor Analysis:** H2b, H4b, H4c, H4d, and H4e.

4.12.2 Hypothesis 2 - Digital Trust negatively affects farmers Perceived Risk of sharing farm data.

- **Finding:** This hypothesis is not supported and statistically not significant ($\beta=0.086$, $p > 0.05$).

Reliability and Pattern Matrix analysis:

- **Digital Trust (DT) Reliability:** An alpha of 0.815 indicates a good level of reliability. The internal consistency across the five variables was substantial, affirming DT as a reliable measure.

- **Pattern Matrix Analysis:** Correlation range for DT was 0.744 to 0.461. H1e showed the highest correlation (loading of 0.744), linking farmers' control over farm data with DT. Conversely, H1f had the lowest correlation, indicating a weaker link between positive experiences and DT.

Descriptive statistics:

- **Digital Trust construct:**
    - Standard Deviation: 0.92681937, indicating moderate variability.
    - Skewness: 0.751, showing a moderate right skew with more low scores.
    - Kurtosis: 0.515, suggesting a distribution close to normal but slightly heavy-tailed.

Non-parametric Analysis:

- **Relationship Between Digital Trust and Perceived Risk:** A positive coefficient of 0.120 suggests a slight, non-significant positive correlation, indicating a weak relationship.

Survey question Frequency results for H2 Digital Trust Construct:

- **H1d:** 52.5% Strongly Agree, 41% Agree. Mean score of 4.41 and standard deviation of 0.761 highlight a consensus on the importance of clear data privacy communication.
- **H1e:** 55.7% Strongly Agree, 39.3% Agree. Mean of 4.49 and standard deviation of 0.649 reflect strong agreement on the importance of data control.
- **H1f:** 37.7% Strongly Agree, 54.1% Agree. Mean of 4.26 and standard deviation of 0.705 show agreement on the significance of positive app experiences.
- **H2a:** 26.2% Strongly Agree, 47.5% Agree. Mean of 3.84 and standard deviation of 1.019 indicate a general agreement on the influence of peer attitudes, with a wider opinion range.
- **H4a:** 41% Strongly Agree, 42.6% Agree. Mean of 4.13 and standard deviation of 0.957 underline the critical nature of data security measures.

Survey Question Revisions:

- **Initial survey questions for H2:** H2a and H2b.
- **Updated survey questions post-Factor Analysis for H2:** H1d, H1e, H1f, H2a, and H4a

4.12.3 Hypothesis 3 - Positive Intention to Share Data has a positive influence on actual sharing of farm data on a DAA.

The survey question for this hypothesis was H3a and was not valid. Factor analysis revealed it was related to the PR construct and H4. The factors analysis revealed that for this study Actual Sharing of Data was not a valid construct so was removed from the conceptual model.

4.12.4 Hypothesis 4 - Perceived Risk has an effect on Intention to Share Data.

- **Finding:** Hypothesis 4 (H4) is not supported and not statistically significant (β=-0.083, p >0.05).

Reliability and Pattern Matrix Analysis:

- **Perceived Risk (PR) Reliability:** An alpha of 0.661 suggests moderate reliability. The four variables show a moderate level of internal consistency, indicating some relation but not fully capturing the same underlying construct.

- **Pattern Matrix Analysis:** Correlation range for PR was 0.665 to 0.430. H3a had the highest correlation (loading of 0.665), showing that positive interactions with the digital application reduce PR. Conversely, H4e had the weakest link to PR, related to financial loss vulnerability.

Descriptive Statistics for PR:

- **Standard Deviation:** 0.89592722, indicating moderate variability.

- **Skewness:** 0.304, showing a slight right skew with more low scores.

- **Kurtosis:** -0.335, suggesting a distribution with lighter tails and fewer outliers.

Frequency results for PR construct:

- **H1c:** 31.1% Strongly Agree, 57.4% Agree on the influence of the service provider's reputation on PR.

- **H3a:** 50.5% Strongly Agree, 47.5% Agree that positive app interaction increases Digital Trust (DT) and continued use.

- **H4e:** 11.5% Strongly Disagree, 52.5% Disagree, 16.4% Don't Know, 16.4% Agree; standard deviation of 1.01 reflects diverse opinions on financial risk association.
- **H5b:** 27.9% Strongly Agree, 54% Agree; mean of 4.05 and standard deviation of 0.784 indicate strong agreement that app benefits foster trust and mitigate PR.

Survey Question Revisions:

- **Initial survey questions for H4:** H4a, H4b, H4c, H4d, and H4e (twice listed).
- **Updated survey questions Post-Factor Analysis:** H1c, H3a, H4e, and H5b.

4.12.5 Hypothesis 5 - A farmer's Perceived Benefits positively affects decisions to share farm data on a digital agricultural application.

- **Finding:** Hypothesis 5 (H5) is supported and statistically significant ($\beta=0.405$, $p < 0.05$).

Correlation Analysis:

- **Coefficient:** A coefficient of 0.347, significant at the 0.01 level, indicates a moderate positive correlation between Perceived Benefits and the Intention to Share Data.

Frequency results for Perceived Benefit (PB) construct:

- **H1a:** 11.5% Strongly Agree, 63.9% Agree. Mean of 3.7 and standard deviation of 0.919 suggest a general inclination to consider community advice about app benefits. 11.5% Don't Know, 9.8% Disagree.

- **H1b:** 16.4% Strongly Agree, 54.1% Agree. Mean of 3.62, standard deviation of 1.098 indicate a trend towards agreement influenced by peers' experiences, with varied opinions.
- **H5a:** 19.7% Strongly Agree, 59% Agree. Mean of 3.95, standard deviation of 0.717 show strong agreement on app benefits correlating with willingness to share data. Notably, 18% Don't Know, the highest among all survey questions for this category.
- **H5c:** 36.1% Strongly Agree, 52.5% Agree. Standard deviation of 0.733 reflects a tight clustering of responses around sharing data for improvements in irrigation and fertiliser optimisation.
- **H5d:** 18% Strongly Agree, 68.9% Agree. Mean of 4.03 and standard deviation of 0.605 indicate a significant inclination to share data upon receiving positive feedback, with a concentrated consensus.

Survey Question Revisions:

- **Initial Questions for H5 Measurement:** H5a, H5b, H5c, H5d, and H5e.
- **Updated Questions Post-Factor Analysis:** H1a, H1b, H5a, H5c, and H5d.

Based on the provided summary of hypothesis findings, the conceptual model was adjusted to exclude the construct "Actual Sharing of Data." This decision was driven by the results from the factor analysis, which suggested that "Actual Sharing of Data" was not a distinct construct but rather related to the Perceived Risk (PR) construct and Hypothesis 1 (H1).

In summary the findings compared to the conceptual model indicated that H1 is not supported or significant and has a weak relationship between DT (dependent variable) and PR (dependent variable). Furthermore, H2 was not supported and not significant, indicating that perceived risk may not be a strong determinant of sharing intentions. H4 was also not supported and not significant, suggesting that digital trust might not play a crucial role in influencing farmers' intentions to share data. H5 on the other hand, was supported and showed a significant positive correlation between perceived benefits and the intention to share farm data, indicating that when farmers see clear benefits in sharing their data, they are more likely to do so.

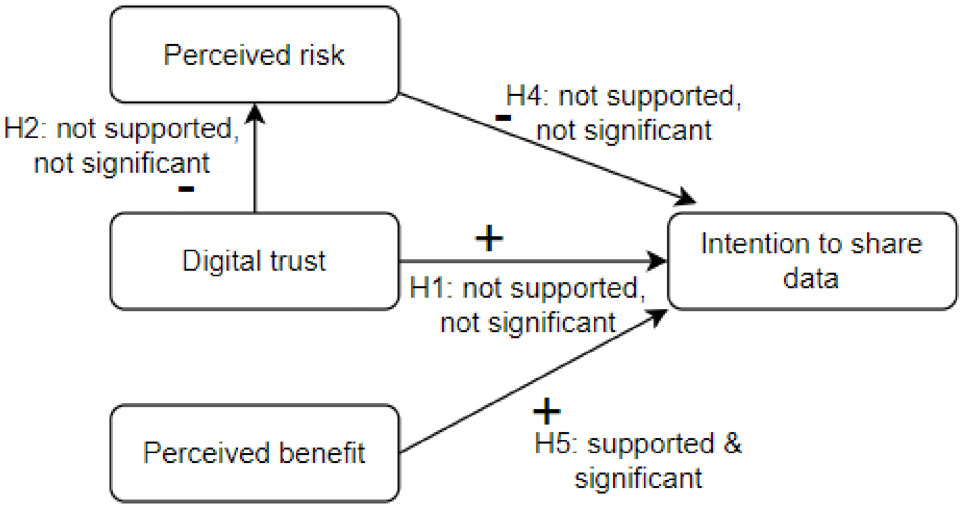


Figure 4: Updated model and hypotheses

4.13 Conclusion

Chapter 4 presented an analysis of the data collected in the study. The chapter began with a description of the data preparation and cleaning processes, ensuring that the dataset was robust and reliable for analysis. This was followed by a statistical examination, employing both descriptive and inferential statistical methods.

Significant trends and patterns were identified in the data, offering preliminary insights into the research questions and an understanding of the perceptions of the sample in regard to sharing farm data.

In the next chapter, the implications of these results in the context of the existing literature and theoretical framework established in earlier chapters is examined.

5 Chapter 5 – Discussion

5.1 Introduction

Chapter 5 delves into a detailed analysis of the findings for each hypothesis, aligning and contrasting them with the insights gathered from the literature review. This chapter aims to not only present the outcomes but also to contextualise them within the broader academic discourse, drawing connections and highlighting distinctions between the results of this study and existing research.

This study was initiated to understand the research problem centred on the limited extent of data sharing among Southern African horticultural farmers using DAAs for precision farming. Three research questions were formulated to guide the study to explore farmers' attitudes towards the risks of data sharing; to highlight the potential benefits of digital applications; and to offer insights for stakeholders to promote technology adoption in Southern Africa's horticultural industry.

The trust-based consumer decision-making model in electronic commerce (Kim et al., 2008) was adapted to create a conceptual framework that aligned with the purpose of the study, to understand sharing farm data perspectives of South African horticultural farmers.

The literature review closely corresponded with the study's main constructs and proposed conceptual model. During the factor analysis of the survey questions, it became evident that the ASOD construct did not apply to this study, given the existing integration of digital technology among respondents. As a result, survey question nine (H3a), which posited that 'Positive interaction with the current DAA will encourage me to continue using it for the next crop season,' was initially aligned with the ASOD construct. However, based on the findings from the Pattern Matrix, this question was reassigned to the PR construct. This reassignment highlights the potential perceived risks if interaction with a DAA is not positive, as it could potentially limit usage and data sharing.

The following section will explore the findings, their implications, and significance in the context of existing literature, structured around the three research questions:

1. What factors of digital trust contribute to farmers deciding whether to share farm data on a digital agricultural application?
2. To what extent does perceived risk impact farmers' decisions to share farm data on a digital agricultural application?
3. To what extent do perceived benefits impact farmers' decisions to share farm data on a digital agricultural application?

5.2 Research question 1: What factors of digital trust contribute to farmers deciding whether to share farm data on a digital agricultural application?

The literature review revealed the following factors that contribute to deciding whether to share data or not on a DAA which were consistent with the study findings: social influence (Regan, 2019), technology challenges (Barrett & Rose, 2022; Pillai & Sivathanu, 2020; Rezaei-Moghaddam & Salehi, 2010; Shi et al., 2022), ease of use (Ejdys, 2018) and compatibility (Regan, 2019) along with third party access to farm data (Wiseman et al., 2019). Furthermore, control and ownership of farm data (Barrett & Rose, 2022; Jakku et al., 2019; Regan, 2019; Van der Burg et al., 2019; Wiseman et al., 2019), risks of ambiguous communication of data privacy (Jakku et al., 2019; Regan, 2019; Wiseman et al., 2019), attitude of peers in the farming community (Blasch et al., 2022; Fox et al., 2021; Pillai & Sivathanu, 2020), evidence of positive user experiences (Barrett & Rose, 2022; Shi et al., 2022) and lack of security measures (Wiseman et al., 2019) were all found to be digital trust factors.

The online questionnaire incorporated survey questions that were pertinent to the first research question, where H1 and H2 were addressed. These questions were designed in alignment with the constructs and relationships defined in the conceptual model.

The study found that Both H1 and H2 were not supported and not significant.

> H1: Digital trust positively affects intention to share farm data on a digital agricultural application.
>
> H2: Digital trust negatively affects farmers perceived risk of sharing farm data on a digital agricultural application.

The findings, implications and significance for research question one will be discussed in relation to H1 and H2.

5.2.1 H1: Digital trust positively affects intention to share farm data on a digital agricultural application.

The primary finding that H1 is not statistically supported ($\beta=0.073$, $p > 0.05$), raises questions. Furthermore, non-parametric analysis showed a very weak, non-significant negative correlation between digital trust and intention to share data. Despite the hypothesis not being statistically significant, the survey responses showed that over 40% of participants agreed with each survey question. This suggests that while the hypothesis may not hold universally or strongly, the factors it examined could still be of relevance in the context of horticultural farmers in South Africa.

It prompts a reconsideration of the various dimensions of DT and how they, in this specific context, influence the decision-making processes of farmers. Pietrzak and Takala (2021) observation about the absence of a universally accepted definition of DT underlines the complexity of this construct and is evident in the diversity of results of this study, which do not support the hypotheses. Conversely, individual survey questions demonstrate a consensus within the sample on a per-survey question basis.

5.2.1.1 Social influence (H2b)

The reliability analysis of the ITSD construct, with an alpha of 0.748, confirms the internal consistency among the variables concerning the intention to share data. This aspect intersects with Venkatesh et al. (2003) emphasis on the role of social influence in technology adoption. The reliable measurement of ITSD underscores the importance of understanding the social dynamics within farming communities and how these dynamics affect trust in digital platforms.

An inverse relationship in ITSD, particularly with H2b, aligns with Durrant et al. (2021), who identified farmers' hesitancy to share data due to reputation concerns and commercial sensitivities. This finding suggests that factors such as perceived risk to reputation and the commercial impact of data sharing play a role in the trust dynamics. The survey data found 63% of respondents either agreed or strongly agreed to reputation concerns limiting sharing their farm data. The remaining 47% either didn't know or disagreed with this statement.

The relationship between digital trust and intention to share data may not be as direct as hypothesised in Kim et al. (2008) but could be reconsidered if farmers had a clearer understanding of digital trust (Venkatesh et al., 2003).

5.2.1.2 Sharing of data with third parties and data control (H4b)

The mixed responses regarding the sharing of farmer data with third parties, as indicated in Hypothesis H4b, revealed that 59% ranged from "don't know" to "strongly disagree" and 41% agreeing with the statement to share their data even if it involves third parties, suggests a nuanced understanding and approach towards data sharing among farmers. Although there was some hesitation, nearly half of the farmers were willing to consider sharing data with third parties, indicating a conditional openness to the idea. These findings differ from Australian farmers who expressed concerns about losing control of farm data constraining participation (Wiseman et al., 2019). This highlights the diverse attitudes towards data privacy and sharing within the agricultural sector, as well as the contrast in attitudes observed across different geographical regions.

5.2.1.3 Technical confidence (H4c)

The varied opinions on technical confidence, as indicated in H4c, show that 67% of respondents agree or strongly agree that having technical confidence is linked with a greater willingness to share farm data. Meanwhile, the remaining third either don't know or disagree with this view. These findings align with those of (Jakku et al., 2019) and Wiseman et al. (2019) who observed that Australian farmers face technical challenges, including issues with system compatibility. Additionally, the differing levels of perceived risk among South African farmers regarding the use of DAAs could potentially highlight the distinct socio-economic and technological landscape in South Africa, which in turn influences digital trust.

5.2.1.4 Compatibility (H4d)

A moderate level of concern about software compatibility was noted among 60.7% of the respondents, whereas approximately 40% either were unsure or disagreed. This finding, in light of Jakku et al. (2019) and Wiseman et al. (2019) research, could suggest a limited knowledge base, which may explain why only just under a quarter of the farmers in the sample responded. Furthermore, an understanding of system integration could potentially be another concern (Wiseman et al., 2019).

5.2.1.5 Ease of use (H5e)

In the study 75.4% responded that ease of use is important. As Rezaei-Moghaddam and Salehi (2010) and Shi et al. (2022) suggest, the functionality and user-friendliness of DAAs could be crucial in determining farmers' willingness to share data.

5.2.2 H2: Digital trust negatively affects farmers perceived risk of sharing farm data on a digital agricultural application.

5.2.2.1 Clear communication of data privacy policies and ownership (H1d)

The study recorded that 93.5% agree that clear communication about data privacy and ownership are critical when deciding to share farm data. This is higher than Wiseman et al. (2019), as 70% of respondents are unaware of or do not comprehend the terms and conditions of contracts associated with service technology providers. The results could be stemming from an imbalance of bargaining power when contracts are ambiguous (Regan, 2019). Furthermore monitoring and implementation of legal frameworks for data regulation in South Africa are lagging, with no processing of claims being made to date (My Broadband, 2023) which could potentially indicate that an understanding of the ownership of farm data still remains vague (Aguera et al., 2020).

5.2.2.2 Attitude of peers about sharing farm data (H2a)

H2a indicates 72% of respondents agree that they regard the attitude of their peers in the community important when considering to share farm data. This is in line with the significant relationship of intention to use digital mobile communication in the agricultural sector of Uganda (Engotoit et al., 2016).

5.2.2.3 Evidence of positive user experiences (H5e)

H5e indicates that 75.4% agree that evidence of positive user experience of a DAA, impacting their decision to share farm data and aligns with the findings of Kim et al. (2008).

5.2.2.4 Lack of security measures (H4a)

The survey question H4a disclosed that 83.6% of respondents agreed that security measures are crucial when deciding to share farm data, with a significant skew towards the higher end of the Likert scale. This finding aligns with Kim et al. (2008) observation that security is a key factor influencing consumer trust in technology adoption. Additionally, the research by Jakku et al. (2019) and Wiseman et al. (2019), which points out the concerns of the absence of Australian security breach legislation, and Abrahams (2022) findings on the weak governmental regulatory controls in South Africa, all underscore the importance of security in the context of data sharing.

Important to note that H3 was originally included in research question one, corresponding with the fifth construct, ASOD. However, as detailed in Chapter 3, it was determined that H3 was not pertinent to the context of this research. Moreover, the related survey question (H3a) showed a stronger correlation with PR rather than with the original construct it was intended to assess.

5.2.2.5 Research Question 1 Summary

The findings from H1 and H2 of research question one, integrated with existing literature, highlight several key factors of digital trust that influenced farmers' decisions to share farm data. Paramount among these factors were concerns about clear communication and data privacy, with a notable 93.5% of respondents agreeing on the importance of these aspects, followed closely by the need for strong security measures. Additionally, the ease of use, evidence of positive user experiences, and the attitudes of peers regarding the use of DAAs were also significant considerations.

However, the influence of social factors (63%) and technical confidence (67%), did not emerge as universally strong concerns. Compatibility issues also figured less prominently. The weakest concerns were related to third-party data sharing, differing from the literature. This disparity suggests a potential lack of knowledge or varying attitudes across different geographical areas.

5.3 Research question 2: To what extent does perceived risk impact farmers' decisions to share farm data on a digital agricultural application?

The literature review for research question two, focusing on the extent of PR on farmers' decisions to share data on DAAs, aligns with the study's findings. It shows that the reputation of digital applications (Durrant et al., 2021; Kim et al., 2008; Regan, 2019), is a significant aspect of PR. Ejdys (2018) highlights the importance of intuitive software interfaces in reducing perceived risks. In the study, financial concerns, which were prominent in the literature (Abrahams, 2022; Barrett & Rose, 2022; Smidt, 2021) were found to be less significant. This observation could be attributed to the sample comprising users already utilising a specific DAA and not having incurred significant financial losses.

Hypothesis 4, formulated to explore the second research question, is underpinned by specific survey questions from the online questionnaire. The ensuing section provides a detailed examination of these questions and their corresponding findings.

5.3.1 H4: A farmers perceived risk negatively affects intention to share farm data on a digital agricultural application.

The study determined that H4 was neither supported nor significant. However, non-parametric correlations indicate a strong association between high levels of PR and low levels of ITSD.

The findings, implications and significance for research question two will be discussed in relation to H4.

5.3.1.1 Reputation of digital agricultural application service provider (H1c)

Research on the reputation of DAA service providers (H1c) reveals that a significant 88.5% of respondents consider the reputation of these providers as crucial in their decision-making process. This finding is consistent with literature

(Jakku et al., 2019; Regan, 2019) that underscores farmers' need for clear and transparent practices in data usage and sharing. Additionally, Van der Burg et al. (2019) and Barrett and Rose (2022) raise ethical issues related to corporate access and control over data, indicating potential unfair advantages for corporations over farmers.

5.3.1.2 Positive interactions with digital agricultural application (H3a)

Positive interactions with DAA significantly reduce perceived risk (PR) and motivate farmers to share crop data. A striking 98.3% of respondents strongly agree that these positive experiences encourage continued app use. This highlights the critical role of user-friendliness in diminishing PR, as supported by Shi et al. (2022)'s research, which further solidifies this link.

5.3.1.3 Vulnerabilities to financial loss (H4e)

The study found that 80% of participants either disagreed or were unsure about the association of financial loss with data sharing through a DAA. This potentially indicates that farmers generally do not perceive significant financial risk in sharing their data via these applications. The findings for H4e, showed a weak correlation with PR, particularly concerning financial vulnerability from sharing farm data. This contrasts with existing literature where Jakku et al. (2019) highlighted the potential costs of digital applications, and Barrett and Rose (2022) raised concerns about errors in data usage impacting crop yields negatively. Moreover, Smidt (2021) pointed out the challenges faced by small-scale farmers with limited incomes, while Abrahams (2022) emphasised the need for government support in Southern Africa to help farmers mitigate these financial risks. A plausible explanation for the study's findings is that the sample comprised of users already employing a specific DAA and not having experienced significant financial losses. This lack of adverse experiences might contribute to their perception of data sharing as a low-risk, potentially beneficial activity.

5.3.1.4 Improved farm management systems (H5b)

A significant 82% of respondents acknowledged that utilising a DAA had positively influenced farm management decision-making, which in turn has reduced PR. This aligns with existing literature, highlighting that DAA are instrumental in enhancing farm management, improved resource efficiency and decision-making. Key benefits could potentially include optimising waste management (Barrett & Rose, 2022), automating various tasks (Colizzi et al., 2020; Wiseman et al., 2019) and offering customised advice for crop norms (Vrchota et al., 2022) Furthermore, these applications centralise data, which streamlines audit preparation and results in time and labour savings (Bland et al., 2023; Musa et al., 2019). This overall improvement in farm management and data handling increases the intention among the sample of horticultural farmers to continue sharing data on digital tools.

5.3.1.5 Research Question 2 Summary

Research question two investigated farmers' perceptions of PR and ITSD on DAA. Interestingly farmers' PR and negative ITSD on DAA, was neither supported nor found significant. Contrary to this, the study revealed a correlation between high PR and low ITSD. Furthermore, it was revealed the importance of the reputation of DAA service providers. These finding aligns with existing literature emphasising the need for transparent data usage practice. Additionally, positive interactions with digital applications were found to significantly reduce PR and encourage data sharing, underscoring the importance of user experience.

A substantial majority of respondents agreed that using DAA has improved farm management. This finding aligns with literature suggesting that these applications enhance farm management by improving resource efficiency, decision-making, and reducing waste. In contrast, the study's findings on vulnerabilities to financial loss indicated that respondents did not associate significant financial risk with sharing data through DAA. The lack of significant financial losses experienced by the users of the current digital app could potentially explain this perspective.

5.4 Research question 3: To what extent do perceived benefits impact farmers’ decisions to share farm data on a digital agricultural application?

The literature review for research question three and how it compares to the findings of this study are as follows:

Kim et al. (2008) and Pillai and Sivathanu (2020) emphasise that perceived benefits, including the usefulness and practicality of the technology, play a critical role in technology adoption among farmers. The literature along with the findings of the study, recognise various perceived benefits that encourage farmers to share data on a DAA; such as enhanced waste management, optimised resource allocation, and improved decision-making capabilities Barrett and Rose (2022) and Colizzi et al. (2020) along with improved efficiency (Aguera et al., 2020), cost savings (Musa et al., 2019). These benefits, coupled with the potential for customising crop norms (Vrchota et al., 2022) and streamlining agricultural audits (Bland et al., 2023), present potential areas why perceived benefits directly impact South African farmers’ decisions to share farm data.

Hypothesis 5 was developed to address the third research question, and the associated survey questions from the online questionnaire. The subsequent section offers an analysis of these questions and their respective findings.

5.4.1 H5: A farmers perceived benefits positively affect decisions to share farm data on a digital agricultural application (PB)

The study determined that H5 was both statistically supported and significant, making it the sole hypothesis that concluded similar findings to the conceptual model (PB and ITSD).

5.4.1.1 Farmers in the community recommendations (H1a)

The findings regarding H1a revealed that 75.4% of respondents agreed that recommendations from other farmers in their community would increase their likelihood to share farm data using a DAA. This indicates a general tendency among respondents to value community advice in their decision-making about data sharing as seen in Blasch et al. (2022) who found that 88.5% of farmers who had adopted precision farming were influenced by knowing at least one other adopter in their social circle. Additionally, research by Pillai and Sivathanu (2020) highlighted that positive feedback from fellow farmers regarding the IoT-A significantly influenced their decision to adopt IoT technology in the agriculture industry. This integration of the study's findings with the literature underscores the significant role of community recommendations and perceived benefits in influencing farmers' technology adoption behaviours.

5.4.1.2 The experiences of other farmers (H1b)

H1b revealed that 70% of respondents agreed that the experiences of other farmers with DAA influenced their decisions to share farm data. This suggests that a significant proportion of farmers are impacted by their peers' experiences (Barrett & Rose, 2022; Wiseman et al., 2019). These studies together underscore the influence of sharing positive user experiences in fostering confidence among farmers to share their own data.

5.4.1.3 The perceived benefits gained (H5a)

The study's findings indicated that 78.7% of respondents agreed that perceived benefits from using DAA correlate with a greater willingness to share data. This aligns with existing literature on the advantages of such applications. Barrett and Rose (2022) noted the benefit of enhanced waste management, particularly in optimising plant nutrition and irrigation requirements. Furthermore, DAA are recognised for supporting farmers in making more informed decisions, saving time, and automating various tasks, including audits, budgeting, and providing recommendations, as highlighted by (Colizzi et al., 2020). Additionally, Musa et al. (2019) emphasised the cost savings achieved through reduced labour and resource consumption, which could potentially underline the importance of perceived benefits in influencing farmers' willingness to share data.

5.4.1.4 Farm data to enhance irrigation and fertiliser optimisation (H5c)

The findings from H5c show that 88.6% of respondents are more likely to share farm data on a DAA if it enhances irrigation and fertiliser optimisation. This high level of agreement reflects their readiness to share data for tangible improvements in farming practices. Supported by literature, this perspective emphasises the global relevance of precision farming for addressing key challenges like water sustainability and fertiliser resource management (Delgado et al., 2011) and highlights the advantages of optimising plant nutrition and irrigation (Barrett & Rose, 2022). These insights affirm the significant impact of perceived benefits, such as better resource management, on farmers' willingness to engage with digital agricultural technologies.

5.4.1.5 Positive feedback on the benefits from other farmers (H5d)

The study's findings for H5d revealed that 86.9% of respondents agree that positive feedback about the benefits of using a DAA from other farmers would encourage them to share their farm data. The literature supports this finding: Blasch et al. (2022) suggest that successful implementation and demonstrable benefits of digital tools can build trust and promote broader adoption within the farming community. Additionally, Regan (2019) points out that evidence of improved performance, as shared by peers, can reinforce confidence in the technology and reduce concerns about sharing sensitive data. These insights underline the importance of positive peer feedback in enhancing farmers' willingness to engage with digital agricultural technologies.

5.4.1.6 Research Question 3 Summary

Research question three revealed that farmers' decisions to share data on DAA are significantly influenced by perceived benefits and peer experiences. Also, importantly this was the only relationship that was statistically supported and significant with regard to the conceptual model.

Key findings include 75.4% of respondents affirming that community recommendations would likely increase their data sharing, 70% agreed that their peers' experiences with such apps impact their own data sharing decisions. Further, 78.7% of the respondents saw a correlation between perceived benefits of using these applications and their willingness to share data, supported by literature citing advantages in waste management and task automation. Interestingly, 88.6% would share more farm data for improvements in irrigation and fertiliser optimisation, potentially highlighting the role of precision farming. Lastly, a notably 86.9% indicated that positive peer feedback would encourage data sharing. These results collectively demonstrate the strong impact of perceived benefits and positive peer feedback on farmers' willingness to engage with digital agricultural technologies.

In conclusion, these results collectively demonstrate the strong impact that perceived benefits and positive peer feedback have on farmers' willingness to engage with digital agricultural technologies. The findings suggest that for broader adoption of these technologies, focusing on showcasing tangible benefits and facilitating positive peer exchanges could be key strategies.

The upcoming chapter will present theoretical and practical contributions, and recommendations for academia, stakeholders, including developers of agricultural digital applications, agribusinesses, and legal advisors in Southern Africa. The researcher hopes to bridge a knowledge gap and provide a deeper understanding of the unique factors affecting horticultural farmers in Southern Africa, currently using DAA. Additionally, the chapter will explore limitations, areas for further research, discuss factors not previously considered and offer a summary of key takeaways.

6 Chapter 6: Recommendations and Conclusion

6.1 Theoretical contribution

The study aimed to address the limited extent of data sharing perceptions among Southern African horticultural farmers, drawing on insights from the literature review emphasising the role of trust in data sharing. The study focused on farmers utilising a specific DAA for horticulture and explored their perceived risks and attitudes toward data sharing. The research questions explored factors contributing to digital trust, the impact of perceived risks on data sharing decisions, and the role of perceived benefits. Key findings highlighted the strong influence of perceived benefits and positive peer feedback on farmers' willingness to engage with digital agricultural technologies. Emphasising tangible benefits and fostering positive peer exchanges was suggested for broader technology adoption in the horticultural industry.

The theoretical contribution lay in investigating Southern African horticultural farmers' attitudes on perceived risks, benefits and digital trust in data sharing. Adapting a trust-based consumer decision-making model from electronic commerce, offering a nuanced understanding of specific constructs, was necessary to understand factors influencing farmers' decisions to share data on DAAs, considering the unique characteristics of this context. This adaptation opened avenues for future research, accentuating the importance of contextual factors in shaping farmers' attitudes.

To deepen theoretical understanding, future research could explore the contextual adaptation of trust models within various agricultural contexts, investigate the influence of cultural factors on digital trust among Southern African horticultural farmers, conduct longitudinal studies tracking attitudes over time, and expand research to include comparative analyses across agricultural sectors. Additionally, exploring the impact of emerging technologies on trust and conducting cross-cultural studies are recommended. Lastly, incorporating ethical considerations into research on data sharing practices among farmers can offer insights into how ethical perceptions influenced decisions related to digital trust. These recommendations could collectively assist theoretical frameworks in the academic understanding of digital trust and data sharing in agriculture.

6.2 Practical recommendations

The pivotal role of perceived benefits, as affirmed by the study, underscores the necessity to highlight the practical advantages of DAAs, such as improved waste management, efficient resource utilisation, and automation of tasks. These benefits directly align with farmers' needs for optimising irrigation and fertilisation, which respondents indicated would motivate them to share data. Furthermore, the study illuminates the substantial influence of community recommendations and peer experiences on farmers' decisions. This suggests a strategy centred around cultivating a community-based approach, where positive feedback and success stories from peers are leveraged to build trust and encourage adoption.

6.2.1 Comprehensive communication, security and trust framework

Development and implementation of an integrated framework for communication, security and trust in relation to farm data sharing.

In response to farmers' apprehensions about sharing farm data, a smart approach for implementation in South Africa would involve the creation and application of a comprehensive framework that harmoniously blends clear communication, stringent security protocols and trust-building strategies. This framework should encompass tailor communication to address farmers' concerns about data sharing with farmer-friendly explanations of how data is used, stored and protected. Set clear timelines for the implementation of security measures, community workshops and regular updates to farmers and be realistic in terms of resources and accessibility for farmers.

Implement end-to-end encryption and regular security audits to quantifiably enhance data protection. Create easy to use feedback mechanisms such as support WhatsApp groups, questions and answers workshops and feedback forms to measure farmers' trust and perception of security over time.

Focus on establishing a reputation for reliability and trustworthiness. Engage with local farming communities to understand and address their specific concerns about data sharing.

By integrating these components, the framework aims to effectively address the dual concerns of data security and trust among farmers, thereby fostering a more conducive environment for the sharing of farm data in South Africa's agricultural sector.

6.2.2 User-centric design and positive experience

Combine the development of user-friendly digital applications with the promotion of positive farmer experiences. Consider a user-centric design philosophy by forming a task group of diverse farmers that form part of the development of the DAA. Ensure that the DAA is suitable for low-bandwidth areas and include features for easy navigation such as clear dashboards, menus, straightforward instructions, and easily recognisable icons. Incorporate case studies and testimonials to highlight benefits and encourage user feedback.

6.2.3 Peer influence, technical literacy, and community engagement

Incorporate the power of peer influence alongside boosting technical literacy and harnessing community endorsements. Facilitate and back peer-driven training sessions and community gatherings where farmers can exchange experiences and advice. Offer educational programs and assistance for digital proficiency and app operation, in collaboration with local governmental bodies such as the Department of Agriculture, Land Reform and Rural Development. Highlight the critical role of collaboration between public and private entities in these programs.

6.2.4 Software compatibility and educating on data sharing

Address software compatibility concerns and educate farmers about third-party data sharing through workshops and online tutorials. Ensure applications are compatible with various devices and provide clear guidelines for third-party data sharing, emphasising benefits and risks.

6.2.5 Risk management and demonstrating benefits

Combine financial risk management strategies with highlighting perceived benefits and positive feedback. Demonstrate the cost-effectiveness of DAA and their impact on farm management. Showcase success stories and encourage positive peer feedback to highlight tangible improvements.

By merging these recommendations, stakeholders can focus on developing DAA that are secure, intuitive, and trusted by the farming community, while also being economically viable and socially endorsed. This approach encourages broader adoption and effective use of digital technologies in agriculture.

6.2.6 Data legislators

Regularities and legislators play a crucial role in shaping the environment within which DAAs operate. Their responsibilities in this context can be outlined as follows:

6.2.6.1 Comprehensive data legislation and farmer rights protection

Combine establishing regulatory frameworks with protecting farmer data rights. Develop comprehensive legislation that covers all aspects of data privacy, security, and farmer rights in the agricultural sector, including ownership, access, control, and informed consent. Ensure DAAs comply with these regulations and provide clear mechanisms for farmers to exercise their rights.

6.2.6.2 Transparency, security, and compliance in data usage

Merge mandates for transparency in data usage with facilitating secure data environments and ensuring compliance with innovation. Require DAAs to disclose their data handling practices transparently, implement stringent data security measures like encryption and audits, and balance technological innovation with strict adherence to data protection laws.

6.2.6.3 Promoting digital literacy, access, and equitable use

Integrate supporting digital literacy and access with ensuring equitable access. Support initiatives to enhance digital literacy among farmers, ensuring they can effectively use DAAs and understand their rights. Develop policies to ensure all farmers, including those in remote areas, have access to digital agricultural technologies.

6.2.6.4 Regulating third-party data sharing and providing dispute resolution

Combine regulating third-party data sharing with establishing clear channels for feedback and dispute resolution. Create clear guidelines for third-party data sharing, protecting farmers' interests and consent. Set up regulatory bodies or services for farmers to provide feedback on DAAs and resolve any disputes, reinforcing data rights.

By consolidating these recommendations, data legislators can focus on creating a robust and holistic regulatory environment that not only protects farmers' data rights but also fosters an ecosystem conducive to the sustainable growth of digital agriculture. This approach ensures transparency, security, and equitable access, encouraging the responsible use of digital technologies in farming.

6.3 Limitations

6.3.1 Limitations of single-cross sectional research design

As noted, this study captured data at a single point in time, which may not reflect changes in attitudes, behaviours, or conditions over time. In the context of rapidly evolving digital agricultural technologies and fluctuating market and environmental conditions, farmers' perceptions and willingness to share data could change significantly. A longitudinal approach would provide a more comprehensive understanding of these dynamics over time, capturing shifts in attitudes or the impact of external factors like policy changes or technological advancements.

6.3.2 Sample representation and generalisability

The sample consists of 260 Southern African horticultural farmers who all use the same DAA (after post data cleaning, only 61 of these responses were considered valid for the study due to missing data), thus the findings can only be generalisable to this sample and not the broader population of different farmers around the globe. This limitation is critical in studies aiming to inform technology development and policy, where diverse perspectives are essential.

6.3.3 Potential technological bias

The data was administered digitally and the respondents are all users of the same DAA, which could inherently bias the sample towards farmers who are more technologically literate or have better access to digital tools. This excludes a segment of the population that may be less tech-savvy or lack adequate digital access, which is particularly relevant in studies about digital agricultural tools.

6.3.4 Cultural and contextual factors

The study's findings might be influenced by specific cultural or regional factors that affect farmers' attitudes towards data sharing and digital tools. Without considering these contextual elements, the study might overlook crucial drivers or barriers to technology adoption unique to different farming communities.

6.3.5 Limited knowledge of researcher

As the researcher is a student, limited experience must be noted in research design and execution. Also, a limited understanding of the statistics software (IBM SPSS) is also a consideration when viewing the feedback and is clearly seen after factor analysis and pattern matrix in Chapter 4 was applied and resulted in grouping the survey questions differently to hypotheses and research questions.

While the study provides valuable insights, these limitations suggest areas where further research could deepen understanding, particularly through longitudinal studies, more diverse sampling, and consideration of cultural, technological and temporal factors.

6.4 Factors not considered

In the context of perceptions of data sharing among South African horticultural farmers, there are several elements that might not have been considered in the original study, but could play a vital role:

6.4.1 Socio-economic status and farm size

The financial capacity and scale of operations can significantly influence a farmer's ability to access and use DAA. Larger, commercial farms might have different perspectives and resources compared to smallholder farmers, affecting their perceptions and willingness to share data.

6.4.2 Digital infrastructure and accessibility

The level of digital infrastructure available in different regions of South Africa can greatly affect the feasibility and perception of using digital agricultural tools. Areas with limited internet connectivity or lack of digital devices may view data sharing differently from those with better digital access.

6.4.3 Cultural attitudes and trust in technology

Cultural factors and the general level of trust in technology and external entities (like government or corporate bodies) can influence attitudes towards data sharing. Understanding the cultural context and historical experiences of South African farmers could provide deeper insights into their perceptions.

6.4.4 Education and digital literacy

The level of education and digital literacy among farmers is crucial. Farmers with limited understanding of digital tools might be more apprehensive about data sharing due to concerns over data misuse or a lack of understanding of the benefits.

6.4.5 Gender and age dynamics

Gender and age may play a role in how technology is adopted and data is shared in the agricultural sector. The perspectives of women and younger farmers, who are often underrepresented in agricultural studies, could provide valuable insights.

6.5 Future research

Future research endeavours are vital for grasping the intricate and ever-changing realm of digital agriculture. The subsequent areas could potentially build on the insights of the current study.

6.5.1 Longitudinal studies on farmers' attitudes and behaviours

Conducting longitudinal research to track how farmers' attitudes and behaviours towards sharing data on DAA evolve over time would be insightful. This could involve periodic surveys or interviews with the same set of farmers over several years. Such a study would capture the dynamics of changing perceptions, influenced by factors like technological advancements, policy changes, market trends and environmental conditions. This research could reveal deeper insights into the long-term adoption patterns of digital agricultural technologies and the sustainability of their use.

6.5.2 Exploring the impact of cultural and regional differences

A comparative study across different cultural and geographical contexts could provide valuable insights. Different regions may have varying levels of technological advancement, infrastructure, education and cultural attitudes towards data sharing and privacy. Researching these differences can help in understanding how DAA can be tailored to meet the diverse needs of farmers in different settings. This could involve cross-country studies or in-depth research within different regions of a single country.

6.5.3 Assessing the influence of emerging technologies and data legislation

With the rapid advancement of technology and evolving data privacy laws, future research could focus on how these changes impact farmers' willingness to share data. This could include studying the effects of new technologies like blockchain, AI-driven farm management systems, or IoT devices in agriculture. Additionally, examining the impact of new data protection regulations and farmers' awareness and understanding of these laws would be beneficial. This research area is particularly timely and relevant, given the increasing digital transformation of agriculture and heightened global focus on data privacy and security.

6.6 Conclusion

In conclusion, this study has explored various dimensions of farmers' perceptions and behaviours towards sharing farm data in the context of DAA, particularly focusing on horticultural farmers in South Africa. Spanning six chapters, the study has navigated from establishing the context and significance of digital agriculture to examining specific factors influencing data sharing, assessing perceived risks and evaluating the impact of perceived benefits.

Key findings have highlighted the relationship of data sharing and the influential power of perceived benefits in shaping farmers' decisions to engage with digital agricultural tools.

The recommendations for academia, various stakeholders, including digital application developers, data legislators and agricultural policymakers, are tailored to address the identified gaps and leverage the opportunities. These suggestions aim to create a more secure, transparent, and farmer-centric digital agricultural environment, ultimately contributing to the sustainable and inclusive growth of the agricultural sector.

This study, therefore, not only adds to the existing body of knowledge on digital agriculture but also offers practical guidance for stakeholders to navigate the complex landscape of farm data sharing in the adoption of agricultural technology. The findings and recommendations serve for further exploration and development in the field, aiming to enhance the efficiency, profitability, and sustainability of agricultural practices through informed and strategic application of digital technologies.

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Appendix A: Research questions and related hypothesis, with the literature references for each survey question.

Research question 1

What factors of digital trust contribute to farmers deciding whether to share farm data on a digital agricultural application.

Hypothesis 1: Digital Trust positively affects intention to share farm data on a digital agricultural application.

The factors of digital trust highlighted in the study are social influence in the form of image and reputation, control and ownership off farm data, ambiguous contracts and user experience.

Survey question 1 - Literature reference: (Pillai & Sivathanu, 2020; Shi et al., 2022; Venkatesh et al., 2012; Venkatesh et al., 2003)

If other farmers in the community recommend using the digital agricultural app, I would be more likely to share my farm data.

Survey question 2 - Literature reference: (Pillai & Sivathanu, 2020; Regan, 2019; Shi et al., 2022; Venkatesh et al., 2012; Venkatesh et al., 2003)

The experiences of other farmers using the digital agricultural app influence my decisions to share my farm data

Survey question 3 - Literature reference: (Jakku et al., 2019; Pillai & Sivathanu, 2020; Wiseman et al., 2019)

The reputation of the digital agricultural app service provider plays a significant role in my decision to share my farm data.

Survey question 4 - Literature reference:(Wiseman et al., 2019)

When considering sharing my farm data it is important that the digital agricultural app clearly communicates its data privacy policies and ownership.

Survey question 5 - Literature reference: (Jakku et al., 2019; Wiseman et al., 2019)

When considering sharing my farm data on the digital agricultural app, it is important that I have control over my farm data.

Survey question 6 - Literature reference: (Kim et al., 2008)

Having a positive experience using the digital agricultural app is important in deciding whether I should share my farm data.

Hypothesis 2: Digital trust negatively affects famers perceived risk of sharing farm data on a digital agricultural application.

Survey question 7 - Literature reference: (Regan, 2019)

The attitude of my peers towards sharing my farm data in precision farming is an important factor.

Survey question 8 - Literature reference: (Regan, 2019)

The attitude of the end consumer towards my decision to share my farm data for precision farming is an important consideration.

Hypothesis 3: Positive intention to share farm data has a positive influence on actual sharing of farm data on a digital agricultural app

The intention to use a digital agricultural application suggested a positive relationship with actual sharing of data in this study.

Survey question 9 - Literature reference: (Shi et al., 2022; Venkatesh et al., 2012; Venkatesh et al., 2003)

Positive interaction with the current digital agricultural app will encourage me to continue using it for the next crop season.

Research question 2

To what extent does perceived risks impact farmers view of sharing data on a digital agricultural application?

Hypothesis 4: A farmers perceived risk negatively affects intention to share farm data on a digital agricultural application.

The perceived risks highlighted in the study are privacy and security, technical challenges, compatibility of software and financial risks.

Survey question 10 - Literature reference: (Wiseman et al., 2019)

The digital agricultural app's data security measures are critical when deciding whether to share my farm data.

Survey question 11 - Literature reference: (Pillai & Sivathanu, 2020)

I will still share my farm data on the digital agricultural app if it is shared with third parties.

Survey question 12 - Literature reference: (Pillai & Sivathanu, 2020)

If I felt more confident in my ability to navigate technical issues with the digital agricultural app, I would be more willing to share my farm data.

Survey question 13 - Literature reference: (Wiseman et al., 2019)

The risk of software compatibility on the digital agricultural app to my current IT infrastructure plays a significant role in my decision to share my farm data.

Survey question 14 - Literature reference: (Jakku et al., 2019; Pillai & Sivathanu, 2020; Wiseman et al., 2019)

I worry that sharing my farm data on the digital agricultural app could make me vulnerable to financial loss.

Research question 3

To what extent does perceived benefits impact farmer's decisions to share data on a digital farming application?

Hypothesis 5: A farmers perceived benefits positively affect decisions to share farm data on a digital agricultural application.

The perceived benefits highlighted in the study are improved decision making, usefulness, ease of use, cost and time savings, waste management and benefits realised by other farmers

Survey question 15 - Literature reference: (Kim et al., 2008; Wiseman et al., 2019)

The perceived benefits I gain from using the digital agricultural app increase my willingness to share my farm data.

Survey question 16 - Literature reference: (Pillai & Sivathanu, 2020; Shi et al., 2022; Wiseman et al., 2019)

The improved farm management decision making benefits I gain from using the digital agricultural app increase my willingness to share my farm data.

Survey question 17 - Literature reference: (Rose et al., 2021)

If I believed that sharing more of my farm data would enhance irrigation and fertiliser optimisation, I would be more inclined to share additional sensitive data on the digital agricultural app.

Survey question 18 - Literature reference: (Pillai & Sivathanu, 2020)

Positive feedback on the benefits of using the digital agricultural app, from other farmers, will encourage me to share my farm data.

Survey question 19 - Literature reference: (Kim et al., 2008; Rose et al., 2021)

The benefits of ease of use impact my decision to share my farm data on the digital agricultural app.

Appendix B - Research questionnaire

Your responses to this survey will be kept anonymous and confidential. By completing and submitting this online questionnaire, personal consent to participate will be implied.

Question 1

If other farmers in the community recommend using the digital agricultural app, I would be more likely to share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 2

The experiences of other farmers using the digital agricultural app influence my decisions to share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 3

The reputation of the digital agricultural app service provider plays a significant role in my decision to share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 4

When considering sharing my farm data it is important that the digital agricultural app clearly communicates its data privacy policies and ownership.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 5

When considering sharing my farm data on the digital agricultural app, it is important that I have control over my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 6

Having a positive experience using the digital agricultural app is important in deciding whether I should share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 7

The attitude of my peers towards sharing my farm data in precision farming is an important factor.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 8

The attitude of the end consumer towards my decision to share my farm data for precision farming is an important consideration.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 9

Positive interaction with the current digital agricultural app will encourage me to continue using it for the next crop season.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 10

The digital agricultural app’s data security measures are critical when deciding whether to share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 11

I will still share my farm data on the digital agricultural app if it is shared with third parties.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 12

If I felt more confident in my ability to navigate technical issues with the digital agricultural app, I would be more willing to share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 13

The risk of software compatibility on the digital agricultural app to my current IT infrastructure plays a significant role in my decision to share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 14

I worry that sharing my farm data on the digital agricultural app could make me vulnerable to financial loss.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 15

The perceived benefits I gain from using the digital agricultural app increase my willingness to share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 16

The improved farm management decision making benefits I gain from using the digital agricultural app increase my willingness to share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 17

If I believed that sharing more of my farm data would enhance irrigation and fertiliser optimisation, I would be more inclined to share additional sensitive data on the digital agricultural app.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 18

Positive feedback on the benefits of using the digital agricultural app, from other farmers, will encourage me to share my farm data.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

Question 19

The benefits of ease of use impact my decision to share my farm data on the digital agricultural app.

Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree

END

Appendix C – Respondent consent form

Title: Perspectives on data sharing by Southern African horticultural farmers

Kathleen Ann Bailie

B Phil Hons Marketing

17 June 2023

Dear respondent,

You are invited to participate in a research study conducted by Kathleen Ann Bailie from the University of the Witwatersrand. The purpose of this study is to investigate the risk perceptions of Southern African horticultural farmers when sharing their farm data on a digital agricultural application.

This form provides you with information about the study. Please read it carefully and take your time to make your decision about participating in the research.

Your participation will involve completing an online survey which will take approximately 10 minutes of your time. Your participation in this study is voluntary. You have the right to withdraw at any point during the study, for any reason, and without any prejudice.

By agreeing to this form, you acknowledge that:

- You have read the information provided above.
- You voluntarily agree to participate.

- You are at least 18 years of age.

If you agree to participate, you will be asked to answer 19 questions with predetermined options where you will select either strongly agree, agree, neutral, disagree or strongly disagree.

The data provided by you in this study will be kept confidential. Data will be stored in a password-protected electronic format.

Risks and Benefits:

There are no known risks to participating in this study. Your responses will be anonymous and cannot be linked back to you. Should you agree to proceed, you will be offered your input into a unique study has been somewhat overlooked - data sharing in the horticultural sector of Southern Africa. This exploration helps to fill knowledge gaps and presents opportunities for future investigations.

This study aims to investigate these perceived risks and provide insights on how the organisation could potentially address them to increase adoption of precision farming practices and enhance the sustainability of the horticultural sector in Southern Africa.

By clicking on the "I agree" button at the beginning of the survey, you indicate that you understand the above information, that you voluntarily agree to participate, that you may withdraw your consent at any time and for any reason without incurring any penalty.

Thank you for considering participation in this study.

If you have any questions, you can contact:

Kathleen Bailie
082 331 4521
8905685J@students.wits.ac.za

Supervisor:
Mitchell Hughes
071 247 9576
Mitchell.Hughes@wits.ac.za

Best Regards,

Kathleen Bailie
B Phil Hons Marketing
082 331 4521
8905685J@students.wits.ac.za

Operations, Development and Marketing Manager at AgriWiz™ Limited
Kathleen@agriwiz.mu

Appendix D – Respondent participation form

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

29 June 2023

Dear Farmers and Agronomists

My name is Kathleen Bailie. I am a Master's student in Digital Business at the University of the Witwatersrand, Johannesburg. My supervisor is Mitchell Hughes. I am conducting research into the perceived risks associated with sharing farm data on digital agricultural applications as identified by horticultural farmers in Southern Africa. The study title is "Perspectives on data sharing by Southern African horticultural farmers".

Gaining insight into these perceived risks will potentially offer insights for diverse stakeholders, such as developers of agricultural digital applications, agribusinesses, and legal advisors. Such insights could be instrumental in enhancing the confidence of farmers when sharing their farm data, thereby increasing adoption of precision farming and thus the productivity and sustainability of the horticultural sector in Southern Africa.

I am therefore inviting you to take part in an online survey questionnaire. There are nineteen (19) questions with predetermined responses where you select either strongly agree, agree, neutral, disagree or strongly disagree. The questionnaire will take no longer than ten (10) minutes to complete.

Your responses will be used in my research study during 2023, and thereafter stored on my private laptop in a password protected file for three (3) years and then deleted. Only I will have access to this to the data.

Your responses will be confidential and anonymous. When I share the results of the research study, I will not include your name or anything else that could identify you. With your permission, other researchers may use the data collected from this research study, but your name and any personal data/information will not be used or passed on.

If you decide to take part, it should be because you want to volunteer. You do not have to take part. You can stop being in the study at any time. You do not have to answer any questions if you do not want to. You will not get any direct benefits if you choose to join the research study.

The questions posed in the questionnaire are not personal in nature and only enquire about your attitudes towards sharing your farm data.

This research study will be written up as a research report. The report will be available on the university library website. If you would like to receive a summary of this report, I will also be happy to send it to you.

If you have any questions during or after, feel free to contact me or my supervisor using the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za

Yours sincerely,

Kathleen Ann Bailie / 8905685J@students.wits.ac.za / 082 331 4521

Supervisor:

Mitchell Hughes / mitchell.hughes@wits.co.za / 071 247 9576

Appendix E – Permission to research from business

AGRIWIZ
INTELLIGENT BY NATURE

AgriWiz Limited:
Suite 005
Grand Baie Business Park
Grand Baie
Mauritius
+27 73 308 6232
www.agriwiz.mu

James Vos
AgriWiz™ Limited
James@agriwiz.mu
083 305 4815
28th June 2023

Kathleen Bailie
University of Witwatersrand / Student no: 890568SJ
Email address: 890568SJ@students.wits.ac.za

Dear Kathleen
I am writing in response to your recent request to conduct research at AgriWiz™ for your master's in digital business at University of Witwatersrand. Your proposed research titled "Perspectives on data sharing by Southern African horticultural farmers" has been carefully reviewed and considered.

We acknowledge the value and importance of the subject matter you wish to explore. As an organisation that believes in the power of data and the transformation it can bring to the agricultural sector, especially for horticultural farmers in Southern Africa, we are pleased that your study amongst the farmers and agronomists using AgriWiz™ Limited, on our behalf, is granted.

We would like to disclose, that while you are presently engaged as a supplier to AgriWiz™ Limited, serving in an operational and developmental capacity, the financial backing for your studies and the decision to pursue this specific area of research is entirely your own initiative.
In granting you permission, we trust that any data obtained will be handled with utmost confidentiality and used strictly for academic purposes. Furthermore, we appreciate your willingness to share the insights derived from your research with us, which we believe will help us identify potential areas for growth and improvement.

We eagerly anticipate your commencement of the research process and will facilitate access to our clients by informing them of your voluntary request for respondents to be involved with your study.
Please feel free to reach out if there is anything more, we can assist you with.

Yours sincerely,

James Vos
Founder, AgriWiz™ Limited
28 June 2023

Appendix F – Supervisor support letter

30 June 2023

Masters of Management in the field of Digital Business (MMDB)
Wits Business School
Faculty of Commerce, Law and Management (CLM)
University of the Witwatersrand

Approval to submit MMDB research proposal: Student Kathleen Bailie (8905685J)

This letter serves to confirm that Kathleen Bailie (8905685J) has been under my supervision for the MMDB research report. I have reviewed her research proposal and found it to be at a suitable level to be submitted to panel. The proposed title of the research is: ***Perspectives on data sharing by Southern African horticultural farmers***.

Should you require any further information I can be reached at the contact details below.

Sincerely

Mitchell Hughes
Programme Director: Digital Programmes
Wits Business School
Tel: 071 247 9576
E-mail: mitchell.hughes@wits.ac.za

Appendix G – Ethics clearance certificate

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/DB8905685J/483

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below)

Project title	Perspectives on data sharing by Southern African horticultural farmers.
Investigator / Researcher	Mrs Kathleen Baillie
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	25 08 2023
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

28 August 2023
Date: