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Effects of Explainable Artificial Intelligence on Trust in Financial Services Digital Platform Ecosystems

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Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Tarun Rohilla

31 March 2024

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"I have no special talents. I am only passionately curious"
- Albert Einstein

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Dedication

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Abstract

The rise of artificial intelligence (AI) within financial services digital platform ecosystems (FSDPEs) presents unique challenges and opportunities for building trust, impacting the outcomes of willingness to transact, collaboration, and network coopetition. This research investigates these outcomes, addressing the limited inclusion of AI in existing FSDPE trust research. It proposes a novel framework, the Digital Platform Ecosystems Trust Outcomes (DPETO) model, to understand how AI empowers trust.

An extensive literature review synthesises cross-disciplinary research, analysing over 200 academic sources. The study employs advanced quantitative analysis techniques, combining Partial Least Squares Structural Equation Modeling (PLS-SEM) with the emerging Necessary Condition Analysis (NCA) method. Data collection utilises a survey administered through the Qualtrics platform, garnering responses from 333 participants sourced from the Prolific platform. This research contributes to IS Trust (information systems) in two key ways: **Conceptual Model:** The DPETO model offers a novel framework for understanding trust within FSDPEs, explicitly incorporating the moderating role of AI explainability. **Research Methodology:** This study introduces the use of NCA within IS research, providing valuable insights into the necessary conditions for trust in FSDPEs.

Additionally, this research presents critical findings which have significant implications for both researchers and practitioners working on FSDPEs and AI.

Meaningful Relationship: A positive relationship exists between FSDPE composition principles like platform AI and value creation, ultimately impacting the outcomes of willingness to transact, network coopetition, and collaboration. **Vital Role of Trust in Transactional Behaviours:** Trust plays a crucial role in facilitating transactional and cooperative behaviours within the FSDPE landscape, as evidenced by the identified relationships across all outcomes.

Mediation Effects: The mediation effect of trust is stronger when influencing FSDPE outcomes related to platform AI with explainability features (xAI). This finding highlights the crucial role of explaining AI's decision-making in building trust within FSDPEs.

These novel contributions demonstrate the significance of incorporating AI explainability into trust models within FSDPEs and advances the broader field of IS trust research.

Keywords: *Digital Ecosystem; Digital Platform Ecosystem; Digital Platform Ecosystem Trust; Trust; Explainable Artificial Intelligence; xAI; Digital Platform Ecosystem Trust Outcomes; DPETO; NCA; PLS-SEM*

Contents

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List of abbreviations (or acronyms)

ACI	Individual Conditional Expectation
AI	Artificial Intelligence
AIC	Akaike information criterion
AICc	corrected AIC
AICu	unbiased AIC
AISeL	Journal of the Association for Information Systems
API	Application Programming Interface
AVE	Average variance extracted
B2B	Business to business
BCa	bias-corrected and accelerated
BCG	Boston Consulting Group
BIC	Bayesian information criteria
BISA	Business Informatics and Systems Accounting
CE-FDH	Ceiling Envelopment – Free Disposal Hull
CF	CrowdFlower
CI	Confidence interval
COVID-19	Coronavirus disease
CR	composite reliability
CR-FDH	Ceiling Regression - Free Disposal Hull
CSV	comma separated values
DARPA	Defense Advanced Research Projects Agency
DE	Digital Ecosystem
DEAI	Digital Platform Ecosystem Artificial Intelligence
DECOLB	Digital Platform Ecosystem Collaboration
DEHCTM	Digital Platform Ecosystem Human Computer Trust Management
DENCPT	Digital Platform Ecosystem Network Coopetition
DETIO	Digital Platform Ecosystem Trust in Organisations
DPETO	Digital Platform Ecosystems Trust Outcomes model
DETV	Digital Platform Ecosystem Trust Value
DEWTT	Digital Platform Ecosystem Willingness to transact
DPE	Digital Platform Ecosystem
DREAMS	Dynamic Reconfigurable Architecture Modelling
EU	European Union
f2	f square
FPE	final prediction error
FRA	Future Research Agenda
FSDPE	Financial Services Digital Platform Ecosystems
GDPR	general data protection regulation
GED	General Educational Development Test
GM	Geweke-Meese criterion
H	Hypothesis
HCTM	human computer trust measurement
HM	Her Majesty’s
HO	Higher Order construct
HQ	Hannan and Quinn’s criterion
HQc	corrected HQ criterion

HTMT	Heterotrait-Monotrait
ICT	Information Communication Technology
IoT	Internet of Things
IRC	Informatics Research Centre
IS	information systems
IT	Information Technology
JD	juris doctor degree
LB	lower bound
LIME	local interpretable model-agnostic explanations
LM	Linear model
LRP	Layer-wise Relevance Propagation
MAE	Mean absolute error
MD	Doctor of Medicine
MIS	Management Information Systems
ML	machine learning
MSP	Multi Sided Platforms
MTurk	Amazon Mechanical Turk
NCA	necessary condition analysis
PDP	Partial Dependence Plot
PLS-SEM	Partial Least Squares Structural Equation Modelling
Q2	Q square (predictive relevance)
R2	R square (coefficient of determination)
rhoa	Omega A
rhoc	Omega C
RMSE	Root-mean-square error
RQ	Research Question
SE	Standard error
SME	Small Medium Enterprises
STDEV	Standard deviation
TIF	theories in flux
TIO	trust in organisations
TPM	Trusted Platform Module
UB	upper bound
UK	United Kingdom
URL	Uniform Resource Locator
USA	United States of America
VIF	variance inflation factor
vs	versus
xAI	Explainable AI
β	Coefficient Std Beta

1 Introduction

"The kinds of question we ask are as many as the kinds of things which we know. They are in fact four: (1) whether the connexion of an attribute with a thing is a fact, (2) what is the reason of the connexion, (3) whether a thing exists, (4) what is the nature of the thing.
These, then, are the four kinds of question we ask, and it is in the answers to these questions that our knowledge consists"

- *Aristotle (Book II of Posterior Analytics)*

1.1 Introduction

Digitalisation is metamorphosing nearly every dimension of industry and related ecosystems, leading them to take emergent forms, such as in the case of Digital Platform Ecosystems (DPEs). As Drucker (1980) said, there is a need to rethink normality in these turbulent times. Embracing change is becoming the new normal for everyone, including society, organisations, and ecosystems. Although the aftermath of COVID-19 pandemic is disrupting all existing ecosystems, including the digital ecosystems, DPEs are anticipated as a remedy to restore recovery (Catapult, 2020). Digital ecosystems are expected to create and deliver value at scale for organisations. These expectations have led interdisciplinary thought leaders to emphasise the construct of trust and how it regulates the dynamics of digital ecosystems (Lillie et al., 2020).

Research on theories of trust has presented ways of establishing trust in distinct contexts. An example of this is the signalling theory (Siegfried, Löbbers and Benlian, 2020), which describes trust-building as synonymous with identity verification in the digital context. Another example explains the digitalisation of trust in platforms and the sharing economy (Mazzella et al., 2016). The levers on value co-destruction, value creation in the B2B context, and ecosystem economies and their digitalisation set the construct of ecosystems in the value space (Jacobides, Sundararajan and Van Alstyne, 2019; Pathak, Ashok and Tan, 2020; Pathak, Ashok and Leng Tan, 2022). Whereby, value co-destruction is defined as “an interactional process between service systems that results in a decline in at least one of the systems’ well-being. System in this case, given the nature of a service system, can be individual or organizational” (Schulz et al., 2021, p.4). And value co-creation being defined as “an active, creative, and social interaction process, based on the need or desire of actors linked together within a service ecosystem, who integrate their resources to support the various value co-creation activities. These activities include idea generation, knowledge sharing, product development, solution implementation and to create win-win benefits” (Pathak, Ashok and Tan, 2020, p.2). However, historical research doubts the role of the platforms in the ways trust is created and argues that much time is required to create trust in the online context (Putnam, 2000).

1.2 Research motivations, problem statement and professional issues

The 2008 financial crisis aftermath has presented unprecedented challenges for businesses, and emergent forms of the new normal have cropped up. These are particularly relevant given the implications of the 2019 pandemic. This research is interested in the economic and technological facets of this new normal (Ahlstrom et al., 2020). Industry 4.0 has posed several challenges around human and AI collaboration and competition concerning intellectual capital (Bogoviz, 2020). Enabled with rapid digital transformation and adjusting to this new normal, businesses have transitioned towards remote working, leaving us with challenges of acknowledging, interpreting and safely managing employee data’s digital exhaust (Leonardi, 2020). Other motivations reside within the IS domain, where the emphasis is given to inculcating machine learning practices in developing novel theories such as Theories in Flux (TIF) (Burton-Jones et al., 2021).

Additionally, questions are being proposed for future research directions to measure the economics of digitalisation and the underlying IT agenda, such as those around the transformation of economic decision making influenced by AI, big data and other related technologies (Burton-Jones et al., 2021). Management scholars ought to engage and advance both theory and practice on the use of AI within the organisational context (Raisch and Krakowski, 2021). To address concerns regarding data regulation and usage, AI governed data trusts are argued for their appropriateness (Rinik, 2020). As per the World Economic Forum, the fourth industrial revolution is urgently requiring rethinking existent governance mechanisms. Raising additional concerns for policymakers because of business model disruption due to the advancement in enabling emerging technology which requires agility both at governmental and industrial level (World Economic Forum, 2018). The European Commission wants to actively advance its existing research centres and digital capabilities to develop a framework that will pave the path for trustworthy artificial intelligence (European Commission, 2020a). A critical EU white paper on artificial intelligence adds details on EU comprehensive plans to address the AI opportunity, emphasising the need for ‘an ecosystem of trust’ enabled with transparent, accountable and explainable AI (European Commission, 2020b).

Similarly, the HM Government encourages technology firms to think about safety first, aligned with their latest digital strategy, where Britain wants to be the best place to start a digital business (HM Government, 2017). However, the lack of expertise around online (platform) safety poses significant challenges. The public sector recognises the role ecosystems such as social media platform companies play in the wake of this and developing and deploying technologies to safeguard the public (ecosystem participants). An example of this is how AI and machine learning (ML) are currently used to moderate and remove malefic content (HM Government, 2018). The European Union has further introduced the EU AI Act, which is one of the first regulations on artificial intelligence, aimed to assess and identify the associated risks of using artificial intelligence within the prescribed transparency requirements, ensuring that the AI applications are safe and trustworthy (European Parliamentary Research Service, 2023). Putting trust at the forefront and as a must where artificial intelligence is involved (Feingold, 2023).

Related practitioner issues

Practitioner reports suggest that a positive step to future preparedness and resilience is to build an ecosystem with trustworthy technology (Lillie et al., 2020). Reports emphasise building a digital environment where trust is at the focal point and has the foundational mechanisms to preserve participants' trust (The Royal Society, 2016). Thus, the trustworthiness of a digital system is the key to further open avenues for innovation and enablement of digital ecosystems. Digital platforms are enablers of digital ecosystems, and the mere introduction of this metaphor introduces further challenges. At the governmental level, the emphasis on further research on the dynamics of digital ecosystems has highlighted the need for platform owners to develop collaboration and diversification strategies and understand the associated levers (European Commission, 2019).

Building trust in these digital ecosystems remains paramount, and yet, considered by only a selected few orchestrators and creators of these digital ecosystems. Additionally, trust is one of the key themes related to the reasons for the failures of ecosystems (Aguiar, Pidun, et al., 2022). Figure 1 highlights the distribution of failed ecosystems at various stages. The total size of the sample of failed ecosystems in this study was 110 and the total number of cases with trust as a critical factor was 57 (Aguiar, Pidun, et al., 2022).

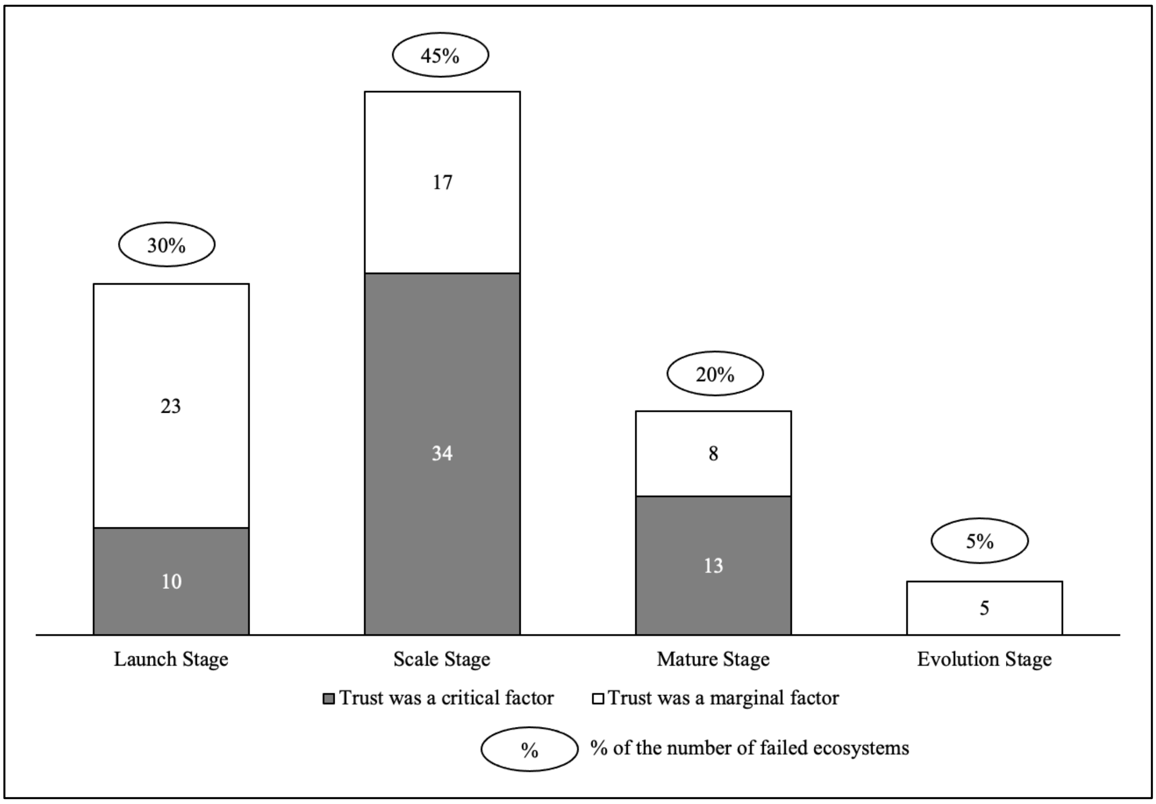

Figure 1: Trust Factor by business stage and ecosystem failure. *Source:* Adapted from Building Trust in Business Ecosystems (Aguiar, Pidun, et al., 2022), p.3

Some practitioner organisations have proposed trust building frameworks that include a layered approach to mitigate the risks of failures in these digital ecosystems, interestingly focusing on embedding trust in the ecosystem platforms. An example of this is the five elements based trust building framework introduced by Boston Consulting Group's Henderson Institute. In this framework, the authors highlight the crucial five elements required to be addressed to build trust as Frictions, Drivers, Games, Locations, and Instruments. It is the location element which is relevant to this research as it pertains to the notion of embedding trust into ecosystems platforms (Aguiar, Pidun, et al., 2022).

This location element is increasingly critical, as these ecosystem platforms evolve to include emerging technologies as their enablers. Additionally, these emerging technologies such as artificial intelligence (including generative AI etc.) is being leveraged as a trust building instrument embedded into these platforms (Aguiar, Pidun, et al., 2022). Key questions around 'what is trust' , 'how to measure', 'perceptions and how companies can improve their trust positions' remain critical to be answered from a practitioner perspective (Aguiar, Williams, et al., 2022).

1.3 Purpose

This quantitative research's key purpose is to establish the conceptual model that links the key factors associated with the presence of artificial intelligence in the digital platform ecosystem and examine the effects of trust on the key digital ecosystem platform participant outcomes of willingness to transact, collaboration, and network coopetition. Digital platform ecosystems in the financial services space are on the rise and the success of these rely on the outcomes delivered to the users. This research was built on the theories of digital ecosystems and platforms as proposed by Jacobides, Adner and others (Adner, 2017; Fuller, Jacobides and Reeves, 2019). It also examined the relevance of trust theories in this context and how they relate to trust in organisations, and human computer trust measurement discipline. With increasing adoption of advanced artificial intelligence techniques, platform trust is an increasing issue in the digital platform ecosystem due to the black box nature of artificial intelligence. This research examines and posits that if there is explainability of these AI algorithms, the explainability will mediate trust in these digital platform ecosystems and hence influence the digital platform ecosystem outcomes of collaboration, willingness to transact and network coopetition. This research agrees with the contextual definition of AI as related to the systems exhibiting intelligent behaviour by analysing their environment, taking actions where suitable and mandated with autonomy as required and achieving specific goals (Sheikh, Prins and Schrijvers, 2023). Artificial intelligence explainability or xAI or Explainable AI is the principle of explaining AI to machines and or humans, contrasting the idea of AI Black Box where AI behaviour cannot be explained (Gunning and Aha, 2019; Barredo Arrieta et al., 2020; Meske et al., 2020).

1.4 Research gaps

Despite technological advancements focused on rethinking the existing theories, models, and frameworks in practically every IS domain, gaps have emerged in the DPE research. These gaps are specifically in the areas of analysis of interdependencies, DPE frameworks, and artefacts such as those around trust methodologies, DPE platform management strategies, DPE governance in line with data security and trust protection, uniform usage of emerging technologies such as AI. Researchers so far have touched upon theories from other disciplines, and DPE specific theories need conceptualisation and development to advance and contribute to DPE research in the IS domain (Senyo, Liu and Effah, 2019), see figure 2.

On a broader ecosystem level, various approaches to interdependence with ecosystems-as-structures have raised several challenges. First, governance needs emerge as a key concern in platform ecosystems. Second, within the multi-sided market context, the absence of a dedicated broker layer within partner links presents a challenge. Lastly, the dynamics of value creation and capture become intricate. Particularly the arrangement of actors and the presence or absence of certain elements within the value network and technology systems significantly influence how value is generated and distributed (Adner, 2017).

Digital platform ecosystems broadly consist of platform owners, mechanisms of value creation and complementor autonomy. This research focuses on the technical properties and associated value creation aspects (Hein et al., 2020). Figure 3 outlines these key building blocks and their positioning at varying levels.

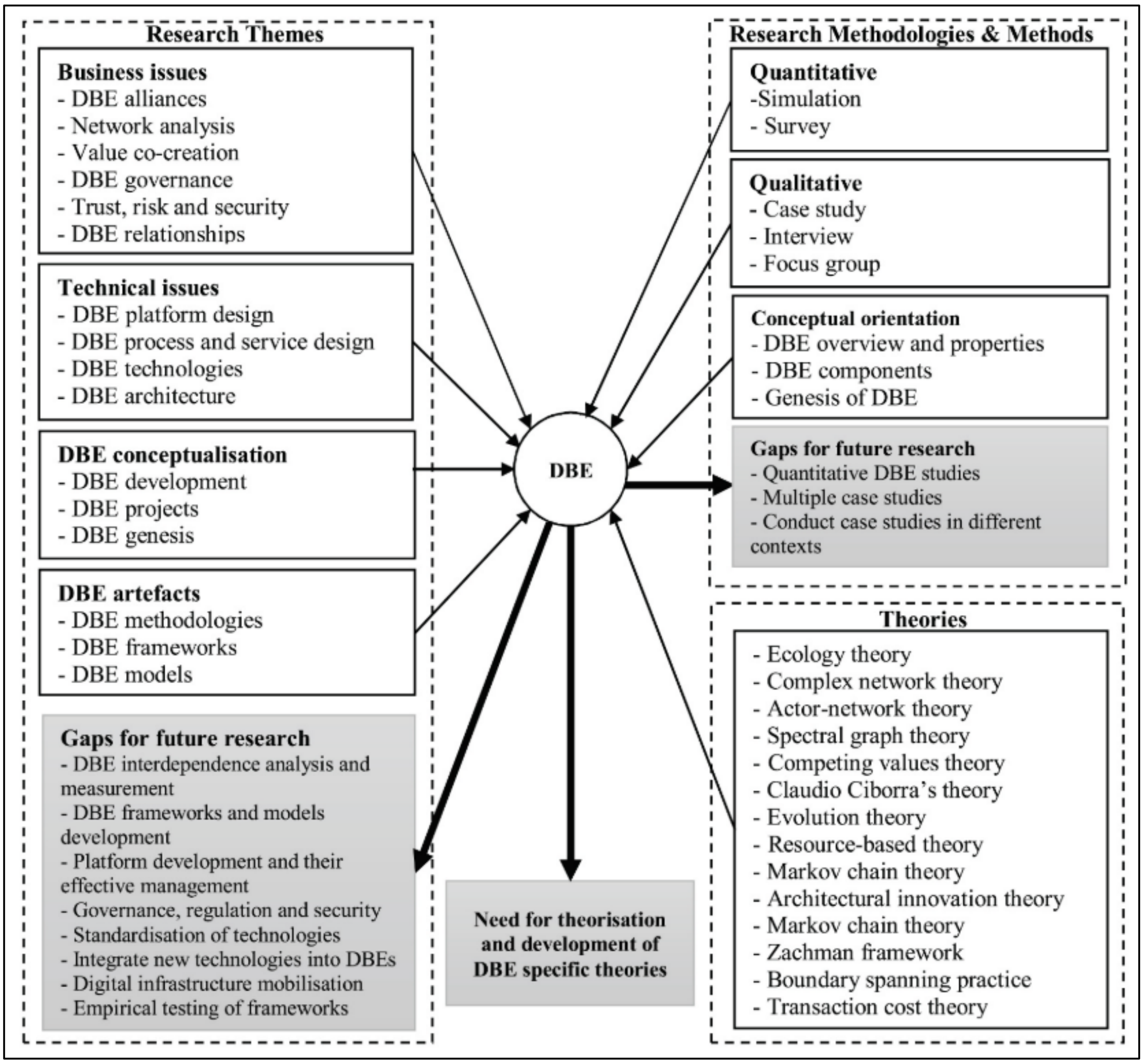

Figure 2: Framework for DBE research. *Source:* Adapted from Digital business ecosystem: Literature review and a framework for future research (Senyo, Liu and Effah, 2019), p. 60

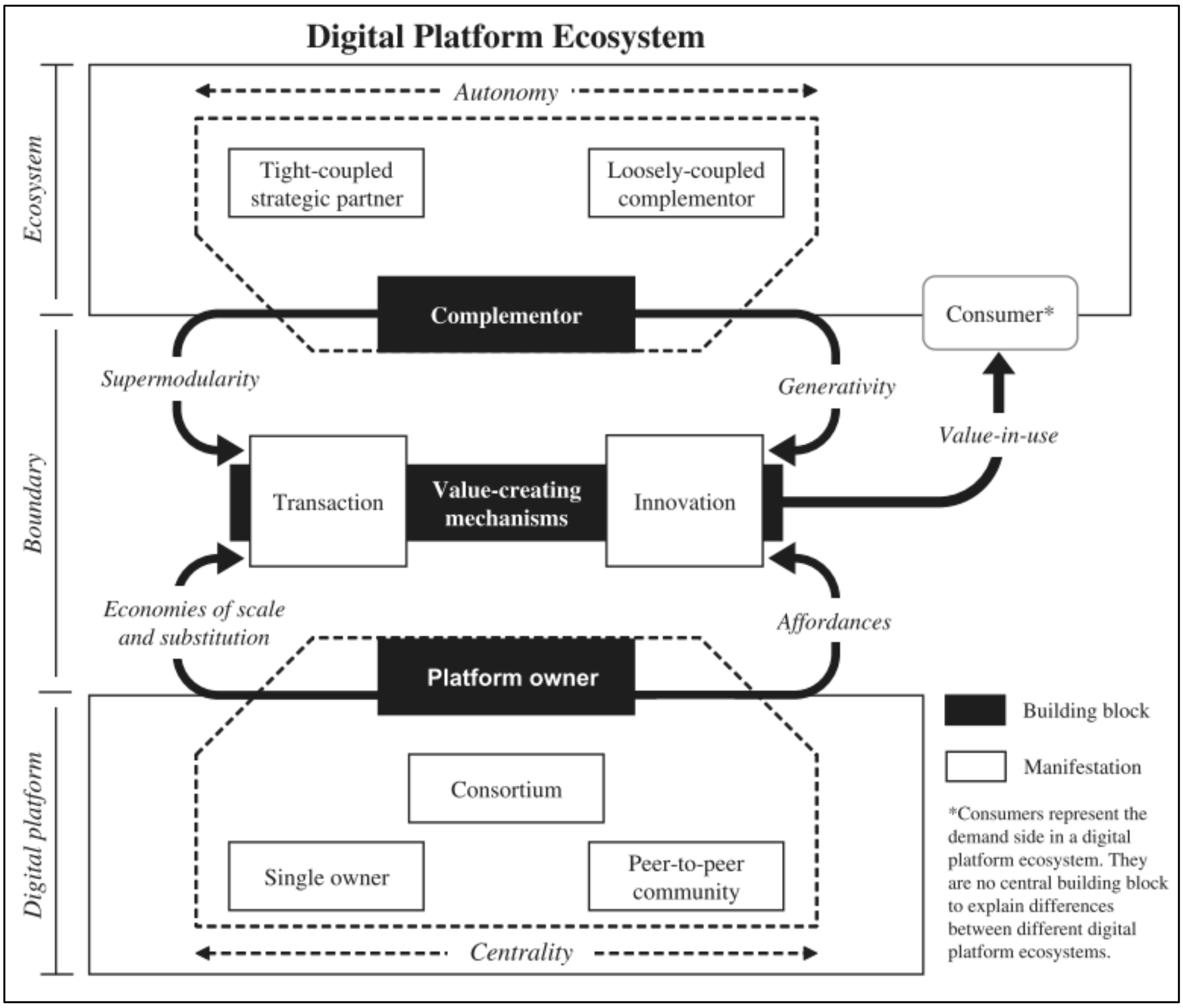

Figure 3: Building blocks of digital platform ecosystems. *Source:* Adapted from Digital Platform Ecosystems (Hein et al., 2020), p. 91

Progress on ecosystems has used the existent siloed researched constructs and applied a set-theoretical lens rather than consolidating existing perspectives (Jacobides, Cennamo and Gawer, 2018). Nevertheless, not enough has advanced to provide technological solutions incorporating emerging technologies to answer ecosystem capabilities challenges such as using data to better serve customers and ecosystem-level diligence (Jacobides, Sundararajan and Van Alstyne, 2019). Furthermore, research has also identified that trust is an issue in the digital platform ecosystems, and emerging technologies such as artificial intelligence are penetrating all aspects of ecosystems (Oxborough et al., 2017), with human-AI collaboration worthy of consideration (Huang, Rust and Maksimovic, 2019).

This thesis pivots on trust issues in DPEs and how they relate to collaboration and value exchange via coopetition and digital transactions. The notion of Type III errors in problematising was carefully considered and explicitly avoided in several aspects, namely: being problem-driven and not advancing towards specific solutions as opposed to previous research papers in the DPE domain, critiquing the DPE research gaps for appropriateness, and generalising enough to contribute across IS domains (Rai, 2017).

To summarise, the following are the key research gaps that this study explores:

- Existing literature have pointed out the lack of analysis concerning the interdependencies in digital platform ecosystem (DPE) research (Senyo, Liu and Effah, 2019). This has created a significant gap, as understanding these interdependencies is crucial for the development of robust digital ecosystems. Furthermore, current frameworks are lacking in their inclusion of trust methodologies, particularly along with emerging technologies such as artificial intelligence (Senyo, Liu and Effah, 2019; Lillie et al., 2020). Integrating such methodologies is critical for fostering secure and reliable digital environments.
- Additionally, previous research has not adequately addressed the broader challenges presented by the absence of trust, especially due to the multi-actor interactions that are foundational to value creation and capture within digital ecosystems (Adner, 2017). This absence of trust can significantly hinder the collaborative potential and innovation within these platforms.
- Research constructs within ecosystem studies have been criticised for their siloed nature (Jacobides, Cennamo and Gawer, 2018). Such compartmentalisation restricts the

development of a holistic understanding of ecosystems, thereby limiting the effectiveness of solutions proposed to enhance trust and collaboration within these digital environments.

- Furthermore, the inconsistent use of the term 'ecosystem,' has led to ambiguity and has hampered the progress in defining and evaluating alternative constructs (Fuller, Jacobides and Reeves, 2019). The clarity of terminology is essential for the advancement of the field, as it underpins all subsequent research and discussion.
- The literature also indicates a limited advancement in understanding the changing role of 'trust' within the information systems (IS) domain. This is a crucial area needing further exploration (Söllner, M., Benbasat, I., Gefen, D., Leimeister, J. M., Pavlou, 2018). As trust evolves in response to technological advancements and societal changes, so too must our approaches to studying and applying it within digital ecosystems.

1.5 Research aims, objectives and questions

To understand and problematise the emergent issues from previously identified research gaps, the research aim for this study was to conceptually *understand the existence of 'ecosystem trust' and how it impacts digital platform ecosystem outcomes.* To do so, the relationship between digital platform ecosystem and related outcomes and the role of explainable artificial intelligence on digital platform ecosystem trust was studied.

This aim was further resolved into the key objectives of this research as outlined below:

- To establish that AI is an enabler of financial services digital platform ecosystems.
- To assess the relationship of trust and outcomes within financial services digital platform ecosystems.
- To assess the impact of AI explainability on trust and outcomes within financial services digital platform ecosystems.

The overarching research question:

"What is the relationship between digital platform ecosystems and outcomes, and how does explainable artificial intelligence impact the relationship between digital platform ecosystem trust and outcomes?"

This overarching research question is further organised in the following sub-questions that were used for this study:

- **RQ1:** How does the digital platform ecosystem itself affect the associated participation outcomes?
- **RQ2:** How does the presence of trust affect the associated participation outcomes?
- **RQ3:** How does digital platform ecosystem trust, involving artificial intelligence explainability, impact digital platform ecosystem participation outcomes?
- **RQ4:** How does the digital platform ecosystem trust, without artificial intelligence explainability, differ from those with artificial intelligence explainability with regards to the digital platform ecosystem outcomes?
- **RQ5:** Within the digital platform ecosystem trust outcomes model proposed in this research, what conditions are meaningful and necessary?

1.6 Conceptual framework for this research

This research applied the concepts aligned with the digital platform ecosystem through an extensive literature review to develop upon previous frameworks and formulate a conceptual framework for the digital platform ecosystem (see Figure 4). This framework includes the key components within the digital platform ecosystems, a higher order (second order construct) construct. These components are the presence of platform artificial intelligence and the related value creation drivers.

Additionally, this research studied the relevant theories with regards to various aspects of trust that are applicable to digital platform ecosystems, as summarised in

Table 6. It references and extends the TIO (trust in organisations) and HCTM (human computer trust measurement) frameworks (Madsen and Gregor, 2000; Bhattacherjee, 2002; Gulati, Sousa and Lamas, 2019), as they were analysed to be closest to the digital platform ecosystem trust. Furthermore, it aligns the key digital platform ecosystem outcomes of network coopetition, willingness to transact and collaboration in the conceptual framework as a means to quantify digital platform ecosystem participation motives (Jacobides, Cennamo and Gawer, 2018; Gawer, 2022; Cusumano, Gawer and Yoffie, 2023).

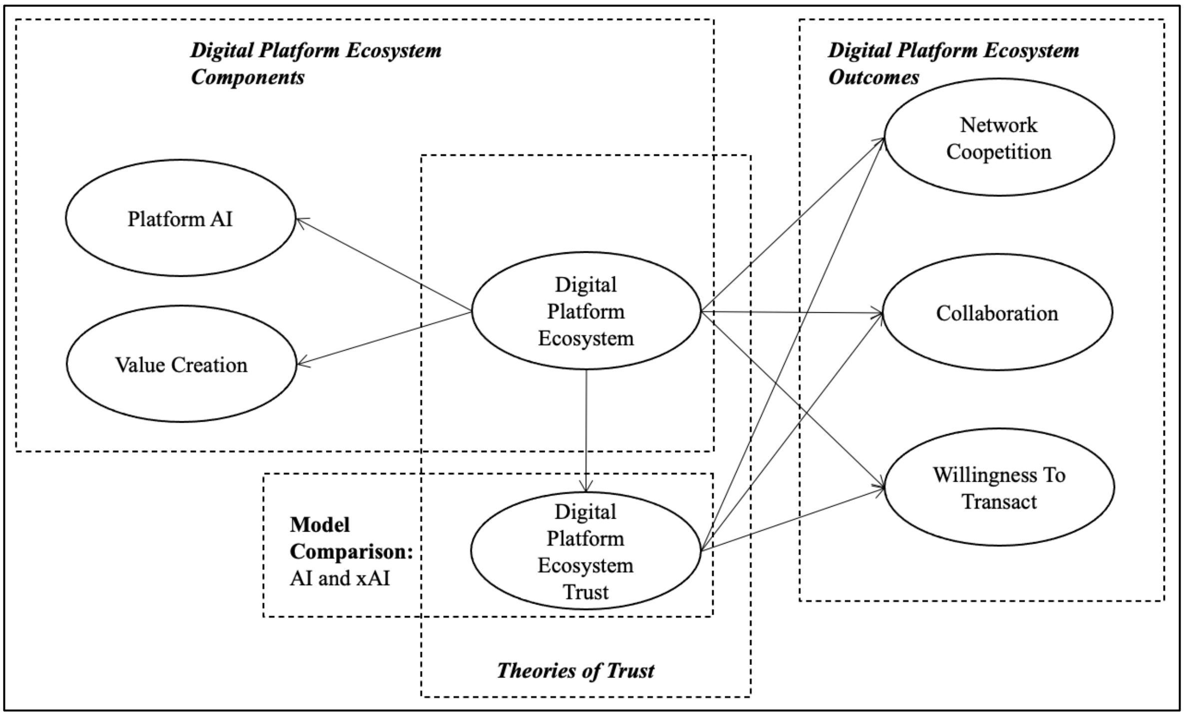

Figure 4: The DPETO conceptual model

1.7 Study purpose

From a positioning, philosophy, and IS domains alignment point of view, interdisciplinary works within the IS domain are still scarce due to the lack of guidelines and set methodologies. This research thesis aims to advance IS interdisciplinary research, especially in innovation areas, following approaches in a complementary fashion (Goes, 2013). IS phenomena, including work in the digital platform ecosystem, are widening in scope at societal and economic levels, leading to a diverse range of data and analysis methods available to researchers to conduct and advance IS domain research (Rai, 2018). The upcoming chapters introduce previous work on digital platform ecosystems, which formed the literature review (Torraco, 2005) and detail the findings in the DPE theory domain, specifically around platforms as a subset of DPEs, trust in DPEs and emerging technologies such as AI and (xAI). This research then describes the methodologies used to review the literature and develop the key model that form the contributions of this thesis. Developing a conceptual model with artificial intelligence explainability as a mediator of trust in digital ecosystems; and measuring its effects on the outcomes of digital platform ecosystems participation. These research contributions provide digital platform ecosystem owners, participants, and users a path forward towards measuring the effects of artificial intelligence embeddedness and other related emerging technologies such as Generative AI and associated risks. By identifying how trust mediates the digital platform ecosystem, digital platform ecosystem providers and owners can use this framework to develop trustworthy and meaningful artificial intelligence based solutions.

1.8 Definitions of key terms

Digital Platform Ecosystem: A digital platform ecosystem is a digital / online platform where participants collaborate, consume, and complement each other's products and services organised by an overarching goal facilitated by a platform owner (Hein et al., 2020).

Digital Platform Ecosystem Participant/Actor: A digital ecosystem platform participant or actor is composed of either individuals or organisations that participate in a digital platform ecosystem (Adner, 2017; Jacobides, Cennamo and Gawer, 2018).

Digital Platform Ecosystem Owner/Provider: A digital platform ecosystem owner / provider is the responsible party for maintaining and managing the digital platform without taking the role of a hierarchical authority (Adner, 2017; Jacobides, Cennamo and Gawer, 2018; Hein et al., 2020; T Kretschmer et al., 2020).

Digital Platform Ecosystem End-User: A digital platform ecosystem end-user is a digital ecosystem participant or actor who is often only interested in consuming products and services on the ecosystem platform (Hein et al., 2020).

AI Explainability (xAI): Artificial intelligence explainability or xAI or Explainable AI is the principle of explaining AI to machines or humans, contrasting the idea of AI Black Box where AI behaviour cannot be explained (Gunning and Aha, 2019; Barredo Arrieta et al., 2020; Meske et al., 2020).

Network Coopetition: Multiple participants on the digital platform ecosystem interacting, often collaborating with direct competition that bring benefits to both (Lascaux, 2020).

Collaboration: Ecosystem participants purposefully interacting on the digital platform ecosystem (Bonardi et al., 2016; Das, 2020; Lascaux, 2020; Pathak, Ashok and Tan, 2020; Steinbruch, Nascimento and de Menezes, 2021).

Willingness To Transact: Ecosystem participants intention on using the digital platform ecosystem for some of their future transactions, including their inclination towards procuring and likelihood of utilising digital platform ecosystem offered goods and services (Bhattacherjee, 2002).

1.9 Chapter summary and thesis structure

In this chapter, the problem statement, and motivations for conducting this research were introduced, highlighting the relevant professional issues, and outlining the purpose of this research. Then, the research gaps pertaining to this research were presented, both from an academic and professional context. Following which, this chapter presented the overarching research question along with a connecting set of questions that accompany the novel conceptual framework which forms the basis of this thesis. This chapter concludes with presenting the rationale and purpose of the study and defining key terms used in the context of this research.

The rest of this thesis is organised as a collection of chapters in continuation to Chapter1: Introduction. Table 1 provides an outline of this thesis structure followed by detailed description of the contents of each chapter.

Table 1: Thesis structure

Chapter	**Title**
Chapter 1	Introduction
Chapter 2	Literature review
Chapter 3	Methodology
Chapter 4	Analysis and findings
Chapter 5	Discussions and contributions
Chapter 6	Limitations and future research
References	References of sources used in this thesis, including books, journal articles, web articles and practitioner reports.
Appendix	List of appendices

Chapter 1 introduces the research topic, provides context for the study, states the research questions, hypotheses, and outlines the significance of the research. It also presents the structure of this thesis.

Chapter 2 highlights the literature reviewed in this thesis. This includes literature on digital platform ecosystems, and their capabilities, and the key digital platform ecosystems outcomes.

This chapter further reviews and discusses the existing literature and relevant theories related to this research topic.

Chapter 3 outlines the research methodology in detail. It explains the research design, data collection methods, participants, and other tools and instruments used. This chapter aims to provide a transparent and replicable description of how the study was conducted.

Chapter 4 discusses how the collected data is analysed using the PLS-SEM and NCA methods. The analysis findings are presented using tables, figures, and graphs where appropriate. The results are discussed regarding research questions and the related hypotheses.

Chapter 5 interprets the findings in the context of the research questions and the existing literature. It discusses the implications of the findings and their contribution to the field of study, methodology and practice. Any unexpected results (such as hypotheses that were not supported) are addressed, and the significance of the research is discussed.

Chapter 6 summarises the main conclusions drawn from the study and further relates them to the research questions or hypotheses. It discusses the study's limitations, such as sample size, data collection constraints, or methodological limitations. Suggestions for future research agenda based on the study's findings and limitations are presented.

2 Literature review

"The ultimate vindication of AI-creativity would be a program that generated novel ideas which initially perplexed or even repelled us, but which was able to persuade us that they were indeed valuable."

– Margret Boden

This chapter provides a review of the literature for this research thesis on digital platform ecosystems and delves into a comprehensive exploration of the existing literature surrounding cross-paradigm combinative practices within the digital platform ecosystems domain. It examines the alignment of specific thematic advancements in IS domains with the constructs of digital platform ecosystems. Through an in-depth literature review, this chapter aims to shed light on the evolving landscape of digital platform ecosystems, focusing on critical related aspects such as governance, trust, artificial intelligence, and explainability. By synthesising various sources, this chapter seeks to provide an integrated and cohesive understanding of the state of knowledge in this domain. To this end, the figure below shows the key bodies of literature reviewed to integrate the concepts related to this research.

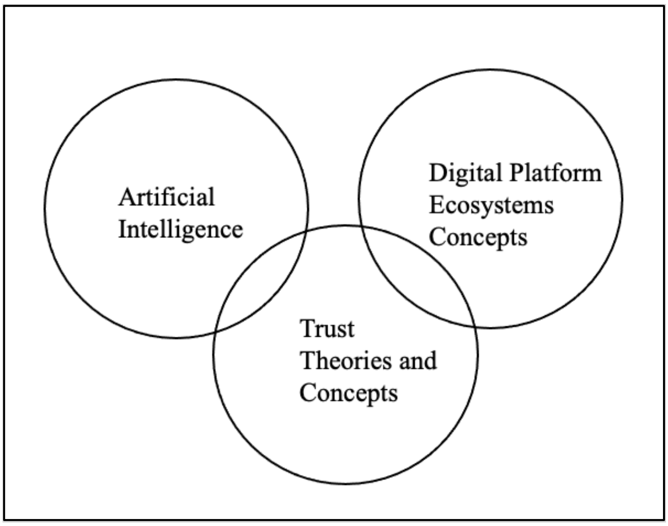

Figure 5: Intersection and integration of key bodies of knowledge

Furthermore, the literature review in this thesis is organised using the framework presented in the figure below. This framework expands and builds upon the previously presented intersection of key bodies of knowledge concerning this research thesis. The relational exchange theory highlights trust as the foundational mechanism for promoting innovation (outcomes, value creation) in international joint ventures (ecosystem arrangements) (Wang et al., 2020).

The literature review is organised into two main sections (see Figure 6). The first section covers literature on digital platform ecosystem and trust. The second section covers literature on digital platform ecosystem components of platform artificial intelligence and related artificial intelligence explainability concepts and the topic of value creation and capture within digital platform ecosystems.

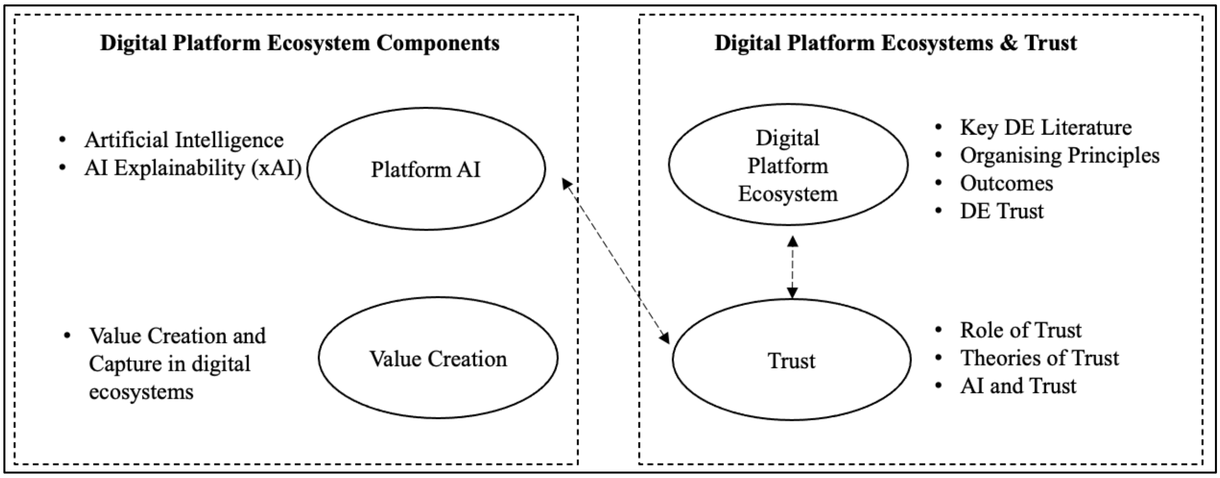

Figure 6: Literature review framework

A detailed mapping of these constructs is presented in the table below (see Table 2), connecting the two sections to the key bodies of knowledge covered in this thesis and the literature review sections that present the details.

Table 2: Literature review framework mapping

Bodies of knowledge	**Literature review theoretical framework section**	**Section title**	**Page number**
Digital Platform Ecosystems	Digital Platform Ecosystem	2.2 Key literature on digital ecosystems	24
	Digital Platform Ecosystem	2.3 The organising principles of digital ecosystems	26
Trust	Trust	2.4 Digital platform ecosystems and trust	28
	Trust	2.4.1 Digitalisation of trust	31
	Trust/Platform AI	2.5 Trust and artificial intelligence	34
Digital Platform Ecosystems	Value Creation and Capture	2.6 Value creation and capture	35
AI	Platform AI	2.7 Artificial intelligence and related issues	36
	Platform AI	2.8 Explainable AI	39

Novel in nature, this research's contribution is an approach to study the digital platform ecosystem domain alongside emerging technologies such as AI and xAI. This research suggests that this type of study was previously inhibited due to the historic absence of IS interdisciplinary work in the DPE domain, specifically using modern quantitative methods such as PLS-SEM and NCA. This literature review chapter reviews the previous work in line with the research questions and forms a basis and grounding for the main contributions of this thesis.

2.1 Literature search strategy

To present the status of the given question, this thesis applied a systematic literature review approach to search and source the relevant publications in the field. It undertakes a broad theorising review in an integrative fashion to effectively coalesce knowledge dispersed in the literature (Leidner, 2018). This initial review contributes to theory in the form of the conceptual model and research propositions presented in the later sections of the thesis. The search was conducted on the key IS domain databases – AISeL, EBSCOhost, Web of Science, Scopus, and ACM Digital Library, ensuring the search was thorough and expansive. The broad scope across the databases was then narrowed down using a combination of the search strings, which were defined keeping in view the critical research questions identified in previous sections. The first search string seeks to find literature covering digital platform ecosystems and AI as this has not been a focus of previous studies. The second search string seeks to find literature that broadly covers digital ecosystems and AI to understand the relationship of AI and DPE at a broader level. The third search string seeks to find literature at the intersection of digital platform ecosystems and the role of trust. The fourth search string examines the ideology of trust, in the context of AI broadly. These search strings were sequentially used to extract results from all relevant databases.

The inclusion and exclusion criteria details are further outlined in Table 3 and Table 4, respectively. These inclusion and exclusion criteria enabled researchers to narrow the literature search results and provide a repeatable criterion. This literature review followed the methodology step by step, focusing on problematisation, finding literature, selection and evaluation, analysis of content, classification, interpretation, synthesis of review (systematic and integrative) and discussion. The guidelines proposed to conduct interdisciplinary business research were followed (Snyder, 2019).

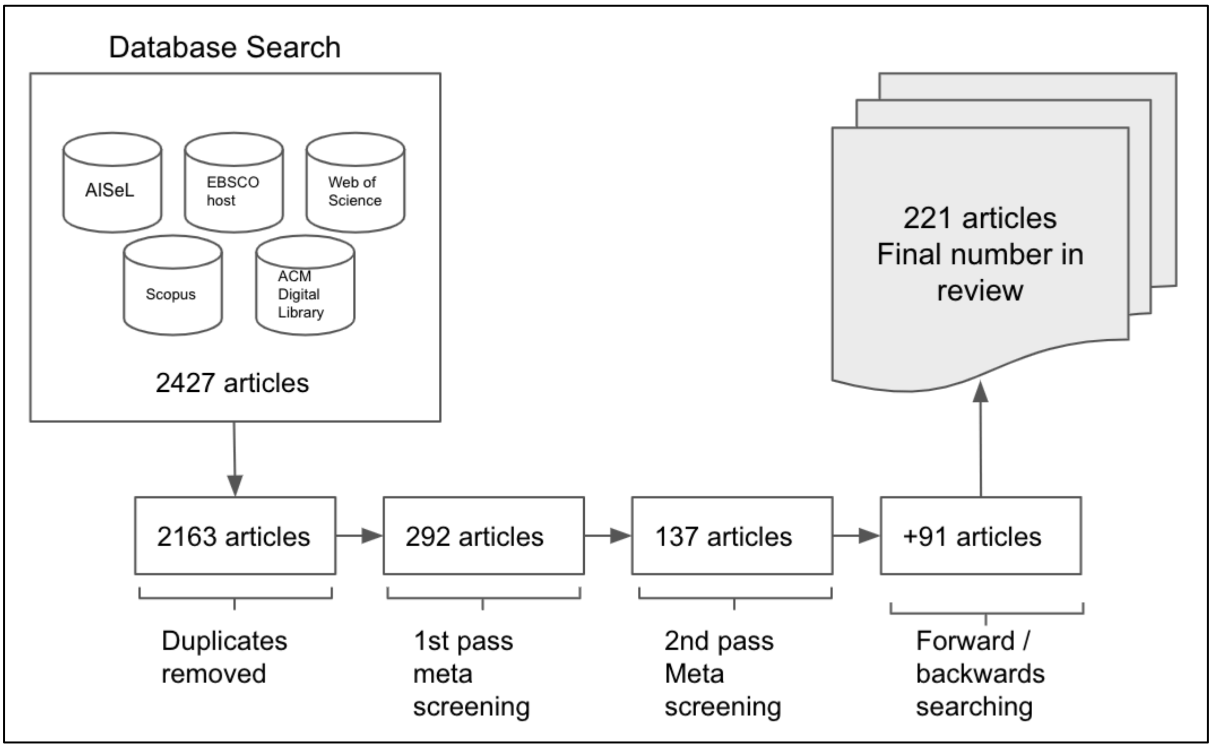

Figure 7: Literature search and selection process

Table 3: Overview of database search strategies

Database	Inclusion criteria	Search keywords
1. AISeL 2. EBSCOhost 3. Web of science 4. Scopus 5. ACM Digital Library	Title, Keywords and Abstract English language Peer reviewed Journal Articles and Conference papers Year 2015 onwards Areas: Business management, Computer Science, Decision Science, Social Science, Information Systems	AI AI explainability artificial intelligence digital ecosystem digital platform digital platform ecosystem ecosystem trust explainable AI multi-sided platform multi sided platform machine learning platform trust trust xAI

Table 4: Overview of exclusion criteria

Category	Explanation
Cloud, BigData, IoT and AI (together)	Excluded where terms are not relevant to this paper, often loosely used
Governance	Excluded all governance aspects except for in the context of AI and technology
Governmental	All governmental and public policy related Governance of AI and with, but not within governments
Regional	Where too specific to a region, e.g., India/Africa and not broad enough
AI & Digital Transparency	Transparency related results were excluded as this is often confused with explainability.
AI Accountability	Excluded AI accountability related studies
AI-Based	Excluded AI-based but included xAI moderated where present
AI Chatbots	
Data	Excluded data protection related issues, such as GDPR, citizen data etc.
Regulation & Compliance	Excluded where only regulation of algorithms is discussed without the context of AI explainability
Simulation	Excluded specific simulation studies to avoid hypothesising
Built for purpose digital platforms Platform monetisation	Enterprise architecture for bespoke digital platforms and use cases
Algorithmic bias, fairness Sentiment analysis	Removed as not relevant to the review focus
AI and Robotics	Excluded where AI and robotics automation is discussed, as this is not relevant to DPE specifically and is a separate research domain
Business model innovation	Removed as not relevant to the review focus

This review followed a step by step methodology, focusing on problematisation, finding literature, selection and evaluation, analysis of content, classification, interpretation, synthesis of review (systematics and integrative) and discussion, as reflected in Figure 7.

The initial analysis of the studies that matched the keyword criterion was meta-analysed based on inclusion and exclusion criteria, reviewing abstracts, keywords, and titles of the studies. Following this, data were classified using open coding and arranged in categorical themes aligned with the search keywords to help synthesise the literature review in an integrative manner.

2.2 Key literature on digital ecosystems

Scholarly works on digital ecosystems approach the concept from diverse angles and interpretations. The initial explanation presents ecosystems based on their inputs, processes, and outcomes, along with the complex relationships that arise among these elements (Adner, 2017). Thus, the concept of the ecosystem as a framework differs from merely being a web of connections. Additionally, the term 'ecosystem' has been employed in varied contexts, resulting in more specific interpretations like 'digital ecosystems'. Such digital ecosystems are characterised by their facilitation of inter-organisational collaborations via digital channels, which take advantage of a modular architecture and operate without central control or a hierarchical authority (Jacobides, Sundararajan and Van Alstyne, 2019). These digital ecosystems surface due to digitalisation capabilities and the ability to connect, collaborate, create value across organisations and ultimately deliver this to customers. In turn, opening an opportunity for technological developments in ecosystem coordination. The organisation of "autonomous yet interconnected companies" has propelled digital ecosystems into the forefront of economic activity, largely owing to the technological modularity that facilitates the management and facilitation of interdependence, as demonstrated within platform ecosystems. Other recent interpretations of DPEs differentiate them from a system of systems framework by emphasising that in DPEs, a collective of entities with distinct objectives and regulations shapes the dynamics of the ecosystem (Cioroaica, Kuhn and Buhnova, 2019). The dynamics of these ecosystems encompass aspects of coordination, collaboration, and the facets of value creation and capture. Ecosystem coordination particularly requires standards and rules, especially because ecosystems often surface in emerging areas. Ecosystem collaboration alongside coordination is an intriguing behavioural avenue to explore to understand participant trust, among other perspectives. Ecosystem participation acceptance is rather grey from a transparency and governance point of view, and determination of the level and form of control at the ecosystem level is non-compliant to the change in modularity.

This research relates to the digital platform ecosystem definition where *platform owners implement mechanisms to foster value creation on a digital platform between the platform owner and an ecosystem of autonomous complementors and consumers (Hein et al., 2020).* Therefore, digital platform ecosystems consist of the platform owners, the value-creation processes, and the contributing complementors.

Based on the literature reviewed, the proposed definition of digital platform ecosystems is - ***cross organisational, value creation and capture interactions, within autonomous complementors and consumers, enabled by digital platforms where trust mechanisms are implemented by platform owners, through modularity offered by technology embeddedness.***

These adaptations to the definition are proposed to clarify a number of key aspects that previous definitions lack. Firstly, that the interactions for value creation and capture are across organisations. Secondly, both the complementors and consumers are autonomous. Thirdly, platform owners facilitate these interactions on digital platforms, embedding trust creation mechanisms that are possible because of modular technological capabilities. It is due to these aspects that digital business ecosystems are increasingly viewed as the central hubs and drivers of organisational upheaval in the age of digital transformation (Hanelt et al., 2020). Table 5 outlines the critical literature forming the basis for this definition.

Table 5: Key literature on ecosystem definitions

Ecosystems View	Reference
Digital business ecosystems	(Hanelt et al., 2020)
Digital ecosystems	(Jacobides, Sundararajan and Van Alstyne, 2019)
Digital platform ecosystems	(Hein et al., 2020)
Ecosystem–as–structure	(Adner, 2017)
Multi-sided platforms	(De Reuver, Sørensen and Basole, 2018)
Platforms as ecosystems	(Alaimo, Kallinikos and Valderrama, 2020)

Additionally, it is crucial to recognise that not all digital platforms constitute ecosystems (Fuller, Jacobides and Reeves, 2019). Due to the emergence of numerous new interdependencies, digital ecosystems have become a key factor in shaping competitive strategy at the organisational level. This includes considerations of value creation scope, re-evaluation of competitive boundaries and awareness of digital monopolies (Subramaniam, 2020). Furthermore, viewing through the ecosystem perspective reveals that value co-creation can occur within both value networks and ecosystems. This concept of value co-creation also extends to other types of ecosystems, such as service ecosystems, where all participants aim to harness capabilities to devise evaluation techniques for assessing the strategic advantages of collaboration and trust-building (Pathak, Ashok and Tan, 2020).

2.3 The organising principles of digital ecosystems

Digital ecosystems are structured upon a multifaceted arrangement of organising principles, rules, and actors, thereby facilitating vast avenues for both value creation and capture. This structuring has led to the emergence of digital ecosystems as reflective of contemporary organisational paradigms within the digital epoch (Gawer, 2022).

The various types of ecosystems emphasised within the period of 2016 to 2021, showcase the evolving dominance of digital platform ecosystems and highlight their transformative potential. For example, within the scope of API-economy-based ecosystems, the primary objective is to promote collaboration through the modular capabilities inherent in APIs (Bonardi et al., 2016), whereas, within the digital platform ecosystem service domain, addressing the critical challenges of communication, interaction, and socialisation via linguistic adjustments is the goal (D'Ulizia, Ferri and Grifoni, 2016). The application of digital ecosystem principles to foster lifelong volunteering showcases the potential of technological modularity (Kapsammer et al., 2017). The discussion on value creation in supply chains posits digital ecosystems as enablers of expanded opportunities for actors (Korpela, Hallikas and Dahlberg, 2017; Ramezani and Camarinha-Matos, 2020).

Further, the use of Information and Communication Technologies (ICT) within rural e-commerce digital ecosystems aims to empower marginalised communities (Leong, Pan and Cui, 2016). Also, the commodification and tradability of data are explored as opportunities through data-driven digital ecosystems (Oliveira and Lóscio, 2018). The contribution towards sustainable digital ecosystems through value co-creation within society is also emphasised (Romanelli, 2018). The shift from central authority to deploying chatbots for customer care within digital ecosystems is innovative (Sangroya, Saini and Anantaram, 2017). So is the strategy of fostering an open digital ecosystem to enhance actor recruitment and participation for value capture (Sun et al., 2016; Elia, Margherita and Passiante, 2020).

The development and utilisation of multi-sided platforms, leveraging Information System (IS) capabilities such as modularity, underline a strategic approach within digital ecosystems (Tan et al., 2015). This is especially true as these platforms also serve as channels for IT affordance realisation (Tan, Tan and Pan, 2016). Notable examples include the digital scholarship ecosystem in universities (Uzwyshyn, 2020) and the digital ecosystem surrounding scientific journals (Wu, 2020).

The significance of complementors in providing products and services for digital platform ecosystem owners is increasingly recognised. This is resulting in marking a pivotal shift in the organisation of economic activities (Gupta, Panagiotopoulos and Bowen, 2020). Empirical studies reveal that incumbents' migration from linear approaches to Multi-Sided Platforms (MSPs) promotes value creation (Dell'Era, Trabucchi and Magistretti, 2021). This is also a trend mirrored in the digital banking sector, where the shift is towards an inverted model to exploit digital ecosystems by platforming (Som and Ram, 2020). The platform model thrives on the network effect, where the addition of each new user group enhances the platform's utility (De Reuver, Sørensen and Basole, 2018).

Participants in platform ecosystems are structured around resource allocations and data linkages, with technological modularity enabling economic vibrance through ecosystem facilitation of actor behaviours and configurations (Alaimo, Kallinikos and Valderrama, 2020). Such value creation examples include leveraging patient journey data in health digital ecosystems (Black and Sahama, 2016) and enhancing information availability for ecosystem participants, e.g. through hackathons in software platform ecosystems (Fang, Wu and Clough, 2021). The support for value creation within digital platform ecosystems is supported by value transactions and the platforms' innovation capabilities (Hein et al., 2020).

The re-evaluation of competition (Jacobides and Lianos, 2021a) and the critical examination and understanding of regulatory dynamics surrounding platforms and ecosystems represent essential areas of ongoing academic discourse, indicating the need for further research (Jacobides and Lianos, 2021b).

2.4 Digital platform ecosystems and trust

Broad definitions of trust are based on the "combination of theoretical background of trust which was a behavioural antecedent from sociology discipline to its antecedent beliefs about trustworthiness of another party" (Gefen, Karahanna and Straub, 2003). As per the above, trust is a willingness of trustor to rely on another trustee. Additionally, this includes setting trustor's concerns with respect to trustee taking situational advantage aside. Additionally, the willingness to rely is conditional on trustee characteristics of ability, integrity, and benevolence (Söllner, M., Benbasat, I., Gefen, D., Leimeister, J. M., Pavlou, 2018). Data protection authorities emphasise how healthy digital ecosystem development practices could be fostered by using trusted AI to tackle ongoing cybersecurity risks (Degli-Esposti and Ferrándiz, 2021). Trust within innovation ecosystems is scrutinised to elucidate its influence on collaboration, interdependency and value creation/capture (Steinbruch, Nascimento and de Menezes, 2021). The crowdsourcing platforms research is progressing towards designing guidance on imbibing platform governance capabilities, especially relevant in the open collaboration scenario (Blohm et al., 2017). Adding to the dominance of the digital platform and raising flags around algorithmic decision making, researchers challenge and seek algorithmic decisions to be more explanatory and open (Di Porto and Zuppetta, 2021). The call for regulatory oversight of platforms arises from their reliance on opaque (black box) technologies and self-regulated trust and reputation (Gamito, 2017).

Empirical studies highlight how immediate trust impacts platforms, examining disintermediation processes (Gu and Zhu, 2021). The meta organisation form of platform ecosystem (an organisation on its own), characterised by modular architecture and governed by a cohesive rule set, presents coordination and competitive challenges, mitigated by technological trust and security solutions (Tobias Kretschmer et al., 2020). In the case of MSPs, platform governance aspects such as trust and data are of significant value (Otto and Jarke, 2019), with the sharing economy's MSPs disrupting industries and raising concerns over trust and risk (Zhang et al., 2018).

Research on trust-building mechanisms such as transaction-based cues, expressive user profiles, identity verification and implicit information, reveals their significance and reliance from a user perspective (Hesse et al., 2020). In the context of software ecosystems, selecting a suitable governance mechanism is a growing challenge and relates to all dimensions such as value creation/capture, coordination and control (Oliveira, Alves and Valença, 2020). Global digital ecosystems grapple with issues of trust and governance, necessitating an understanding of the regulatory landscape (Jacobides, Sundararajan and Van Alstyne, 2019).

Commercial trust is being reinvented by the abundance of digital signals of trust, which also calls for standardisations. Platform driven companies are transitioning from corporate towards platform governance, leveraging emerging technologies for actor/participant engagement, advocating for openness (Fenwick, McCahery and Vermeulen, 2019). Although most digital ecosystem platform owners navigate platform governance autonomously, external regulatory pressures such as GDPR compliance, hint at a collaborative approach (Gorwa, 2019).

Understanding offline behaviours of ecosystem participants (and personas) is crucial for implementing effective platform design changes, transcending simple algorithmic solutions (Koo and Eesley, 2021; Riedl, Whipple and Wallace, 2021). Studies on sharing economy platform ecosystems, like Airbnb highlights the importance of compliance measures and perceived control in value creation (Leoni and Parker, 2019). Digital ecosystem participant governance through compliance and content moderation strategies reflects a shift towards a non-hierarchical decision-making supported by technology (Seering, 2020; Vaccaro, Sandvig and Karahalios, 2020).

The challenge for e-governance domain[1] reflects a broader reconsideration of market structures and governance methods where the public interest is being challenged due to a shift in the ways traditional markets were structured (van der Graaf, 2018). Research advocating for next-generation digital platforms suggests rethinking existent bias in platforms and fostering human-AI collaboration, aiming for accountable, transparent, and less dominant ecosystems (Rai, Constantinides and Sarker, 2019).

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[1] Illustration is based on the social traffic data analysis of the navigation app Waze.

2.5 Digitalisation of trust

Within the realm of inter-organisational interactions, the significance of formal contracts and relational governance has consistently been positively acknowledged for fostering trust, which in turn, enhances value co-creation (Cao and Lumineau, 2015). This in turn influences the dimensions of ecosystems (Steinbruch, Nascimento and de Menezes, 2021). Addressing trust issues is essential for promoting ethical governance in ecosystems, thereby facilitating their evolution (Jacobides, Sundararajan and Van Alstyne, 2019). As ecosystems are B2B, under the lens of transaction cost, the loss of participant/actor trust can lead to value co-destruction (Pathak, Ashok and Tan, 2020). This research posits that trust in digital platform ecosystems entails crucial elements such as trust beliefs (based on perceptions), the influence of trust (dependency on the trusted entity), and trust behaviours (like information sharing), which collectively manifest as institution-based trust, relying on the notions of situational normality and structural assurances (Siegfried, Löbbers and Benlian, 2020). These trust dimensions and implications relevant to DPEs are presented in Table 6.

Research highlights (see Table 6) the role of perceived effective self-regulation in e-commerce and social networking platforms in cultivating trust (Mutimukwe, Kolkowska and Grönlund, 2020). Moreover, in environments marked by coopetition, trust and distrust emerge as key value drivers for performance, prompting an inquiry into their relevance within the DEP context (Raza-Ullah and Kostis, 2020). Various trust theories offer insights into establishing trust across diverse settings, with the signalling theory (Siegfried, Löbbers and Benlian, 2020) highlighting the reduction of information asymmetry between actors (signaller and signalee) as a means to signal trustworthiness in digital platforms.

Table 6: Trust dimensions and implications for Digital Platform Ecosystems (Lascaux, 2020)

Role of Trust	Implications
Inter-Organisational level	• Weak trust may erode cooperation • High trust allows more vital partnering • Trust is fundamental to develop a partnering strategy • Partnering with competitors is likely, if perceived, to be honest and reliable • Trust is a necessary complement to managing cooptative contractual frameworks • High levels of trust facilitate knowledge exchange • Positive interaction effects exist in trust-based relational Governance.
Inter-Network level	• Decision to join network coopetition is fostered by reputation-based trust, third party legitimation • Trust-based coordination techniques for operating procedures are more effective than contracts.

The relational exchange theory highlights trust as the foundational mechanism for governance, promoting innovation in international joint ventures (Wang et al., 2020). This raises the question of its applicability to digital social media platforms, where trust appears to be positively correlated with engagement, e.g. in social media (Håkansson and Witmer, 2015). The journey to establishing platform trust involves fostering collaborative engagements, instigation of authenticity, expertise and calculative assessments (Jacobides, Sundararajan and Van Alstyne, 2019).

Digital technologies play a pivotal role in enhancing trust in virtual/digital and contactless environments, as evident in the sharing economy (Mazzella et al., 2016). SMEs and digital ecosystem owners, like BlaBlaCar, have experimented with a variety of trust-building mechanisms to bolster platform trust, employing digital tools to facilitate trust without physical interactions (Mazzella et al., 2016). By the usage of the right digital tools, individuals could acquire the right amount of trust, by using frameworks such as DREAMS. This framework integrates declarations, ratings, engagement, activity, moderation and social aspects to nurture online trust (Mazzella et al., 2016).

Trust measurement and management in digital platforms necessitate innovative approaches, such as online dispute resolution systems and standards that gauge trust based on the fairness of expectations (Abedi, Zeleznikow and Bellucci, 2019). The mediation of institutional trust through digital platforms introduces novel services that foster trust (Bodó, 2020). Although their awareness of underlying algorithms (Dogruel, Facciorusso and Stark, 2020) enhance users' independence. This reduces their sole reliance on the system trust, which is a somewhat archaic concept (Kroeger, 2015). Crowdfunding platforms[2] exemplify how trust can evolve over time through experiential learning, supported by theories like the trust transfer theory and swift trust theory. These explain that in digital platforms, trust is not based on historical relationships and instead develops over time with experiential learning, hence inducing institution-based trust (Moysidou and Hausberg, 2019).

Exploring decentralised and non-public electronic identification services and other technological advancements could further influence trust in digital platforms and explain these systems' decision-making (Gupta et al., 2021). Trust in the computing context[3] pivots on the predictable behaviour of platforms and their alignment with their predefined goals (Hosseinzadeh et al., 2020).

In the realm of digital platforms and ecosystems, including cloud platforms, trust is reliant on the integrity of their various components, highlighting the requirement for verifiable ownership to the transacting parties. Establishing trust-building practices, such as the creation of digital twins, additionally highlight essential facilitators: digital participation feedback and ratings,

[2] Crowdfunding platforms are a form of a digital platform that bring investors and entrepreneurs together.

[3] Initially proposed by Intel as TPM (Trusted Platform Module)

digital social capital[4] (Putnam, 1995) and digital authentication methods (Jacobides, Sundararajan and Van Alstyne, 2019). This reiterates the critical role of transparency, as studies have shown that an increase in trust correlates with increasing levels of transparency (Mercado et al., 2016).

Undoubtedly digital platforms and the ecosystems they enable have difficulties in building trust within. Fraud and deceit in digital ecosystems such as those in the digital cryptocurrency space necessitate the importance of trust in the digital space and its protection against dislocation. It all boils down to digital platforms and ecosystems owners competently designing systems, prioritising trust by implementing measures such as encryption and other trusted authentication techniques, which can be interpreted and explained (The Royal Society, 2016). As digital platforms exhibit organisational characteristics, there is a need to establish the control-trust dynamics within the ecosystem participants and actors' perspectives and the managerial implications (Long and Sitkin, 2018).

Furthermore, the positive correlation between contracts and trust within the buyer-supplier environment accentuates trust's critical importance in facilitating value creation/capture and negotiation process (Charterina, Landeta and Basterretxea, 2018). The question arises whether emerging technologies can serve as a moderating force in this context. The use of technological mediators for trust is not a novel concept; such technologies have revolutionised the establishment of both institution-based trust and citizen trust across digital platforms and their algorithmic governance systems.

2.6 Trust and artificial intelligence

In the context of digital ecosystems, the significance of big data has escalated, with data governance and the facilitation of trusted knowledge sharing becoming critical as the onus

[4] Digitised version of the physical world and real-world capital

transitions from single to networked organisations (Janssen et al., 2020). As such, data emerges as a foundational element, with artificial intelligence (AI) acting as a crucial facilitator (Marsh et al., 2020). Discussions surrounding digital trust have expanded into the realm of AI policy-making emphasising the imperative to maintain human oversight within AI systems (Robinson, 2020). Despite the continued increase in human responsibility rather than the perceived task take-over by AI, the need for AI literacy and contextual rationalisation remains (Trunk, Birkel and Hartmann, 2020). This requirement is underpinned by the expectations that AI must be understandable and explainable by humans to cultivate the trust that is conducive to value creation (Cobey and Boillet, 2018).

The European Commission has echoed this statement, aiming to position itself as a frontrunner in the development of trustworthy AI (European Commission, 2020a) (European Commission, 2020b). This objective reflects broader industry concerns about clarifying the dynamics of trust among stakeholders and participants within the ecosystem in the context of AI adoption (Oxborough et al., 2017). Drawing an analogy to the development of trust in a loyal pet, establishing trust in technologies like AI is recognized as an essential preliminary step. Trust, in any context, requires time to develop, is easily compromised, and once broken, can be challenging to mend (Siau and Wang, 2018; Winfield and Jirotka, 2018). This highlights the intricate balance between leveraging AI's capabilities and ensuring its alignment with ethical standards and human values.

2.7 Value creation and capture

On the subject of value creation and capture, ecosystems, data and applying emerging technology remains an area needing further investigation (Cortez and Johnston, 2017). As participants and agents with AI ecosystems endeavour to foster value, their actions inadvertently lead to the collateral co-destruction (refer to definition in chapter 1) of value

(Pathak, Ashok and Tan, 2020; Schulz et al., 2021). Given the societal role and influence of digital platforms and ecosystems, their inherent values are in the limelight (Belli and Zingales, 2020). As posited earlier in this thesis, technology unfolds value creation (Schiavone et al., 2021) and information collaboration in digital ecosystems (Romanelli, 2018). This is due to its ability to learn from the interactions within B2B sales ecosystems (Rusthollkarhu, Hautamaki and Aarikka-Stenroos, 2020). In the realm of knowledge-intensive firms and their networks (digital ecosystems), the digital transformation of processes is instrumental in enhancing collaborative value extraction (Ashok, 2018). The traditional ecosystems 1.0 are characterised by their static nature, a tendency to favour convenience over strategic decision making, and lack an overall vision and path for impact, creating the necessity for ecosystems 2.0. These evolved ecosystems strategically identify control points, leverage advanced technological capabilities, and undergo a redesign to optimise value creation and capture (Chung et al., 2020). Furthermore, the advent of technology-enabled contractual agreements influences the engagement levels of participants within digital ecosystems and has implications for the dimensions of trust, thereby imposing limitations on the potential for value-creation (Das, 2020).

2.8 Artificial intelligence and related issues

Artificial intelligence (AI) represents a concept marked by diverse definitions and wide-ranging interpretations. It is therefore critical, at the outset, to differentiate between the concepts of general artificial intelligence and narrow artificial intelligence, as delineated by Broussard (2018). General artificial intelligence encompasses the notion of computer software processing the capability to autonomously think and act, a technological zenith yet to be achieved in contemporary research and development (Raj and Seamans, 2019). Conversely, narrow artificial intelligence pertains to computer software that employs advanced algorithmic approaches to identify patterns within data and predict future outcomes. This variant of AI, through its algorithmic processing, learns from the analysis of existing data sets, an operation commonly associated with the field of machine learning. However, it is imperative to note that such learning by machines should not be comingled with the cognitive learning processes observed in biological entities (Raj and Seamans, 2019). Furthermore, the application scope of machine learning predominantly targets the prediction and estimation of unknown variables utilising a specified data set, as highlighted in the works of Athey (2018) and Mullainathan & Spiess (2017) (Raj and Seamans, 2019). Machine learning methods vary widely. They include simple logit models and complex algorithms. These algorithms, called neural networks, mimic the human brain's pattern recognition. This range shows machine learning's broad use, from basic statistics to replication of human thought processes (Raj and Seamans, 2019).

Neuro-symbolic artificial intelligence is a cross-disciplinary field. It merges machine learning, specifically artificial neural networks, and deep learning, with symbolic computing techniques found in AI's knowledge representation and reasoning subfield. This integration seeks to amplify AI systems' effectiveness and efficiency (Hitzler et al., 2022). Additionally, Neuro-symbolic AI represents a specialised area within AI that integrates neural and symbolic methodologies. The term neural refers to techniques rooted in artificial neural networks, notably deep learning, which has driven substantial advances and heightened interest in AI over the last decade. Symbolic methods involve the use of formal languages for explicit knowledge representation. This includes formal logic, and the algorithmic manipulation of these language elements, or symbols utilised to attain specific objectives. Primarily, neuro-symbolic AI employs formal logic principles from the knowledge representation and reasoning subfield of AI (Hitzler et al., 2022). Explainable AI systems rely on symbolic AI. Explaining the input-output behaviour and the internal activation states of deep learning networks is an increasingly critical area of research. This is due to the opaque nature of current systems, which obscure biases and often do not offer explanations for their decisions. There is an increasing recognition that explanations should go beyond just the raw inputs of the system and incorporate background knowledge (Hitzler et al., 2022).

Other researchers define artificial intelligence as a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to fulfil specific goals and tasks through relevant adaptation (Haenlein and Kaplan, 2019). The field of artificial intelligence (Ernst, Merola and Samaan, 2019) encompasses the capability of complex machines to execute predictions based on extensive data sets. These predictions are particularly relevant in complex and unstructured contexts (Heath, 2019). Although gaining popularity recently, neural networks (Linde and Schweizer, 2019) were conceptualised in the 1950s and 1960s, initially inspired by the human brain's anatomical structure. There is little difference between the antecedents of neural networks and recent work except for the gigantic availability of both computing power and available data. Due to the reduction in the computational costs and the rise of cloud computing, a surge in AI-drive products and services across various domains has happened, which includes computer vision and natural language processing (Linde and Schweizer, 2019). Practitioners (PwC) put the differentiator between AI and general-purpose software as the ability of the intelligent agents to take actions: informational; wellbeing; engaging; predicting behaviour & demand (Oxborough et al., 2017).

On a meso level, researchers argue (Haenlein and Kaplan, 2019) for the necessity of demystifying the AI black box as AI permeates organisations even further. AI's role in corporate governance and decision-making is becoming increasingly indispensable (Hilb, 2020). The impact of AI on actor collaboration within service ecosystems for value creation remains an area ripe for further validation (Manser Payne, Dahl and Peltier, 2021). Equally, AI has become a means for innovation at the digital platform level (Yablonsky, 2020), leading society and ecosystems towards a realistic AI (Brock and von Wangenheim, 2019). To address the black box risks of complex AI models, an explainability-accuracy trade-off needs to be managed with possible envelopment solutions (Asatiani et al., 2021). Algorithmic decision making within digital work platforms such as Upwork is non-transparent, forcing digital workers to adapt and comply (Bucher, Schou and Waldkirch, 2021), a sentiment shared by public sector workers (Criado, Valero and Villodre, 2020).

New challenges like GDPR[5] seek to balance the innovation delivered by technologies such as AI with care for privacy and explainability (Monterossi, 2019; El-Gazzar and Stendal, 2021). A step towards achieving business benefits for ecosystems would be platforming AI automation and augmentation (Raisch and Krakowski, 2021), making AI deviate from unexplainable results (Benbya, Davenport and Pachidi, 2021). The penetration of AI into digital ecosystems, as evidenced by ontologies-based ecosystem modelling (Biermann et al., 2016) and the use of digital platform data for machine translation (Brynjolfsson, Hui and Liu, 2019), highlight the evolving applications of AI. However, concerns over data confidentiality and the credibility of digital ecosystems persist, requiring a data-driven approach that includes explainable AI to establish credibility (Livraga and Viviani, 2019). Finally, governmental policymakers emphasise the critical need for explainable AI to foster trust in digital platforms and ecosystems, addressing the risks associated with AI's black-box nature (Pedreschi and Miliou, 2020).

2.9 Explainable AI

Despite their expertise in prediction, black box AI systems suffer from a lack of explanatory capacity, a gap that explainable AI (xAI) is positioned to fill, thereby enhancing trust and reducing ambiguity and facilitating human understanding of AI (Barredo Arrieta et al., 2020). A definition that resonates with the DPE context is xAI aiming to "produce more explainable models, while maintaining a level of prediction accuracy and enable human users to understand,

[5] GDPR is EU wide general data protection regulation

appropriately trust and effectively manage the emerging generation of AI partners" (Adadi and Berrada, 2018). Central to xAI is the construction of shared meaning, often facilitated by intelligent agents through various methodologies like Scoop, Post-hoc and Intrinsic, and employing tools such as LIME, decision trees or shapely, to name a few. These explanations could have several other roles, such as transfer of knowledge, learning, persuasion and social explanation (Miller, 2019). Persuasion is one of the potentially relevant use cases of xAI as it could directly relate to trust generation and decision analysis. If the explanation aims to generate trust from a participant (at a system level), persuasion could be used as a vehicle to modulate agent decisions to generate trust (Miller, 2019). Many of these xAI works have not been developed due to ethical concerns (Kirchner et al., 2016).

xAI is considered vital for users to effectively comprehend and manage AI results, thus increasing trust in them. Explanations are necessary for the justification, improvement and discovery of AI systems (Meske et al., 2020) and can be tailored based on factors like complexity and model dependency. Human interpretability of AI models is an emerging area of interest, though current understanding of which models are interpretable by humans is limited (Lage et al., 2019). This understanding is critical for advancing AI and xAI, including the development of evaluation taxonomies (Chromik and Schuessler, 2020). In active learning experiments, xAI has proven to support trust calibration (Ghai et al., 2020). Moreover, in government context, explainability is anticipated to preserve public trust (Harrison and Luna-Reyes, 2020), as highlighted within the latest policies (Information Commissioner's Office and The Alan Turing Institute, 2020). Empirical studies indicate a user preference for explanation by example, with methods like LIME being favoured (Jeyakumar et al., 2020), and significant research in the space is conducted by agencies such as DARPA (Mueller et al., 2019).

Explainability can also supplement situational and source data, aiding in areas like medical diagnosis (Wang et al., 2019) and concept-based explanations may help counteract human bias

(Ghorbani et al., 2019). Incorporating measures to accurately gauge feature importance, cognitive bias and social expectations could influence the broader adoption of these models (Hooker et al., 2019; Miller, 2019). Yet, the debate continues over the application of explainable AI, with suggestions to pair it with human-led impact assessments (Hamon et al., 2021).

Progress in xAI design practices (Liao, Gruen and Miller, 2020) includes platforms like Google Brain's TensorFlow (Yu et al., 2018), which offers a scalable and flexible interface for expressing and executing a variety of algorithms, including deep neural network models with over a dozen use cases (Rucci and Casile, 2005). TensorFlow aims to bridge the gap in training and the usage needs of neural networks that are critical to xAI. Most of these learning models are heavily reliant on the training and inferential dynamics, particularly those based on neural networks and data-dependent reinforcement learning (Yu et al., 2018). Making these models more understandable, either low or prime in terms of functionality, is the next step towards generating trust in these models. Tools like the What-If Tool (Wexler et al., 2020) are open-source and help develop further human understanding into these models using visual aids and, unlike traditional AI, do not heavily rely on sample data, making them less cumbersome to work with.

Furthermore, the increasing interest in explainability, especially with advancements in generative AI, highlights its importance in elucidating algorithmic decisions and associated data to stakeholders at various levels.

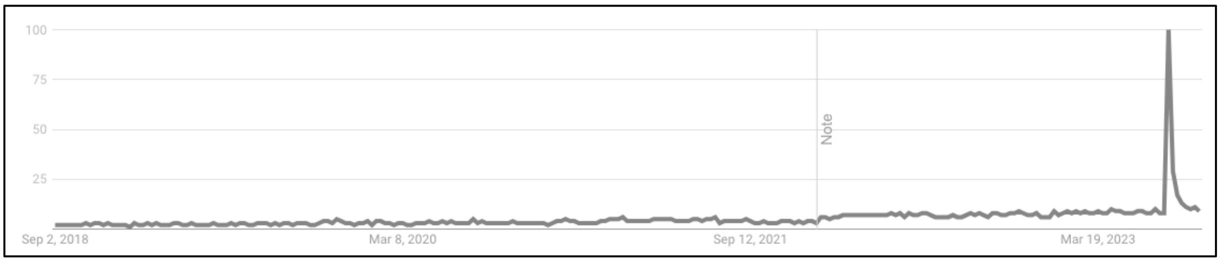


Figure **8**: Google trends interest over time for "Explainable Artificial Intelligence" topic

Explainable artificial intelligence also has key related concepts that are critical to be called out (see Figure **9**) , and these are vital for establishing context and topic terms adjacency (Adadi and Berrada, 2018). As a robust tool for reasoning artificial intelligence-based decisions, explainable artificial intelligence (xAI) can help at varied levels by providing explanations to justify, explanations to control, explanations to improve and explanations to discover (Adadi and Berrada, 2018) (Barredo Arrieta et al., 2020). These can be further translated into the key goals that xAI delivers on: Trustworthiness, Causality, Transferability, Informativeness, Confidence, Fairness, Accessibility, Interactivity, Privacy awareness (Barredo Arrieta et al., 2020). This research thesis investigates the aspect of trustworthiness associated with explainable AI by bringing the concept of trust around artificial intelligence and the effect of xAI on it. Ontology generally relates to the assumptions made about the nature of reality and therefore decides how the researcher sees the world in relation to their field (Saunders, Lewis and Thornhill, 2019). In terms of ontology, xAI methods can be intrinsic by definition hence model-specific or post-hoc usually model-agnostic and have scope (global or local) (Adadi and Berrada, 2018).

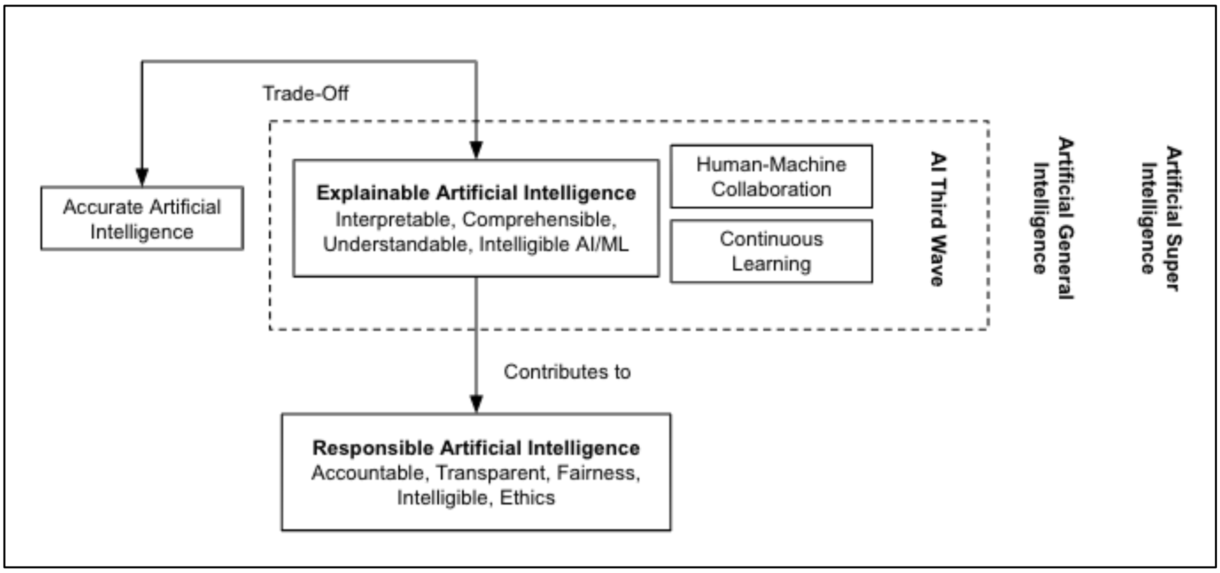


Figure 9: Schematic view of xAI related concepts. *Source:* Adapted from Peeking Inside the Black-Box: Survey on XAI (Adadi and Berrada, 2018), p. 52142

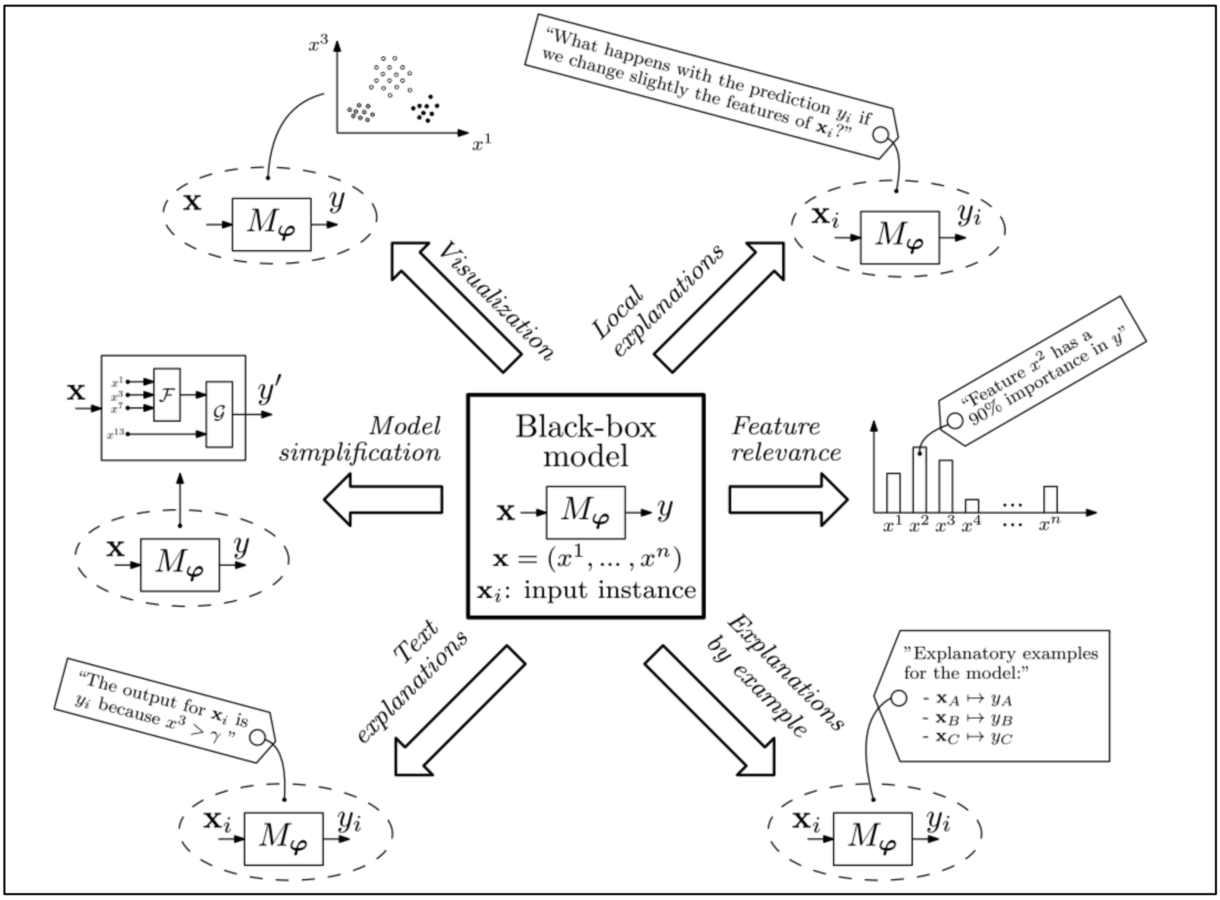


Figure 10: Different post-hoc explainability approaches. *Source:* Adapted from Peeking Inside the Black-Box: Survey on XAI (Barredo Arrieta et al., 2020) Fig 4, p13.

Table 7 highlights the key explainability techniques with a distinctive mapping with intrinsic or post hoc, global, or local scope and if the technique is model specific or agnostic.

Table 7: Types of explainability techniques. Adapted from Peeking Inside the Black-Box: Survey on XAI (Adadi and Berrada, 2018) Vol.6, p52152

Techniques	**Post-hoc or Intrinsic**	**Local or Global**	**Model Agnostic or Model Specific**
Activation maximization	Post-hoc	Global	Agnostic
Counterfactuals explanations	Post-hoc	Local	Agnostic
Decision trees	Intrinsic	Global	Specific
Decomposition	Post-hoc	Local	Agnostic
Feature importance	Post-hoc	Global/Local	Agnostic
Individual Conditional Expectation (ACI)	Post-hoc	Local	Agnostic
Layer-wise Relevance Propagation (LRP)	Post-hoc	Global/Local	Agnostic
LIME	Post-hoc	Local	Agnostic
Model distillation	Post-hoc	Global	Agnostic
Partial Dependence Plot (PDP)	Post-hoc	Global/Local	Agnostic
Prototype and criticism	Post-hoc	Global/Local	Agnostic
Rule extraction	Post-hoc	Global/Local	Agnostic
Rule lists	Intrinsic	Global	Specific
Saliency map	Post-hoc	Local	Agnostic
Sensitive analysis	Post-hoc	Global/Local	Agnostic
Shapely explanations	Post-hoc	Local	Agnostic
Surrogate models	Post-hoc	Global/Local	Agnostic

2.10 Research questions and hypotheses

Table 8: Research questions and hypotheses

Research question	**Relevant hypotheses**
RQ1: Using the digital platform ecosystem model developed in this research, how does digital platform ecosystem affect the associated participation outcomes?	H1: Digital platform ecosystem will have positive effect on digital platform ecosystem outcomes of willingness to transact. H2: Digital platform ecosystem will have positive effect on digital platform ecosystem outcomes of network coopetition. H3: Digital platform ecosystem will have a positive effect on digital ecosystem outcomes of collaboration.
RQ2: Using the digital platform ecosystem model developed in this research, how does presence of trust affect the associated participation outcomes? *DPETO model without artificial intelligence explainability in mediator trust.*	H4: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of willingness to transact will be mediated by digital platform ecosystem trust. H5: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of network coopetition will be mediated by digital platform ecosystem trust. H6: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of collaboration will be mediated by digital platform ecosystem trust.
RQ3: Using the digital platform ecosystem model developed in this research, how does digital platform ecosystem trust involving artificial intelligence explainability impact digital platform ecosystem participation outcomes? *DPETO model with artificial intelligence explainability influenced digital platform ecosystem trust mediator.*	H7: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of willingness to transact will be mediated by artificial influence explainability influenced digital platform ecosystem trust. H8: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of network coopetition will be mediated by artificial influence explainability influenced digital platform ecosystem trust. H9: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of collaboration will be mediated by artificial influence explainability influenced digital platform ecosystem trust.

Research question	Relevant hypotheses
RQ4: How does the digital platform ecosystem trust without artificial intelligence explainability differ from those with artificial intelligence explainability with regards to the digital platform ecosystem outcomes?	H10: Digital platform ecosystem trust when mediated with artificial intelligence explainability influenced digital platform ecosystem trust is a stronger predictor model of digital platform ecosystem outcomes in comparison to non-explainability influenced digital platform ecosystem trust.
RQ5: Within the digital platform ecosystem trust outcomes model proposed in this research, what conditions are meaningful and necessary?	H11: Digital platform ecosystem trust mediator is a meaningful and a necessary condition for collaboration. H12: Digital platform ecosystem trust mediator is a meaningful and a necessary condition for willingness to transact. H13: Digital platform ecosystem trust mediator is a meaningful and a necessary condition for network coopetition. H14: Digital platform ecosystem Platform AI is a meaningful and a necessary for collaboration. H15: Digital platform ecosystem Platform AI is a meaningful and a necessary for willingness to transact. H16: Digital platform ecosystem Platform AI is a meaningful and a necessary network coopetition. H17: Digital platform ecosystem outcome of collaboration is a meaningful and a necessary condition for willingness to transact. H18: Digital platform ecosystem outcome of network coopetition is a meaningful and a necessary condition for willingness to transact. H19: Digital platform ecosystem outcome of network coopetition is a meaningful and a necessary condition for collaboration. H20: Digital platform ecosystem outcome of willingness to transact is a meaningful and a necessary condition for collaboration. H21: Digital platform ecosystem outcome of collaboration is a meaningful and a necessary condition for network coopetition.

Research question	**Relevant hypotheses**
	H22: Digital platform ecosystem outcome of willingness to transact is a meaningful and a necessary condition for network coopetition.

2.11 Research relevance to cross-paradigm combinative practices and alignment with IS domain specific thematic advances

Cross-paradigm combinative practices within the information systems (IS) domain refer to the approach of integrating different research paradigms and methodologies to address complex IS phenomena. Information systems are multifaceted, often necessitating diverse perspectives and methods to understand, design, implement, and evaluate them. These practices can lead to more robust, comprehensive, and nuanced insights than single-paradigm approaches (Rai, 2018). In the IS field, combinative practices are particularly relevant given the interdisciplinary nature of the field, which spans technical aspects of computing systems, psychological and social aspects of human-computer interaction, organisational impacts of technology, and economic and policy considerations of digital transformations (Rai, 2018).

This review of digital platform ecosystems fits well into cross-paradigm combinative practices in IS research. The related motivations and potential examples from both theoretical and methodological perspectives are summarised in Table **9**: Cross-Paradigm Combinative Practices in Digital Platform Ecosystems Domain. This thesis explores the theories of trust relative to ecosystems and their participants; based on a literature review, *it aims to conceptually understand the existence of 'ecosystem trust' and how this impacts value creation and ecosystem outcomes.* Remaining specific to the IS domain while contributing to their advancements required understanding the essential DPE constructs from previous thematic analysis based research (Senyo, Liu and Effah, 2019) in alignment with the IS domains and their thematic advancements as represented in Table 10: IS Domains Specific Thematic Advances and their alignment with Digital Platform Ecosystems Constructs. As per the domains outlined in the table, this research covers the IS Trust domain and the relevance to DPE Trust.

Additionally, the topic heavily focuses on practitioners' strategies and learning from the digital economy.

Table 9: Cross-Paradigm Combinative Practices in Digital Platform Ecosystems Domain. Adapted from Beyond Outdated Labels: The Blending of IS Research Traditions, MIS Quarterly Vol. 42 No. 1 pp. iii-vi/March 2018 (Rai, 2018)

Cross-Paradigm Combinative Practices in Digital Platform Ecosystems Domain (Rai, 2018)

		Non-Paradigmatic Practices: **Theoretical Perspective**	Non-Paradigmatic Practices: **Method**
Paradigmatic Practices	**Theoretical Perspective**	**Cross-Paradigm Theoretical Combination** ***Motivation:*** Boundary conditions definitions, conceptual view of constructs and relationships to gain a holistic understanding across paradigms. ***Example:*** Behavioural theories such as those on DPE boundary conditions to understand DPE effects of DPE designs on social indicators such as collaboration and underpinning drivers.	**Paradigmatic Theory-Non-paradigmatic Method Combination** ***Motivation*: ** Develop, evaluate, and refine paradigmatic theories by application of methods from other paradigms ***Example:*** Combining behavioural theories and other IS perspectives with methodologies such as text mining methods , necessary condition analysis etc. to measure constructs.
Paradigmatic Practices	**Method**	**Paradigmatic Theory-Non-paradigmatic Theory Combination** ***Motivation:*** Leverage theoretical views from other paradigms ***Example:*** Using DPE related theories with other behavioural theories on IS domains such as Use, Trust etc., to develop artefacts and insights.	**Cross-Paradigm Methods Combination** ***Motivation:*** Generating complementary insights by applying methods with varying objectives, data requirements and approaches. ***Example:*** Grounded theory or qualitative clustering to discover DPE concepts and combine with additional approaches.

Table 10: IS Domains Specific Thematic Advances and their alignment with Digital Platform Ecosystems Constructs

IS Domains	DPE Constructs Proposed	Relevance to Thematic Advances (IS Domain Advances)	Relevance to DE Terminology (Senyo, Liu and Effah, 2019)	Relevance to Ecosystems as structure constructs (Adner, 2017)
IS Trust (Söllner, M., Benbasat, I., Gefen, D., Leimeister, J. M., Pavlou, 2018)	DPE Trust	Between people and organisations Between organisations Between people and technology	DPE Business Issues: Participants trust; Value co-creation DPE Artefacts: Trust models	Links Activities Actors
IS Control & Governance (Saunders *et al.*, 2020)	DPE Control & Governance	As a governance/control means As a governance context As a control enabler (Platform Governance & Infrastructure/platform control)	DPE Business Issues: Trust, security; Governance DPE Technical Issues: DE Platform governance	Positions
IS Use (Burton-Jones, Stein and Mishra, 2020)	DPE Use Cases (DPE Outcomes) DPE Artefacts	Development of theories Human aspects of use such as human coping, emotion Usage process, configurations, and simulations	DPE Artefacts: Frameworks and theories; Integration of emerging technologies DPE Technical Issues: DPE Platform design and architectures	

2.12 Chapter summary

This chapter conducted a comprehensive investigation into the cross-paradigm combinative practices within the digital platform ecosystems domain. The chapter began by outlining its scope and purpose to examine the alignment between thematic advancements in IS domains and digital platform ecosystem constructs. The literature search strategy and exclusion criteria were detailed, ensuring adherence to a systematic approach to the review process.

The chapter then delved into the core concepts of digital platform ecosystems, summarising the body of knowledge. The literature concerning ecosystems and their definitions was then synthesised, providing readers with a foundational understanding. The organising principles of digital platform ecosystems were explained in further detail, explaining the underlying mechanisms that drove their functionality.

As the chapter progressed, the focus shifted towards the critical themes of trust within digital platform ecosystems. The concept of trust in the context of digitalisation was explored, highlighting its role in the modern technological landscape. Thereafter, the relationship between artificial intelligence and trust was analysed, offering insights into how AI impacted establishing and maintaining trust in digital platform ecosystems.

Furthermore, the chapter examined the nexus of artificial intelligence and explainability. The role of explainability in fostering user trust and comprehension of AI-driven processes within digital platform ecosystems was emphasised.

Overall, this chapter provided an all-encompassing view of the current knowledge regarding cross-paradigm combinative practices in the digital ecosystems domain. It synthesised diverse sources of literature to present a cohesive understanding of topics ranging from the foundational concepts of digital ecosystems to the nuanced interplay between artificial intelligence, and trust. Through this comprehensive review, the chapter laid the foundation for the subsequent exploration of emerging trends and potential future directions in this discipline and presented the key research questions and related hypotheses for this thesis.

3 Methodology

"Research is any conscious premeditated inquiry – any investigation which seems to increase one's knowledge of a given situation."

– Herbert Goldhor

The methodology chapter is the backbone of this research thesis as it focuses on outlining the systematic approach to address the research questions and objectives. The strategies and techniques chosen to conduct this study provide a comprehensive roadmap for the research process. This chapter delves into the various vital components underpinning this study's overall methodological framework. These include research philosophy, design, methods, sampling techniques, data collection instruments, procedures, data preparation, analysis procedures, and considerations of validity, reliability, ethics. Each element contributes to the rigour and credibility of the research outcomes and provides insights into the rigour and integrity of the study's approach. This also establishes credibility and impact and ensures that the findings are insightful and trustworthy.

3.1 Research methodology

As a general plan towards answering the key research questions, it was critical that this research design covered all elements required. To align with the research design development framework, it followed the research onion (Saunders, Lewis and Thornhill, 2019), a natural progression from the selection of philosophical approaches and the approach to theory development (see Figure 11).

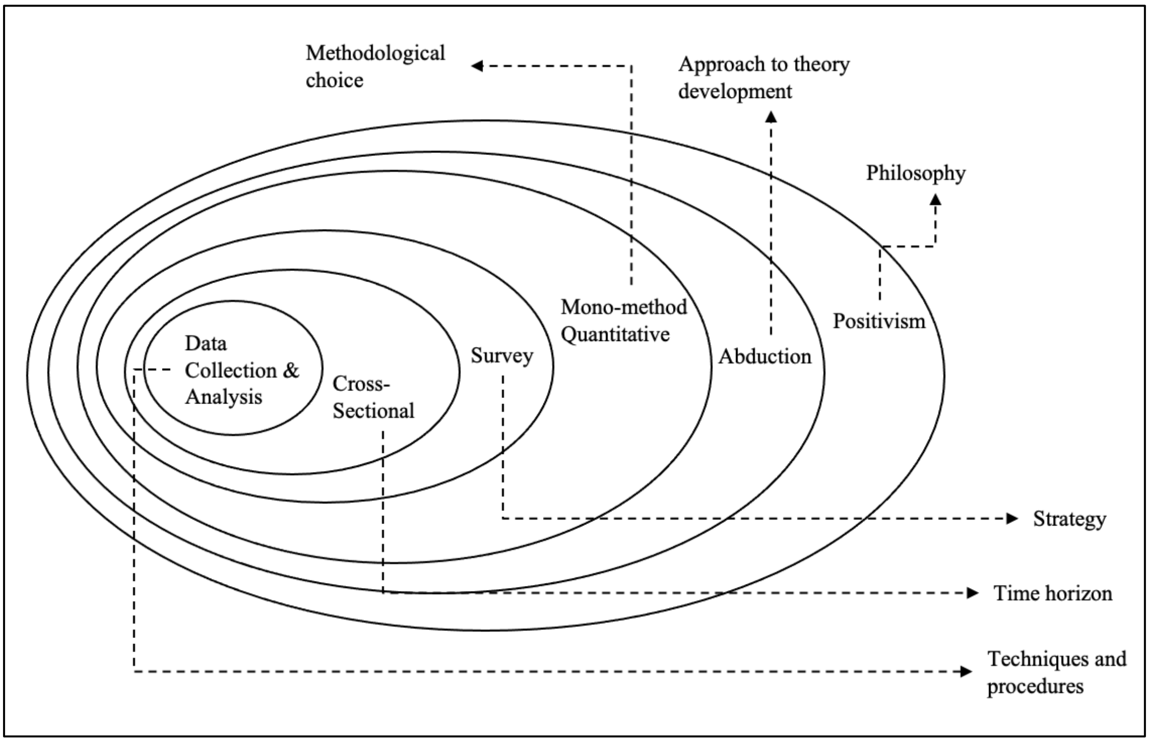


Figure 11: The research onion adapted from Saunders, Thornhill, & Lewis, 2019 p174

From a methodological choice, this research used a quantitative research design in alignment with positivism, using a highly structured data collection approach (Saunders, Lewis and Thornhill, 2019). For this exploratory research, a quantitative approach was chosen instead of a qualitative one as a quantitative approach can be beneficial in establishing patterns, frequencies, and potential relationships within a dataset about which little is known. Additionally, a quantitative approach in research is employed primarily for its ability to provide objective measurements and produce results that are statistically reliable and generalizable to a broader population (Creswell, 2014). The nature of the research questions guided the choice of quantitative methodology alongside the aforementioned intended outcomes of the study, including the availability of the sources of data.

This research maintained a mono-method quantitative stance in this study as it used a single survey design based data collection technique, also maintaining the key characteristics of quantitative research where:

- Remained independent from those who were being researched
- Referring participants as respondents
- Study examined relationships between independent and dependent variables
- Using probability sampling to ensure there is generalisability
- Using highly structured and rigorous data collection instruments and methods
- Results are collected in numerical and non-numerical as well as standardised formats
- Using advanced statistical and modelling techniques for data analysis, PLS-SEM and NCA
- Interpreting statistical results and using them for the derivation of results

Employing a mono-method quantitative approach, where a single quantitative method is utilised throughout offers several advantages. This ensures consistency in data collection and analysis, enhancing the reliability of the findings. Compared to other quantitative approaches, these can provide a more comprehensive understanding of the phenomenon under investigation by leveraging a combination of data sets. Prolific platform was utilised to source research survey participants and further described in the below sections of this chapter.

Explanatory in nature, this study aimed at answering the key relationships between the digital ecosystem value drivers such as AI, the associated outcomes of willingness to transact, collaboration and network coopetition and how it is mediated by trust generated through explainable artificial intelligence techniques. This research used a survey strategy not just because of its popularity in the business and management research, but because of its ability to collect specific variables which were critically required to test the hypotheses defined for this research. It also helped gather data as a snapshot in time, conducting a cross-sectional study.

For this research, a step by step research methodology was followed. This methodology was developed using the work of Churchill (Churchill, 1979). Although set in the context of market research this methodology not only provides a suggested procedure for developing better measures but serves as a basis for a methodological way to conduct complex research projects requiring and including multiple variables. This step-by-step methodology was then operationalised during the various phases of the research – initial literature review phase, systematic literature search, data collection instrument design, pilot study, refinement based on the pilot study followed by final data collection, cleansing, analysis, hypothesis testing and reporting of the findings.

The pilot study was conducted on the Prolific platform with a survey designed on the Qualtrics survey platform. There were a total of 40 respondents included in the pilot study, these respondents were balanced with a 50/50 percent distribution criteria across male and females. Pre-screening criteria was applied, with finance employment-sector and industry selection through the Prolific platform. The pilot study respondents were located mostly in the UK (27 respondents) and the some in the USA (12 respondents) and ranged from organisations of varying sizes, with 48% respondents from organisations with 1000 or more employees and overall, 3/5th of the pilot study respondents working for a large organisation in financial services (with 500 or more employees). Over half of the pilot study participants were digital platform ecosystem end-users in the financial services domain. 63% of the pilot study participants agreed that digital platform ecosystems exhibit black box behaviour. When asked about the role of artificial intelligence in digital platform ecosystems, 80% of the pilot study respondents agreed that AI is an enabler of the digital platform ecosystem. Furthermore, 88% of these respondents agreed that explanations foster trust within digital platform ecosystems, with 3/4th agreeing that digital platform ecosystems employ AI enabled decision making. The key outcomes of the pilot study were around the validation of the personas of the participants, validation of the role of AI within the context of digital platform ecosystems, validation and quantification of the AI associated black box issues and the issues of trust regarding AI within digital platform ecosystems. As an additional outcome of the pilot study, the PLS-SEM model was further refined to introduce higher order digital platform ecosystem construct and removal of the moderator construct and related measurement items. Additionally, the research process framework by Peffers (Peffers et al., 2007) has relevance to this research, as this research is oriented towards creation of successful artefacts – in this case a new validated research model. See Figure 22: The DPETO (Digital Platform Ecosystem Trust Outcomes) model.

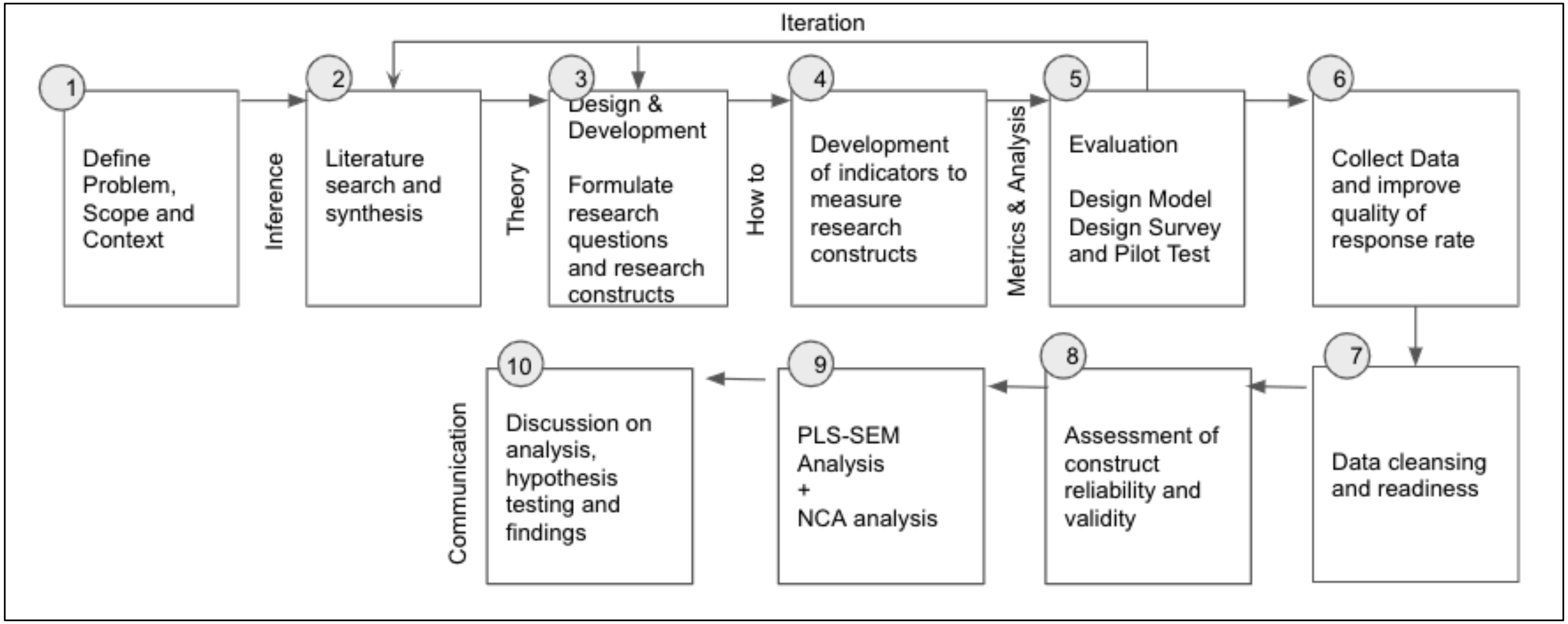


Figure 12: Research methodology process. Adapted from (Churchill, 1979; Peffers et al., 2007)

3.2 Research design

As discussed in the previous section, this research study follows a quantitative research strategy. On this basis, the stages of the quantitative research design incorporating a PLS-SEM and NCA methodologies include the following (Henseler, Ringle and Sarstedt, 2015; Dul, 2016; Hair et al., 2017):

1. Conceptual framework development grounded in theoretical underpinning and existing literature
2. Hypothesis formulation, positing relationships between variables
3. Operationalizing constructs, ensuring measurement variables are established
4. Data collection in accordance with the constructs and scales
5. Data preparation where the collected data is cleaned and validated
6. PLS-SEM analysis, where the hypothesised model is analysed to estimate relationships and asses the predictive power of the model
7. NCA analysis to explore necessary conditions in the data set that much be present to achieve a desired outcome
8. Interpretation of results to draw conclusions about the relationships and conditions within the data
9. Reporting of findings

Details about each step are further discussed in the sections below. This overall research design is aligned with the research methodology process described in the section above. Figure below presents this research design in a visual manner.

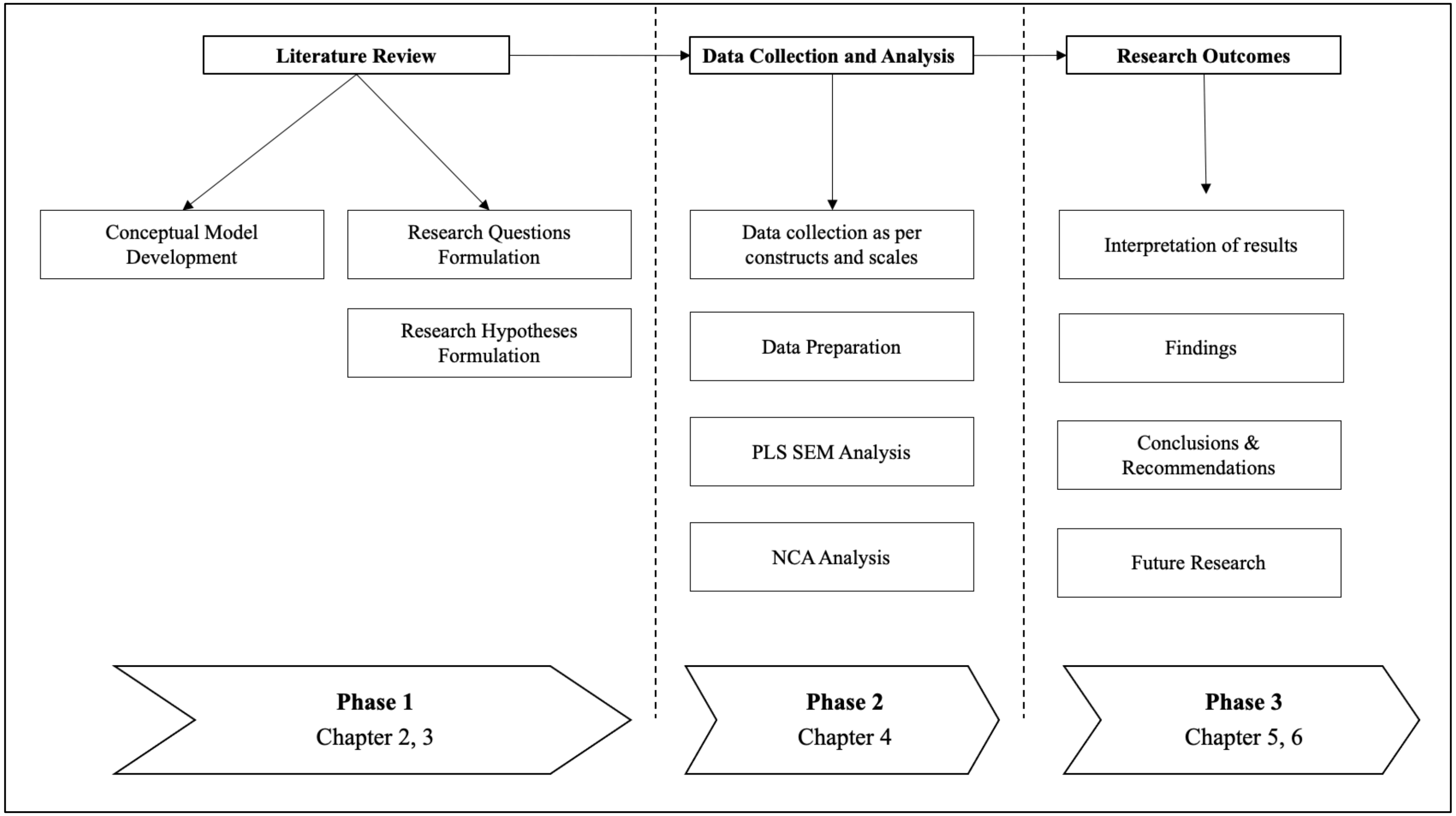


Figure 13: Research design for this study

3.3 Research philosophy

Referring to a system of beliefs and assumptions towards the development of knowledge, the philosophical underpinnings with regards to this research were aligned. Making a number of assumptions as this research progressed through every stage, including those pertaining to the research realities or ontological assumptions, about human knowledge or epistemological assumptions and about the researchers' own and how those values influence the process (Burrell and Morgan, 2016). These assumptions also play a critical role in the way researchers formulate the research questions, select the use of methods and how findings are interpreted (Crotty, 1998). But there is not one best philosophy that fits in the discipline of business and management research and often it is a mere reflection on one's own beliefs and assumptions with regards to the key philosophies and the research design undertaken (Tsoukas, Knudsen and Press, 2003).

From an ontology (nature of reality) perspective, a realist view independent from the research is aligned with the philosophy. From an epistemological (acceptable knowledge) position point of view, it aligns with 'positivism,' using existing theory to develop hypotheses that can be further proven or disproven via relevant analysis of related data. Staying as far detached as it can from the research and maintaining a value free independent view so as not to instigate any influence on the findings, thus remaining external to the data collection process (Saunders, Lewis and Thornhill, 2019).

Positivist view entails a typically deductive and very structured methodology whereas in the case of this research, it follows an abductive approach, and a quantitative method of data analysis. Abduction, or abductive reasoning in research, is an approach that begins with an observation or set of observations and then seeks to find the simplest and most likely explanation. Figure 14 describes the abductive research process and Figure 15 describes the abductive process for this research. This process, unlike deduction or induction, does not start with a hypothesis or theory but rather with surprising facts or puzzles that the researcher aims to explain. Abductive reasoning generates new hypotheses and theories by inferring the most likely explanations for the observed phenomena (Saunders, Lewis and Thornhill, 2019). In abductive reasoning within research, the objective is to utilise known factors to formulate hypotheses that can be empirically tested and are potentially generalizable, emerging from the interplay between specific and general facts. This reasoning approach mandates that data collection serves an exploratory function, aiming to unearth themes and patterns that conform to an established conceptual framework and are subject to subsequent empirical testing. Theoretically, abduction is aligned with the generation or refinement of theory, allowing for the integration of existing theories where relevant and the development or alteration of new theories as necessitated by the data (Kovács and Spens, 2005; Saunders, Lewis and Thornhill, 2019).

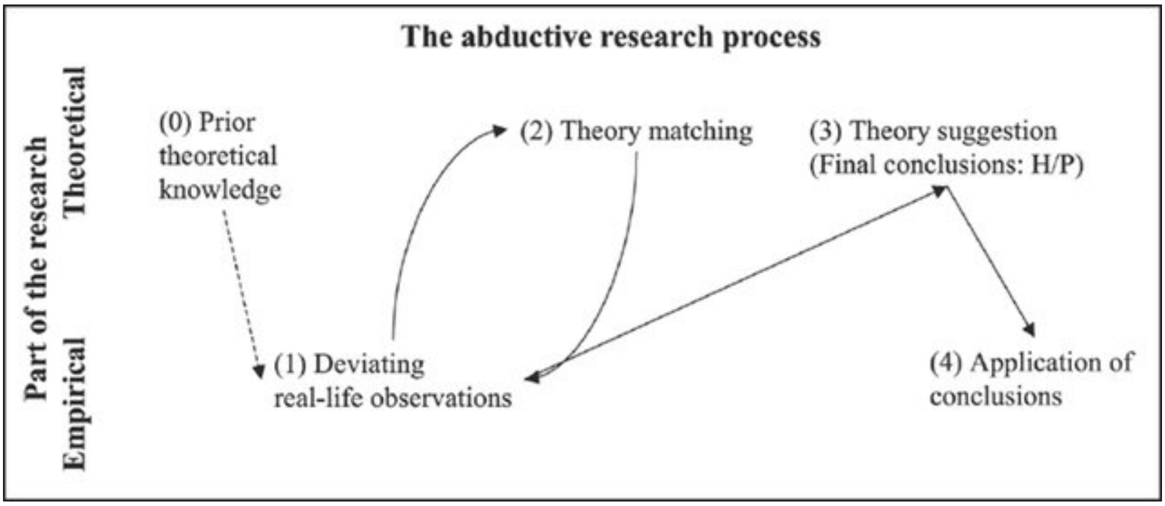


Figure 14: The abductive research process. Adapted from (Kovács and Spens, 2005)

This research also follows an advanced two stage quantitative statistical analysis methodology, beginning with a partial least square structural equation modelling (PLS-SEM) (Hair et al., 2017) analysis followed by conducting necessary condition (NCA) analysis (Dul, 2019). This research aligned with the guidelines for the combined usage of PLS-SEM and NCA, that enabled the exploration of hypothesis following both a sufficiency logic and necessity logic

(Richter et al., 2020) . Usage of PLS-SEM and NCA as a blended approach, complements the advanced methods of PLS-SEM and checks for robustness (Hair et al., 2021). There are several benefits of using this PLS-SEM and NCA multimethod approach. The combined PLS-SEM and NCA approach delivers value through combining varied views on causality and helping researchers further their understanding of theoretical relationships underpinning the research constructs, adding clarity through differentiation of the related causal logics (Richter et al., 2020, 2021). Recent published research in non IS domains have exhibited use of this combined methodology of PLS-SEM analysis followed by NCA, opening up opportunities to adopt this approach in IS domains (Shoukat et al., 2023). This combination delivers practical value as researchers use PLS-SEM to identify factors producing best outcomes and NCA to identify factors critical to achieve a particular outcome, the must-haves, and should-have factors for asserting practical implications.

Assuming that there is a 'certain' reality, as positivists, the necessary assumptions and hypotheses were formulated and tested empirically, generalising the results with broader implications that extend beyond the defined research boundaries. This thesis focuses on a PLS-SEM and NCA within the positivist framework (Dul, 2019), assuming that:

- This research has tried to capture reality as it is
- Selected a dataset that represents this reality
- Have undertaken measurements to quantify the properties of the selected data
- Have considered and applied falsification when testing the formulated hypotheses
- Have proposed implications and generalisations that are beyond the selected data set

As highlighted above, the approach to theory development is abductive reasoning which begins with observed surprising facts (Ketokivi and Mantere, 2010), such as digital platform ecosystems outcomes of willingness to transact, collaboration and network coopetition in this case. Abductive approach is applicable also because the data was collected to explore the related phenomenon associated with the digital platform ecosystem, trust and artificial intelligence in the platforms and identify related themes and patterns. This research then used this data to create a novel 'Digital Platform Ecosystem Trust Outcomes' – the DPETO framework which was further tested through survey based data collection instruments analysed with PLS-SEM (Partial Least Square – Structural Equation Modelling) and NCA (Necessary Condition Analysis) methods of analysis. One can argue that this research thesis does not take an abductive approach in its purest form but neither does it fit the charter for a prescribed deductive approach. Conversely, if a deductive approach is considered in the context of this research, it remains insufficient and only conveys a sense of incompleteness of the research.

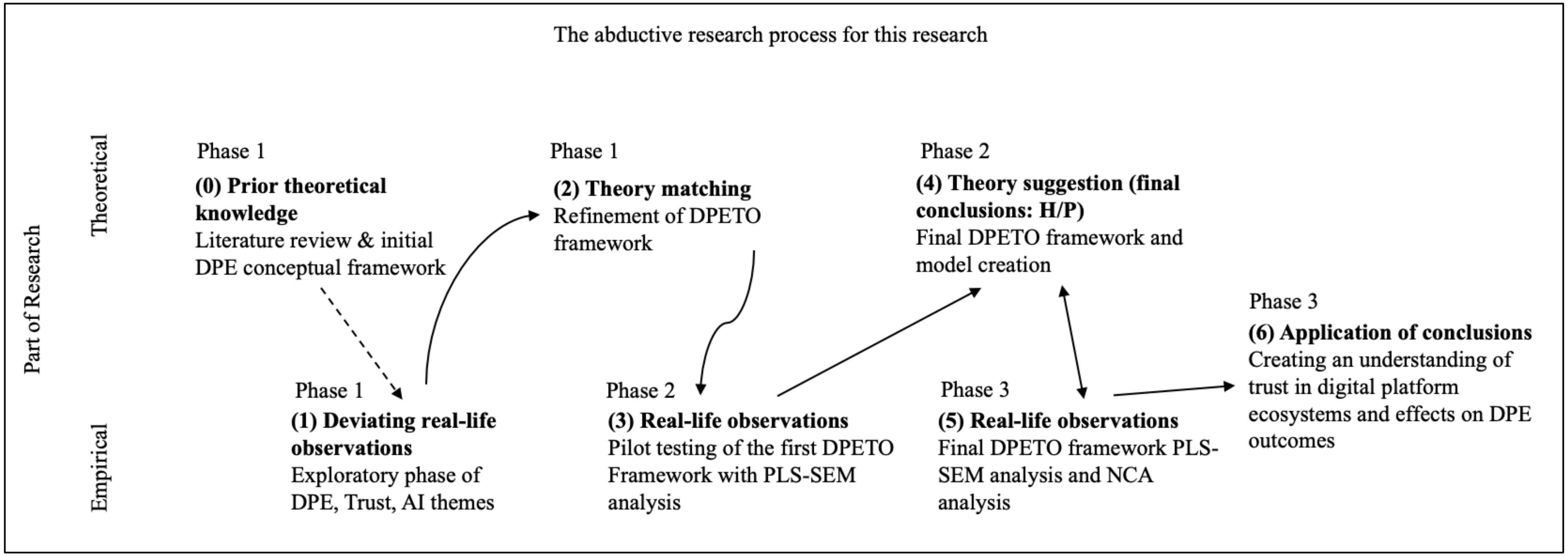


Figure 15: The abductive process for this research

3.4 Population and sampling

In line with the research questions and objectives of measuring the effects of AI explainability in financial services digital platform ecosystems required to select a data set and hence aligning the research strategy to a sampling strategy to achieve statistical generalisability. As the research was being very focused, it was closer to the probability sampling as a technique as it required each selected case' probability to be known and equal in nature, which in turn helped to make statistical inferences from the sample data collected, in turn helping the answer the research questions and fulfil the research objectives of this research. This research used 'simple random' (Saunders, Lewis and Thornhill, 2019) sampling technique which involves selecting randomised samples from the dataset. This was the most suitable sampling technique given that a feasible sampling frame with target population was available, and it was not dispersed across a large geographical area.

The target population for this digital platform ecosystem quantitative study was predominantly located across the United Kingdom (UK) and United States of America (USA). Thereafter, applying a balanced distribution criterion meant that a balanced distribution for this study was achieved, evenly distributing the male and female participants. The platform of choice "Prolific" at the time of running the study did not provide the researcher with an option to distribute across non-binary genders. This study was made more inclusive by including this as a question within the survey and captured this additional participant attribute. This research also applied several pre-screen criterions to the available pool of participants to ensure that the participants were relevant to the digital platform ecosystem in the financial services domain. These pre-screen criteria are further highlighted in Table 11. Apart from the pre-screen criteria that was available to the researcher from Prolific, further qualifying were asked (18 year participant consent) along with clarifying questions (requesting participants to describe the financial services digital platform ecosystem they are experienced in) within the first few sections of the survey questionnaire (see Appendix A).

Table 11: Participant pre screening

Criteria	Details	Pre-Screener Question
Employment-Sector	Finance	Which of the following best describes the sector you primarily work in?
Industry	Finance and Insurance	Which of the following categories best describes the industry you primarily work in (regardless of your actual position)?
Computer Programming	Yes, No	Do you have computer programming skills?
Previous Studies	Exclude participants from previous studies	This screener will exclude all participants from the selected studies regardless of their submission status. Please note this list only includes studies which are completed. Read about preventing certain participants from accessing your study.
Cryptocurrency Exchanges	Binance, Coinbase, Kraken, Crypto.com, Revolut, Gemini, FTX, KuCoin, Gate.io, Bitfinex, Other, I do not own any cryptocurrency	Which of these cryptocurrency exchanges do you use?

To compute the sample size N, this research referred to the a priori power analysis procedure (Faul *et al.*, 2007). In a priori power analysis, the sample size is calculated as per the function of the required power level (1- β), prespecified significance level alpha and the population size effect size is to be detected with probability 1- β. Other methods of sample size calculation in the application of partial least square structural equation modelling include the rule of the 10, which indicates that the sample size should be greater than ten times the number of structural paths directed at a particular construct (Hair et al., 2017). This rule only provides a rough guideline to the researchers and therefore, considerations should be made against the type of study, model and other data related characteristics (Marcoulides and Chin, 2013). This research therefore followed the power analyses approach based on the part of the model with the largest number of predictors (Hair et al., 2017). It then calculated the number of samples, indicating the required effect size f^2 values of 0.15 which indicates a medium effect of an exogenous construct on an endogenous construct (see Figure 22). This configuration of G*Power (Faul et al., 2009) provided us an output of the required total sample size of 119. Further to this, a graph of total sample size vs. power was plotted, exhibiting that for a power of 0.95, a total of 119 respondents are required (see Figure **18**: Graph of total sample size vs power). Additional to the output shown in numerical format, G*Power also displays the central and noncentral test statistic distributions, alongside the criterion and the respective error probabilities.

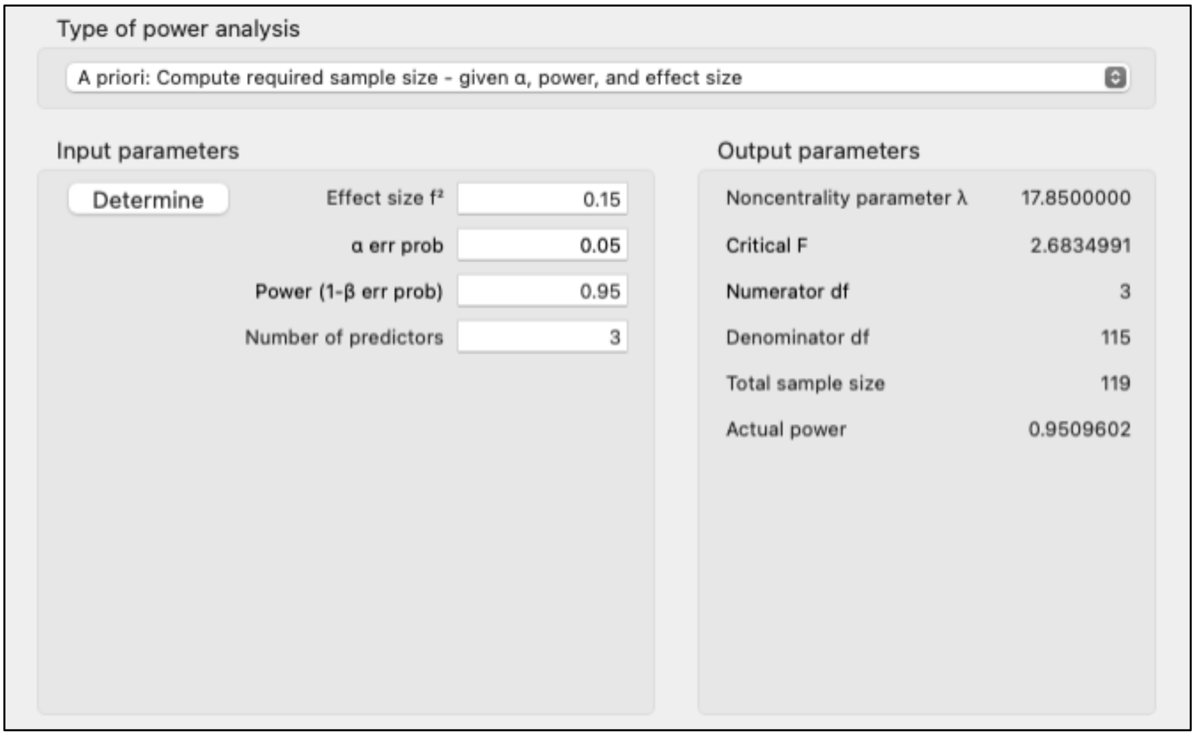


Figure 16: G*Power A priori power analysis configuration

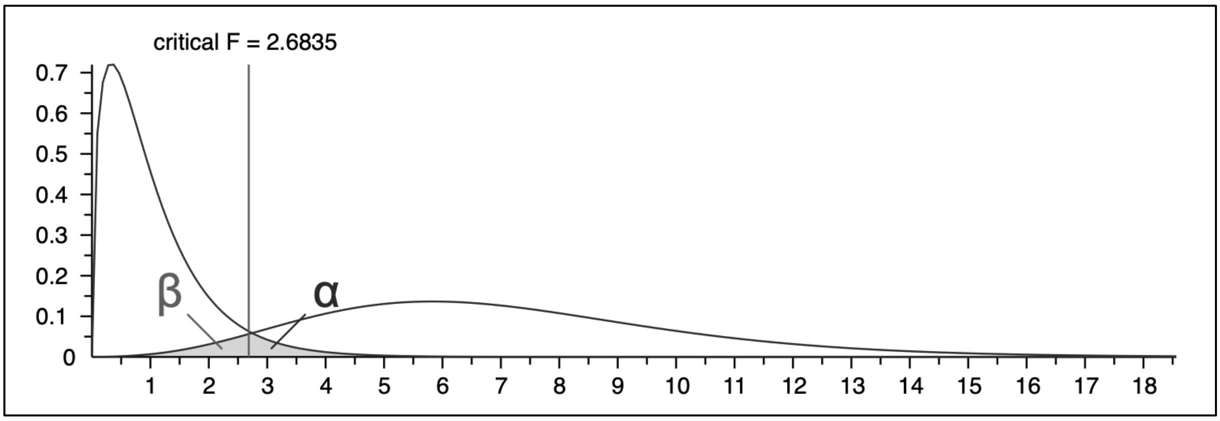


Figure 17: Central and noncentral distributions

Table 12: Protocol of power analysis

F tests - Linear multiple regression: Fixed model, R^2 deviation from zero

Analysis:	A priori: Compute required sample size	
Input:	Effect size f^2	= 0.15
	α err prob	= 0.05
	Power (1-β err prob)	= 0.95
	Number of predictors	= 3
Output:	Noncentrality parameter λ	= 17.8500000
	Critical F	= 2.6834991
	Numerator df	= 3
	Denominator df	= 115
	Total sample size	= 119
	Actual power	= 0.9509602

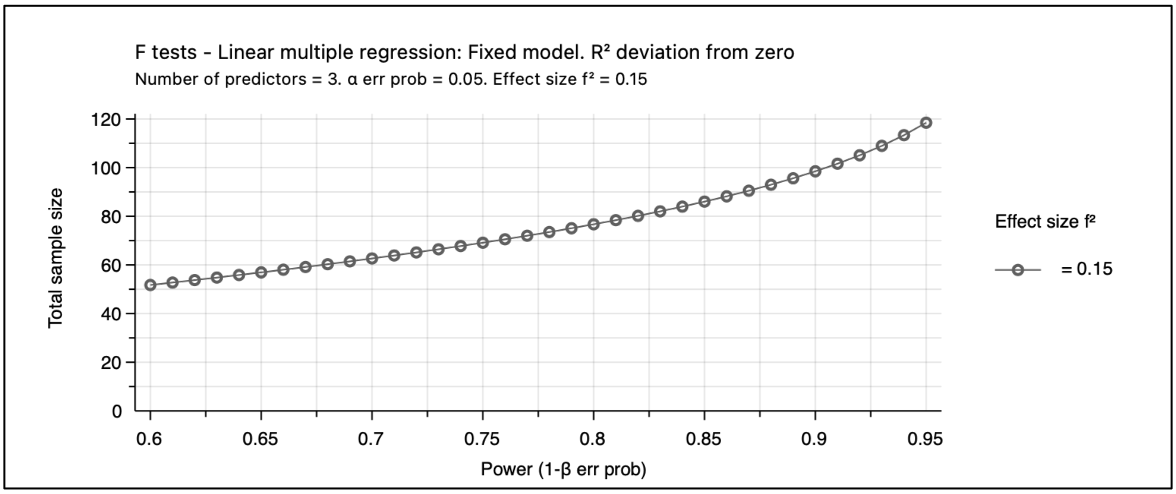


Figure 18: Graph of total sample size vs power

3.5 Research setting

This quantitative exploratory research was focused on participants located primarily in the UK and USA at the time of completion of the study survey. The biggest challenge for this research was to find the participants who have the specific skills and background required for the purpose of this study. To mitigate the challenge of finding the relevant participants for this research, it considered three main platforms, Amazon Mechanical Turk (MTurk), CrowdFlower (CF) and Prolific Academic. To clarify, these platforms are not examples of digital platform ecosystems referenced in this study, instead, are platforms that can be used to source participants or respondents for survey based and other types of studies. The most relevant used platform in the context of studies on explanations pertaining to artificial intelligence was MTurk, utilised for recruiting participants for experimentation (Ghai et al., 2020). However, it has been found that MTurk has exhibited participant non-naivety and dishonesty, and participants on Prolific Academic produced data quality higher in comparison to other platforms (Peer et al., 2017) as well as high diversity. Data quality is critical in the context of sourcing research participants using online platforms, with regards to aspects such as dishonesty, comprehension, and attention. Prolific provided high data quality on all measures whereas studies have found MTurk to show low data quality in comparison (Peer et al., 2022). Therefore, the researcher proceeded with running the participant sourcing on the Prolific platform, which is being increasingly used by researchers from a diverse set of recognised academic and professional institutions. Participants were compensated directly by the platform according to their estimated study completion time, taking a median time of 11 minutes and 26 seconds. For this study, there were a total 1597 eligible participants after applying the pre-screening criteria from a total participant pool of 121,250 at the time of publishing this study on the Prolific platform.

3.6 Data collection instrumentation design and procedure

For this research study, the researcher developed a questionnaire, ensuring that the response rate, reliability, and validity of the data (Saunders, Lewis and Thornhill, 2019) by ensuring:

- Design of individual questions
- Questions are presented optimally and appear with visual clarity
- Accompanies with explanations aligned with the purpose
- Planned and executed carefully and managed carefully upon receiving the completed responses

These questionnaires were self-completed, distributed to the respondents via the Prolific platforms electronically. Pre-screened respondents on the Prolific platform accessed the questionnaire through a browser hyperlink on their computer. The researcher acknowledges the blurring of the devices, but limited the respondents to complete the questionnaire using a computer or a tablet device as this was critical to the way the questionnaire appeared on multiple devices (Kozinets, 2015). Participants were given a description of the study and the expectations.

Prolific platform allowed the participants to be automatically routed to the questionnaire which was hosted on Qualtrics online survey platform provided by Henley Business School, University of Reading. This research used Qualtrics to create the online survey questionnaire for this PLS-SEM based study aligned with other similar research studies which used PLS-SEM analysis and conducted the survey through Qualtrics to collect respondent data (Lee and Hallak, 2018; Herjanto, Amin and Purington, 2021; Torres-Moraga et al., 2021).

Each participant on the Prolific platform has a unique ProlificID to track participation aligned with the Prolific participant profile. This research additionally added specific configuration parameters required by Prolific to integrate the survey with Qualtrics (see Figure 19).

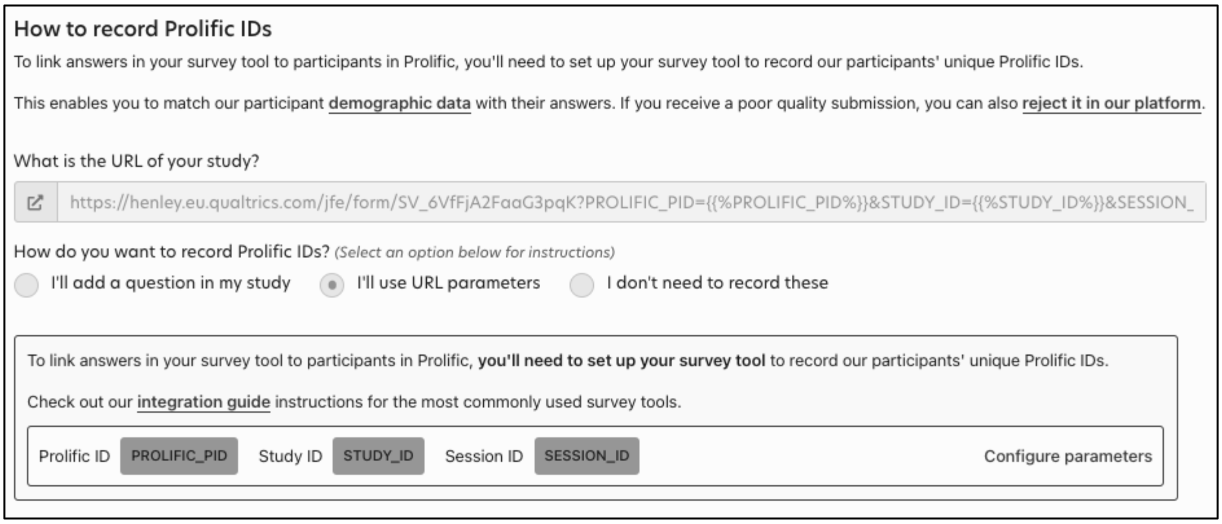


Figure 19: Prolific - Qualtrics survey configuration

To confirm the respondents' completion of the Qualtrics survey study, Prolific platform required the participants to enter a unique completion code to record their completion. The researcher chose the option to provide the completion code at the end of the survey questionnaire which was then manually copied and pasted by the participants to confirm the completion of their study participation (see Figure 20). This survey code was built within the questionnaire designed on Qualtrics platform. Data was recorded and managed from within the Qualtrics platform and was available to be downloaded in multiple formats supported by statistical analysis platforms such as in Microsoft Excel supported formats and CSV (comma separated values) format.

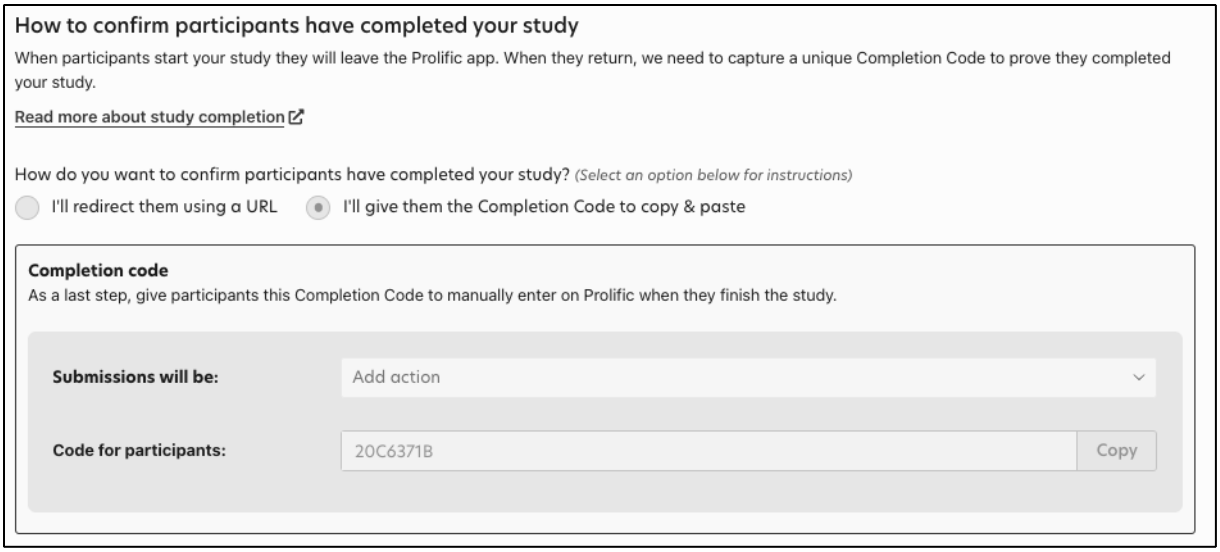


Figure 20: Participation confirmation code

3.7 Data preparation

Data was exported from Qualtrics into CSV format and eliminated incomplete responses. The researcher received a total of 333 completed responses from 535 responses that were recorded on Qualtrics but not completed by the respondents. This data set was then imported into RStudio Workspace and was cleaned to remap the Qualtrics questions to variable codes. Furthermore, the data set was transformed to numerical data and missing values were coded to -99 (Hair et al., 2017). Questions answered in the Qualtrics survey were a combination of Likert scale 7 point, Likert scale 5 point, yes and no, multiple choices and open ended text entry questions. For PLS-SEM analysis of the data variable questions were answered on a 7 point Likert scale.

3.8 Measurements development

The researcher designed the research instrument from pre available scales used in previous related studies and other measurement items that were found through the extensive literature review process. The research instrument contains a total of 92 variables which include a combination of indicators used to measure the demographics and other information. Of this, there were a total of 43 reflective scale indicators. Eight of these indicators measured the independent construct of digital platform ecosystem higher order, second order construct and respective sub-constructs of digital platform ecosystem value creation and digital platform ecosystem platform AI. 19 indicators measured the independent construct of digital platform ecosystem trust. Three indicators measured the dependent construct of willingness to transact, three indicators measured the dependent construct of network coopetition, and 10 indicators measured the dependent construct of collaboration. All these indicators were measured on a seven point Likert scale, accommodating for greater variation versus a five point Likert scale (Lietz, 2010).

It was found that there were not enough research studies in this domain and hence there were no readymade scales that could be leveraged in this research. Using the appropriate guidelines, this research leveraged theory and availability of constructs where appropriate and developed new scales to measure these constructs (Mackenzie, Podsakoff and Podsakoff, 2011; Boateng et al., 2018; Pillet et al., 2023) . This research was able to leverage some of the predeveloped scales for constructs such as willingness to transact, network coopetition and collaboration, however, these required adjusting to make them relevant to this research. The respondents were signed-posted appropriately for them to be guided towards answering the questions associated with the measurements items. For a detailed list of measurements for each construct, see Table 13.

Table 13: Development of key construct measurements

Construct Name	Indicators	Measurement development rationale
Dependent variables		
Network Coopetition	Three reflective indicators measured on a seven point Likert scale	(Lascaux, 2020)
Willingness To Transact	Three reflective indicators measured on a seven point Likert scale	(Bhattacherjee, 2002)
Collaboration	Ten reflective indicators measured on a seven point Likert scale	(Pathak, Ashok and Tan, 2020) (Bonardi et al., 2016) (Das, 2020) (Steinbruch, Nascimento and de Menezes, 2021) (Lascaux, 2020)
Independent Variables		
Digital Platform Ecosystem	Construct is a higher order (second order) construct, eight repeated indicators of the two first order constructs as below.	(Adner and Kapoor, 2010) (Adner, 2017) (Jacobides, Sundararajan and Van Alstyne, 2019)
Platform AI	Five reflective indicators measured on a seven point Likert scale	(Gamito, 2017) (Di Porto and Zuppetta, 2021)
Value Creation	Three reflective indicators measured on a seven point Likert scale	(Hein et al., 2020)
Trust	Nineteen (19) reflective indicators measured on a seven point Likert scale	TIO: (Bhattacherjee, 2002) HCTM: (Gulati, Sousa and Lamas, 2019)

The Digital Platform Ecosystem variable in this research conceptual model was examined as a second order construct (see Figure 4: The DPETO conceptual model). This is due to the complexity of the construct and hence the operationalisation at the higher level of abstraction (Hair et al., 2017). As per Hair et.al, higher order models often involve testing second-order structures that contain two layers of components. Digital platform ecosystem in this research is defined at different levels of abstraction, represented by first order components Platform AI and Value Creation that capture the attributes of the digital platform ecosystem. This modelling approach as per the guidelines, leads to more parsimony and reduces model complexity and guidelines were followed. (Hair et al., 2017).

3.9 Data analysis procedure

The PLS-SEM method of analysis in this research was used as it enabled this research to estimate the digital platform ecosystem model (including its complexity and associated constructs indicator variables and paths) without the need of distributional assumptions on data (Hair et al., 2019). The use of PLS-SEM as a method of analysis for this research focuses on testing a theoretical framework from a prediction perspective. This includes the research objective to better understand the way established theories in the digital platform ecosystems and platforms trust are evolving in complexity and require a modern method of analysis for conducting exploratory research for development of theory. The causal-predictive approach to structural equation modelling element of PLS-SEM was another reason to choose this as method of analysis as it emphasises prediction in estimating statistical models designed usually for causal explanations (Hair et al., 2017).

This research uses PLS-SEM method of analysis as distribution is of concern along with the normality of data. Furthermore, the PLS-SEM method of analysis provides latent variable scores that can be used for follow-up analysis. This research used these for NCA (necessary condition analysis) analyses in combination with PLS-SEM analysis (Richter et al., 2020).

SmartPLS software was used for examining the proposed Digital Platform Ecosystem Trust Outcomes model (DPETO model) (Hair et al., 2017). This model was analysed to assess the effect of explainable artificial intelligence on trust, by comparing two models with xAI and without xAI in the trust mediator. Similar research studies have analysed models with PLS-

SEM techniques and measured associated mediation effects of multiple predictors of mediation (Cheah et al., 2019). Furthermore, these studies have employed an in-sample prediction (model selection criteria) and out-of-sample prediction (PLSPredict) to understand reality (Cheah et al., 2019). This research took a similar approach and compared the two models to measure mediation effects, in-sample and out of sample model comparison criteria to answer the research hypotheses.

Following the reflective measurement model assessment including the loadings, Cronbach's alpha, composite reliability $\mathbf{rho_c}$ / $\mathbf{rho_a}$, AVE and HTMT, this research carried out the structural model assessment VIF values, explanatory and predictive power, path coefficient significance and relevance as well as model comparisons (Hair et al., 2019).

This research takes an innovative approach to analysis by extending the analysis of PLS-SEM by combining it with a relatively less known and newer approach of necessary condition analysis (NCA) (Dul, 2019). NCA enabled this research to be able to explore and validate hypotheses by following a sufficiency logic and necessity logic (Richter et al., 2020). This combined usage of the two methods of analysis enabled us to identify the must-have factors that were required for the digital platform ecosystem outcomes in accordance with the necessity logic and the additive sufficiency logic (Richter et al., 2020). As per the guidelines (see Figure 21) the latent variable scores were transferred to a new datafile in R where the R package for NCA was used to run the NCA.

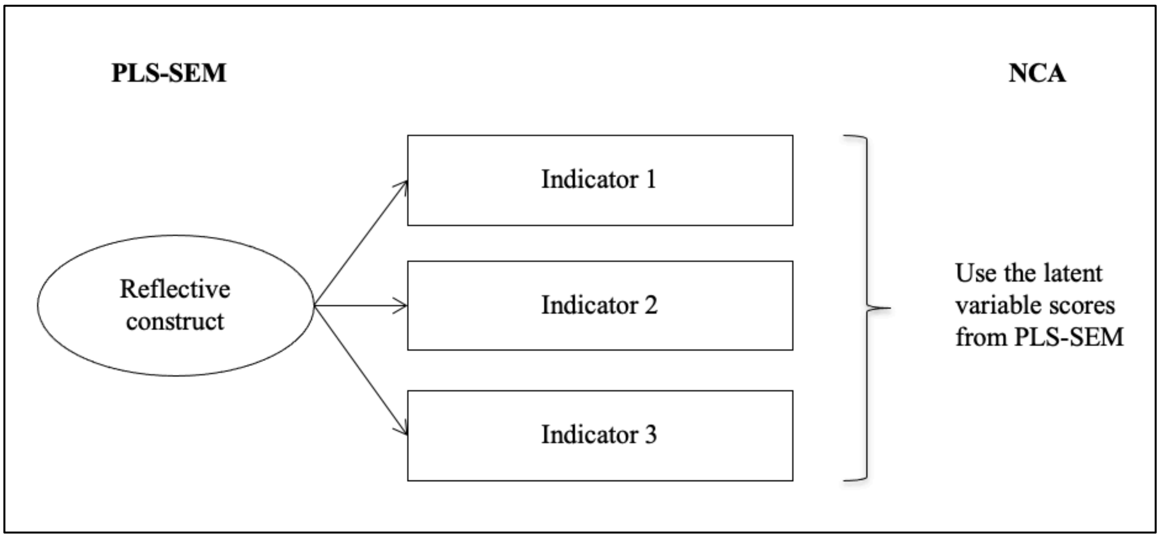


Figure 21: Constructs/indicators to be tested in NCA (adapted from (Richter et al., 2020))

To expand on the current body of knowledge on digital platform ecosystems and how artificial intelligence explainability affects trust and related digital platform ecosystem outcomes, this research tested a combination of hypothesis and the related model (the DPETO model) theorised in this research (see Figure 22: The DPETO (Digital Platform Ecosystem Trust Outcomes) model).

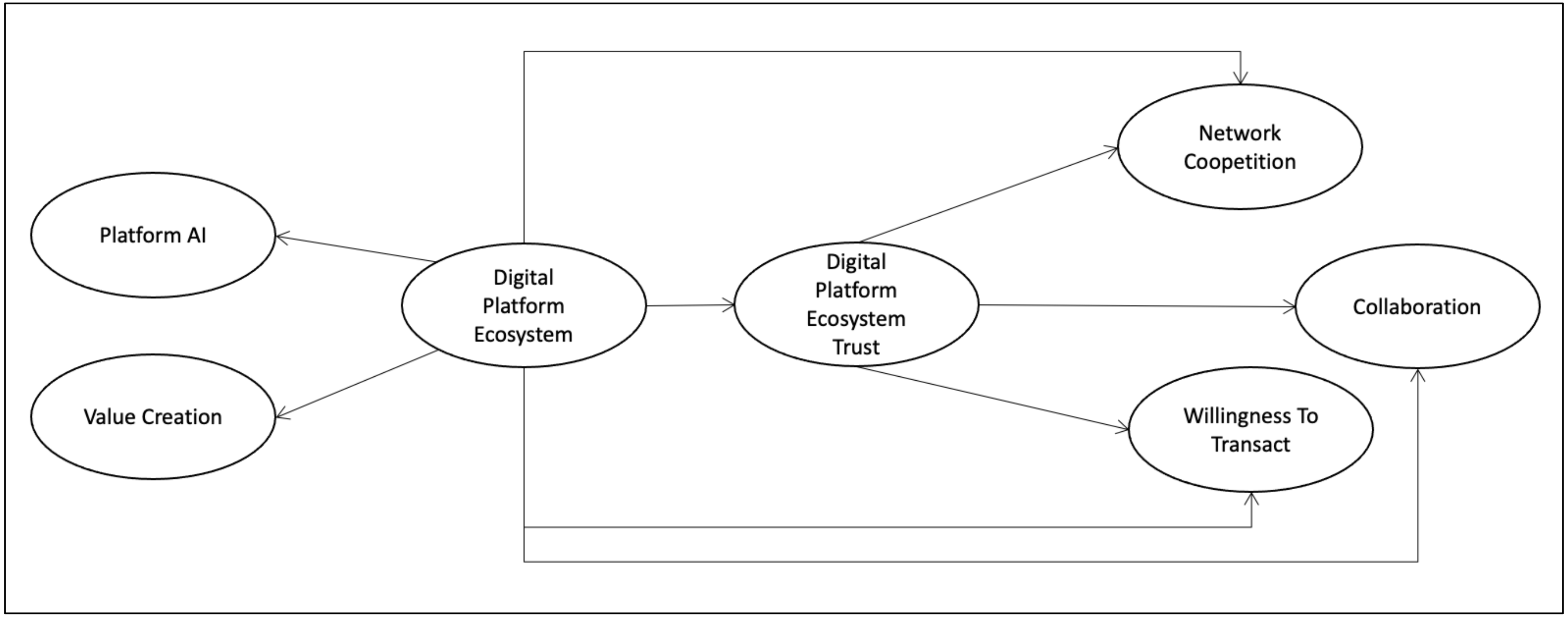


Figure 22: The DPETO (Digital Platform Ecosystem Trust Outcomes) model

3.10 Validity and reliability

Generally, there is a potentially large gap between the hypothesised concepts that are sought to be measured by researchers and the measurement constructs that are employed for that purpose (Rossiter, 2011; Rigdon, 2012). This gap warrants for the appropriate reliability and validity assessments to be conducted by leveraging multiple criteria, in case of this research, to evaluate the reflective measurement models (Hair et al., 2017). Additionally, emphasis should be made on the content validity of the measures and the extent of representation of the domain of the construct being measured (Bollen and Lennox, 1991) . Furthermore, this research utilised a PLS-SEM analysis to establish the composite reliability (Hair et al., 2017).

3.11 Ethical considerations and assurances

This research conforms to the ethical considerations as prescribed by University of Reading, research ethics guidelines on 'Data Protection and Research' and 'Data Management Planning.' To stay compliant, this research followed all requirements set forth in the guidelines and all ethical requirements were adhered to and followed in this research study. Researchers requested appropriate consent from the participants, participation was voluntary, data collection ensured privacy, and the relevant consent forms were provided to the participants at the beginning of the study (see Appendix A). All participants were sourced from Prolific platform and were pre-vetted and pre-screened for age limitations, background experience and other demographic data.

Results, as discussed in the results and discussion section of this research thesis, should be considered alongside potential bias associated with the interpretation of theoretical definitions and their application in conceptual model development for the purpose of this exploratory research study. Results should also be viewed with a potential for bias associated with the participant demographics and representation of the participants' self-elected experience. This research was limited to participation from the UK and USA, and this can be further extended to study the proposed phenomenon over a more global and geographically dispersed demographic participation constitution. Furthermore, as per the recent elements in the areas of technological capabilities associated with this research, this research model can be extended to be studied over a period in a longitudinal manner to understand the effects of artificial intelligence explainability on trust in digital platform ecosystems over a longitudinal study period.

3.12 Chapter summary

This chapter provided a detailed overview of the methodology employed in the research, illuminating the steps and decisions that guided this study.

The chapter began by discussing the chosen research philosophy, which established the philosophical stance of the study. This research philosophy directed the approach to knowledge and reality and ultimately highlighted how it influenced the research design and methods for this research. Moving forward, this chapter elaborated on the selected research design and methods**.** It also detailed how the study followed an advanced quantitative data analysis approach, justifying the selection based on the research questions and objectives. The procedures employed, including surveys and associated measurement instruments were outlined, and explained how the selected methods aligned with the research goals. The chapter also shed light on the decisions made regarding population and sampling. It also provided clarification on the study's target population, along with the criteria for inclusion and exclusion, and expanded on the sampling technique adopted. The rationale for selecting a specific sampling strategy was rooted in its relevance to the research scope and objectives. Additionally, insights were provided into the research setting, describing the context in which the study took place, highlighting how the setting influenced data collection and the overall research process.

The chapter also discussed the details of data collection instrumentation and procedure, explaining the tools and instruments employed to gather data. The procedures followed during data collection were also outlined, emphasising on consistency and replicability. To ensure the reliability and validity of the findings, the approach to data preparation was discussed by detailing the steps to clean, organise, and pre-process the collected data which is necessary to facilitate an accurate analysis. With regards to the measurements development, this explained how the variables were operationalised, scales were developed, ensuring the comprehensiveness and relevance of the measurement items to the research questions. As the data analysis procedure is a crucial aspect of this research, the methods and techniques employed to analyse the collected data, along with other combinations that were utilised, were further explained. This chapter also highlighted the thoroughness of the approach in developing meaningful conclusions from the data analysed presenting the research hypotheses that guided this study. These hypotheses articulated the expected relationships that the study aims to validate. The chapter additionally detailed the ethical considerations and assurances that governed this research.

4 Analysis and findings

"Errors using inadequate data are much less than those using no data at all"

– Charles Babbage

This chapter provides the details of the research findings through the analysis of the data collected for this research. This chapter includes a comprehensive exploration of the research's core components, aiming to uncover the hidden insights within the data. Additionally, this chapter presents a holistic view of the research outcomes by analysing response rates, delving into descriptive statistics on survey respondents, performing PLS-SEM analysis, analysing the conceptual DPETO model path relationships, and evaluating the model measurements, providing details on the model selection criterion and other results. Furthermore, this chapter provides an in-depth assessment of various aspects of the PLS-SEM analysis such as internal consistency reliability, convergent and discriminant validity, multicollinearity, and testing for direct and mediated relationships. This chapter also details the process of applying the model selection criterion, prediction assessments, and the integration of Necessary Condition Analysis (NCA) with PLS-SEM analysis techniques. The chapter also provides the results of the analysis of the research hypotheses and provides explanations of their significance or insignificance.

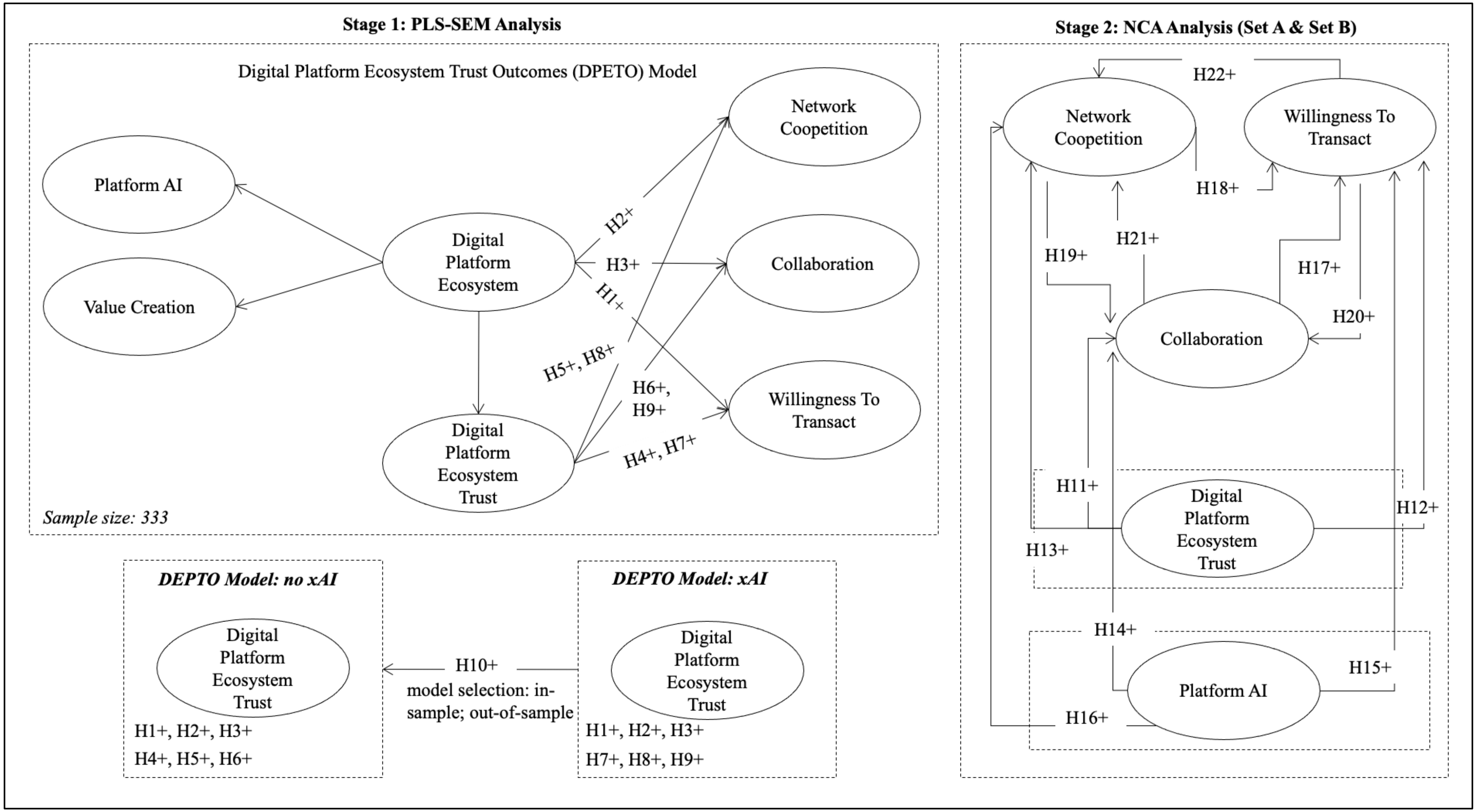


Figure 23: Analysis approach and stages

4.1 Response rates

This study targeted professionals who were experienced in the domain of financial services and were aware of the significance of a digital platform ecosystem in the financial services domain and context. This population sample was made up of a combination of personas that the participants self-identified with – digital platform ecosystem end users, digital platform ecosystem participants and digital platform ecosystem owners, also see **3.5 above**. Prolific platform, after the application of the relevant filters, narrowed the eligible participants to a total of 1597 out of the 120,722 participants that matched the survey without applying the pre-screening criterion. Of the eligible participants, 535 respondents attempted the survey. Of the 535 responses received, 333 responses were complete and were selected to be included in this study. A high response rate helps with the reduction of non-response bias and also that the sample is representative (Groves et al., 2008).

4.2 Descriptive statistics

The responses received from 333 participants who provided the complete responses to the survey were broadly categorised into three main categories from a digital platform ecosystem perspective, and self-identified as one of the three personas defined at the beginning of the survey:

1. Digital Platform Ecosystem Participants
2. Digital Platform Ecosystem Owners
3. Digital Platform Ecosystem End-Users

The respondent sample analysed for this research includes a broad range of participants, representing a diverse age group, sectors that they work in and educational and organisational background. The diversity in the respondent group helps researchers combine the causal power with the generalizability of population base samples, the approach followed by this research.

However, this should be combined with considerations where a variety of samples are utilised in order to advance knowledge, especially in scientific domains (Mullinix et al., 2015). Following the guidelines of generalisation, drawing inferences from sample cases, is standard practice within the domain of quantitative research. This research follows the key goals of being able to provide a meaningful and contextual narrative of the research cases, using a combination of generalisation models, the classic sample to population (statistics based generalisation) and analytical assessment based generalisation (Polit and Beck, 2010).

Tables below, provide the details of the frequency of the respondents based on the demographic and distribution criteria that this research applies to segment the respondents.

Table 14: Descriptive statistics on respondent predominant persona classification in the financial services digital platform ecosystem

Predominant Persona	**Frequency**	**Percentage**
A Digital platform ecosystem End-User in the financial services domain	164	49.20%
A Digital platform ecosystem Participant in the financial services domain	149	44.70%
A Digital platform ecosystem Owner in the financial services domain	20	6.00%

The data collected was organised on the basis of predominant personas of the respondents and almost half of the respondents for this study were Digital platform ecosystem end-users in the financial services domain (see Table **14**). Another significant persona of the study respondents were the digital platform ecosystem participants, accounting for 44.7% of the total respondents. Only 6% of the respondents were digital platform ecosystem owners, and this should be considered while generalising the findings and implications of this research.

In terms of the demographics of the respondents, the majority (78%) of these reported their current country of residence as the UK (United Kingdom), followed by 21% from the USA

(United States of America). Therefore, the majority of end-user base generalisations and future implications from this research should be aligned with this representative group of respondents (see Table 15).

Table 15: Descriptive statistics on respondent country of residence

Current country of residence	Frequency	Percentage
UK	261	78.40%
USA	70	21.00%
Other	2	0.60%

Furthermore, during the pre-screening phase of this research, it was ensured that there is a 50% gender balance maintained in the respondents (see Table 16). Prolific platform provides the ability to recruit participants with a pre-set gender inclination, however, this research also provided a provision to report respondent preferences should they choose not to report on gender identification questions. This research does not take gender based differences in account and this criterion has not been applied to the data set when it was used for PLS-SEM based data analysis method.

Table 16: Descriptive statistics of respondents gender description

Gender	Frequency	Percentage
Female	165	49.5%
Male	165	49.5%
Prefer not to say	3	0.9%

Over half of the respondents reported their highest level of education attained to be bachelor's degree in college (f-year). This was followed by master's degree (17.7%), some college but no degree (12.60%), associate degree in college (6.9%), high school graduate (6.9%) and 2.10% with a professional degree (JD, MD). See Table 17.

Table 17: Descriptive statistics of respondents level of education

Highest Level of Education Attained	Frequency	Percentage
Bachelor's degree in college (4-year)	177	53.20%
Master's degree	59	17.70%
Some college but no degree	42	12.60%
Associate degree in college (2-year)	23	6.90%
High school graduate (high school diploma or equivalent including GED)	23	6.90%
Professional degree (JD, MD)	7	2.10%
Doctoral degree	1	0.30%
Less than high school degree	1	0.30%

Most respondents reported the type of sector they are from as the private sector (87.4%). Further to this, 11.70% of respondents reported to be from the public sector. These descriptive statistics outlining the respondents sector data is representative of the alignment of practical implications of this research and should be considered with appropriate considerations. See Table 18.

Table 18: Descriptive statistics of respondents sector

Type of Sector	Frequency	Percentage
Private Sector	291	87.40%
Public Sector	39	11.70%
Other (Please specify)	3	0.90%

Additionally, about 61.6% of the respondents work for a large organisation in the financial services sector with 500 or more employees. See Table 19.

Table 19: Descriptive statistics of respondents size of organisation based on the number of employees

Number of Employees	Frequency	Percentage
1000 or more	172	51.70%
500 to 999	33	9.90%
250 to 499	28	8.40%
100 to 249	25	7.50%
05 to 09	21	6.30%
1 to 4	17	5.10%
20 to 49	16	4.80%
50 to 99	11	3.30%
10 to 19	10	3.00%

In terms of job roles, there was a varied mix of respondents in terms of job roles (see Table **20**). This included respondents with job roles as Managers (27%), Specialists (26.4%), Consultants (18.60%), and some at Senior Manager (7.80%) and Director (3.90%) levels.

Table 20: Descriptive statistics of respondents' job role

Job role	**Frequency**	**Percentage**
Manager	90	27.00%
Specialist (e.g. Engineering services, Software Development etc.)	88	26.40%
Consultant (e.g. External contractor, advisor etc.)	62	18.60%
Other	39	11.70%
Senior Manager	26	7.80%
Director	13	3.90%
Executive Management	10	3.00%
Senior Director	5	1.50%

4.3 Stage 1: PLS-SEM analysis

One of the first steps in the PLS SEM analysis is to follow a diagrammatic approach that outlines the key hypotheses and the relationships with the variables in a graphical manner (Hair et al., 2017). This diagram is referred to as a 'Path Model' and consists of two key elements: the inner model also known as the structural model and the measurement model. The structural model is used to describe the relationship between the latent variables. The measurement model is used to describe the relationships between the latent variables and their corresponding measures, also known as indicators (Hair et al., 2017). This research used SmartPLS software for conducting PLS-SEM based analysis, using an academic licence subscription (Ringle, Wende and Becker, 2022). Initially, SmartPLS version 3 software was used and was further upgraded to SmartPLS version 4 and subsequent releases as communicated by the software provider (Ringle, Wende and Becker, 2022). The path models are built on theory, measurement theory and structural theory (Hair et al., 2017). The path model, along with latent variables for the DPETO conceptual model are represented in Figure 24: The DPETO PLS path model – path relationships. This research has two variations of the path model, where the mediator DPE Trust is tested with and without artificial intelligence explainability based measures and hence is tested for comparison of effects. Figure **25** and Figure **26** present the measurement items and

PLS results of the DPETO model without artificial intelligence explainability respectively. Figure **27** and Figure **28** present the measurement items and PLS results of the DPETO model with artificial intelligence explainability respectively. These are additionally discussed in detail and envaulted with results presented in Stage 1: PLS-SEM results.

4.3.1 The DPETO model – path relationships

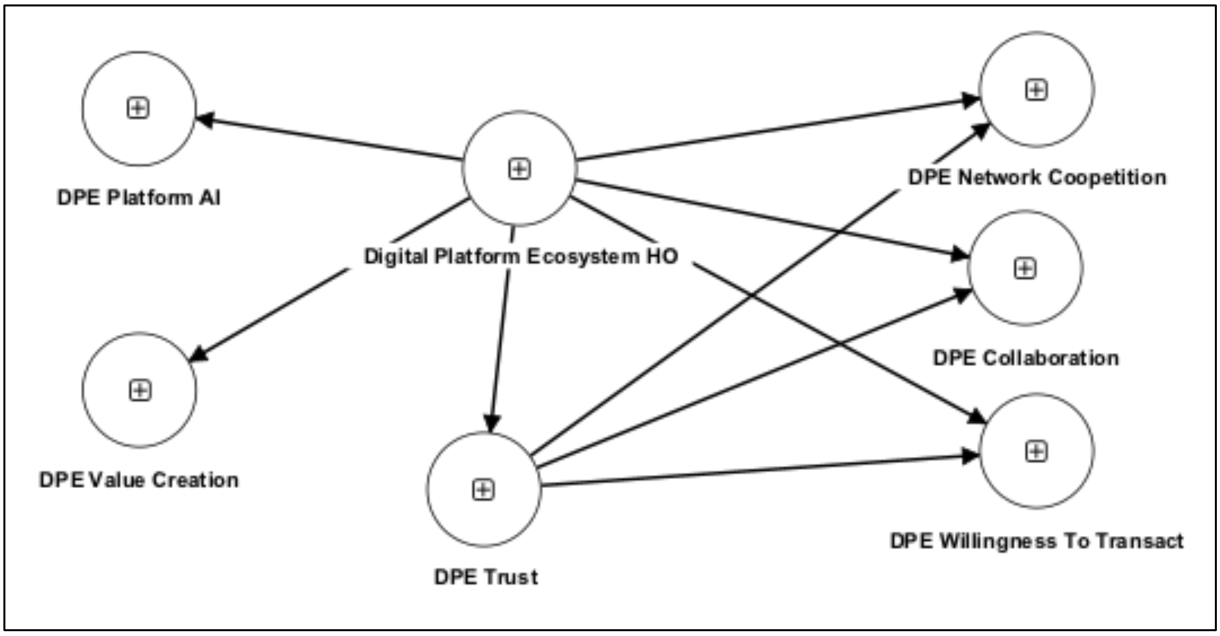


Figure 24: The DPETO PLS path model – path relationships

4.3.2 Measurement items: DPETO model – no-xAI

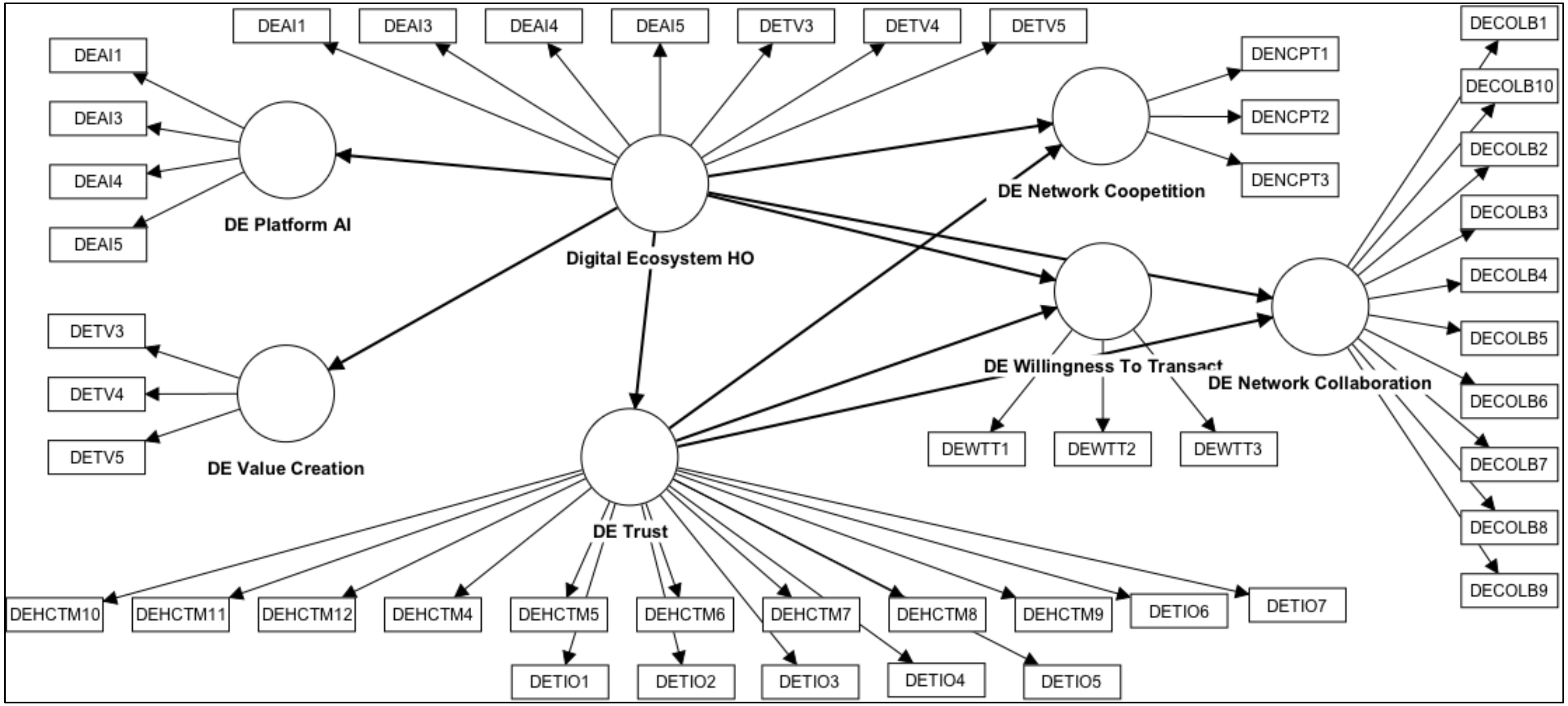
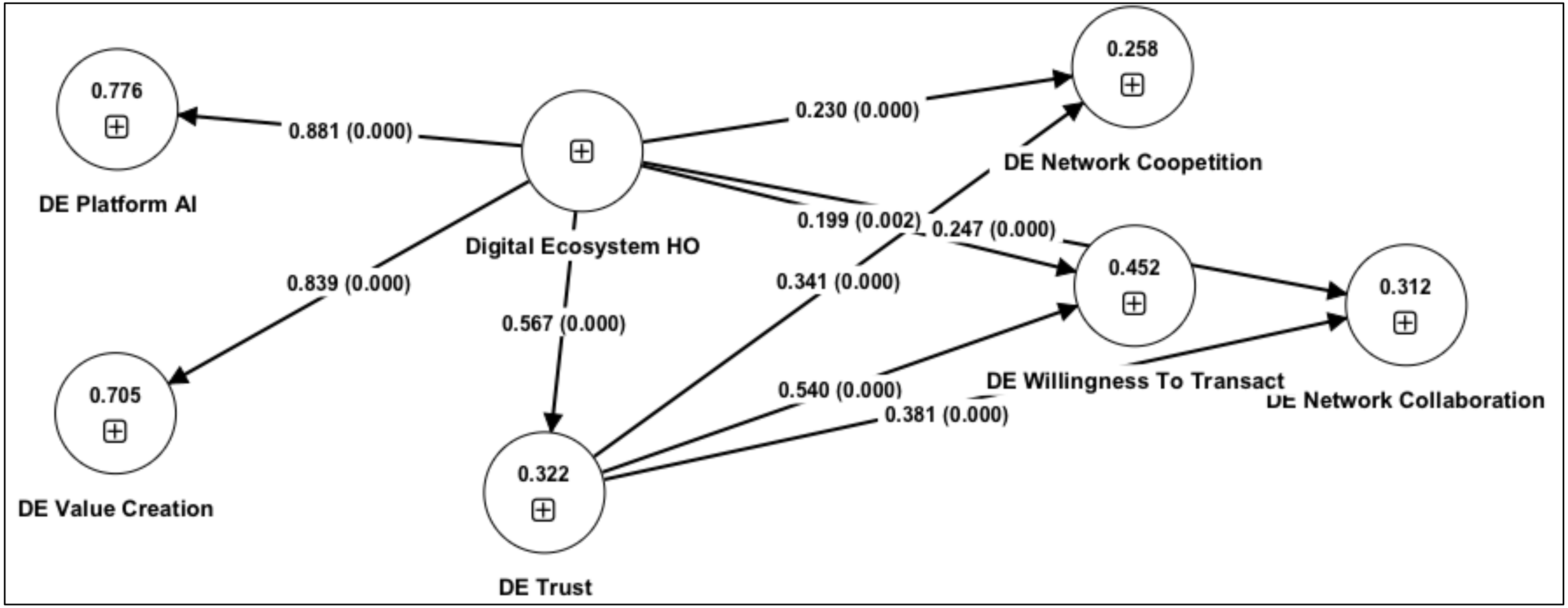


Figure 25: Measurement items: DPETO model – no-xAI

4.3.3 PLS Results: DPETO model – no-xAI



Constructs R-square values. Inner model Path coefficients and p values

Figure 26: PLS Results: DPETO model – no-xAI

4.3.4 Measurement items: DPETO model – xAI

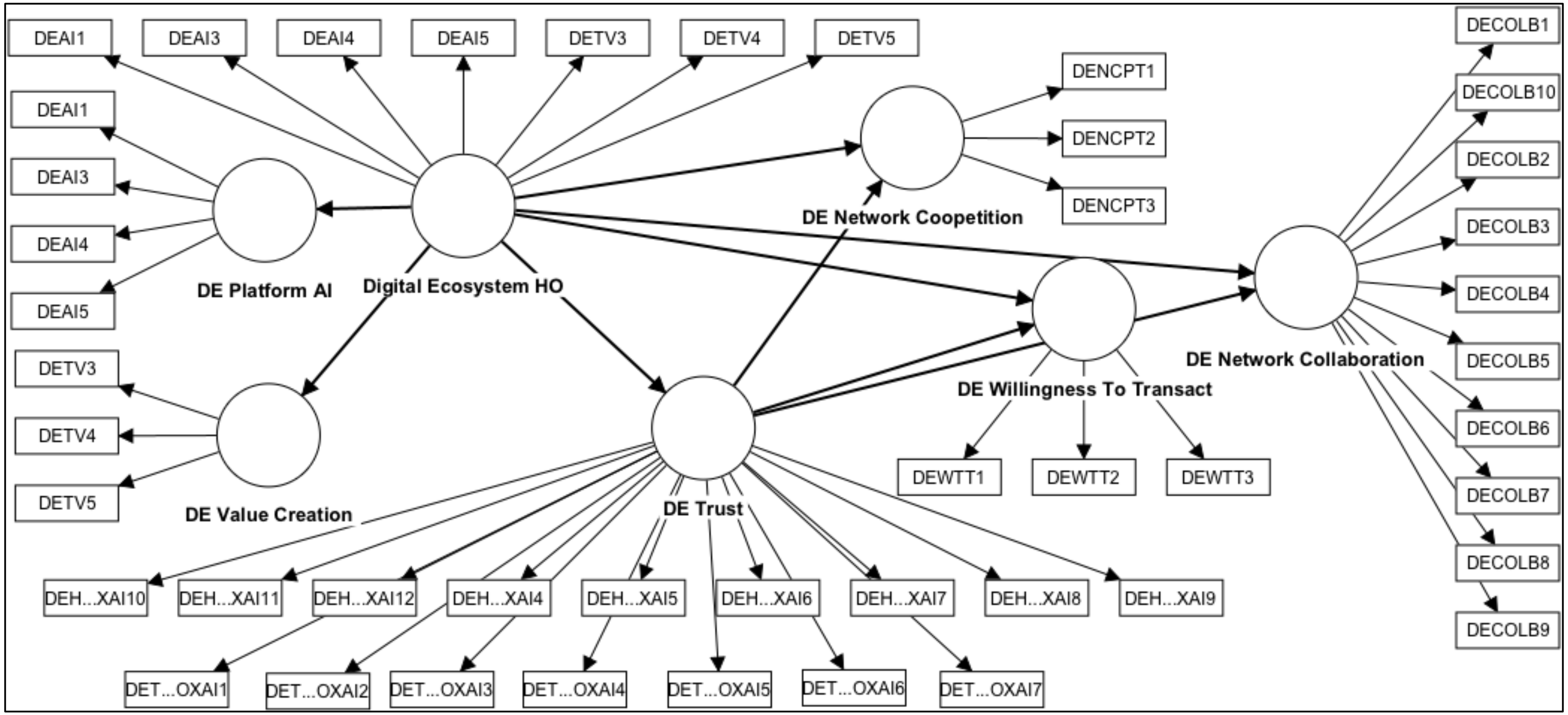
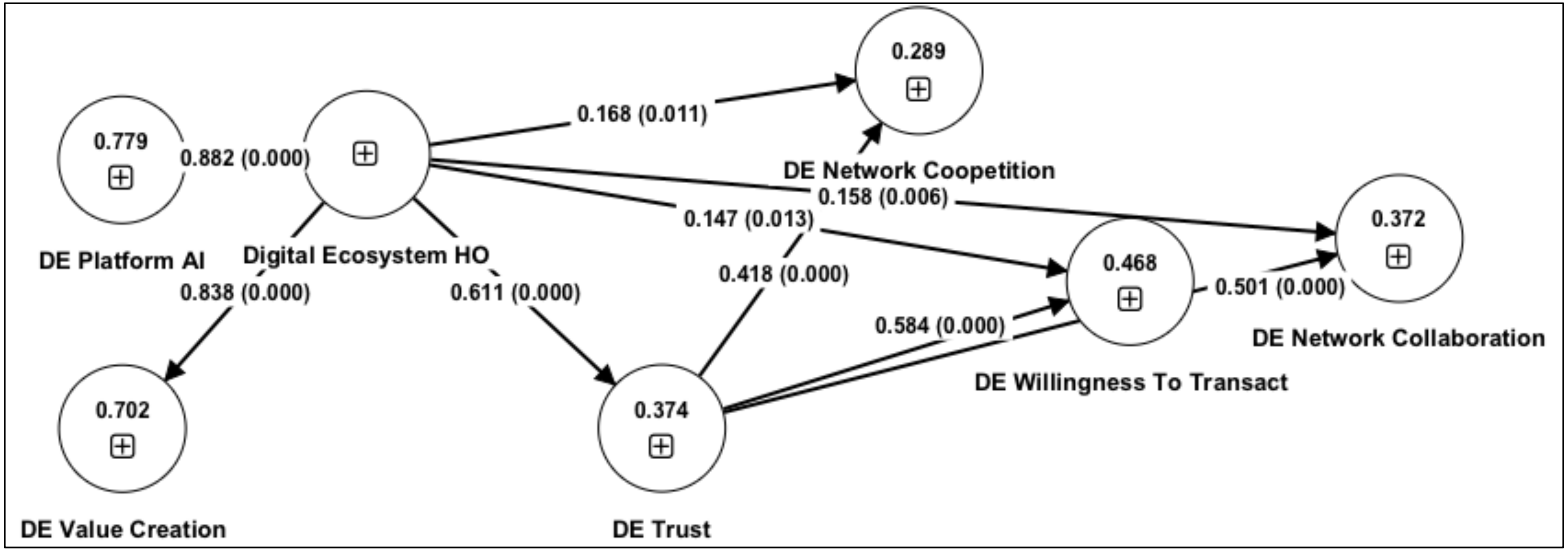


Figure 27: Measurement items: DPETO model – xAI

4.3.5 PLS results: DETO model – xAI



Constructs R-square values. Inner model Path coefficients and p values

Figure 28: PLS results: DPETO model – xAI

4.4 Stage 1: PLS-SEM results

4.4.1 Measurement model assessment – measurement scale and model loadings

4.4.1.1 Internal consistency reliability and convergent validity

The measurement models used in this study are of reflective nature and are hence assessed on their validity and internal consistency reliability. To carry out this assessment , the specific measures of convergent validity and discriminant validity were assessed. This assessment of the reflective model included evaluation of reliability of measures at the indicator level for indicator reliability and at a construct level for internal consistency reliability (Hair et al., 2019) . Generally recommended indicator loadings are above the threshold value of 0.708, explaining the indicator's variance of above 50% levels and hence being reliable (Hair et al., 2021). However, researchers in the domains of social sciences, particularly in with newly developed scales have resulted in weaker outer loadings of less than the threshold value of 0.7 (Hair et al., 2021). In such instances, the suggestions are to consider the removal of indicators with outer loadings (0.40 < outer loadings <0.70) but only in cases where the removal leads to an increase in composite reliability. This was considered and it was found that there were no significant differences based on the indicator removals. There were a total of four (4) indicators below the 0.4 mark in the measurement DPETO model – no-xAI (out of a total of 43 indicators), and a total of three (3) indicator below the 0.4 mark in DPETO model – xAI with xAI (out of a total of 43 indicators), and following the general guidance, these indicators were deleted. In certain cases, even though the general guidance is to remove those with outer loadings below 0.40, indicators can be retained if there is mixed evidence of high individual item reliability (Hulland, 1999). Examples of similar studies include, one where four out of the 18 item loadings were less than 0.4, second, with one third of the loadings below 0.4, retaining a significant number of low-reliability items in the final analysis (Hulland, 1999). The recommended advice of interpreting the results based on the low-reliability items with caution (Hulland, 1999) in both models was noted.

The **rho_c** values instead of **rho_a** values are reported, which is also one of the primary measures for composite reliability. This is intentional as **rho_a** is used in a consistent PLS to correct over time and when under estimation that occurs in **rho_c** and Cronbach's alpha. The items on the scale are viewed as distinct elements, measuring distinct elements of the underlying concept and not completely linked as these are non-historic scales due to the unique nature of this research setting, using the **rho_c** values (Hair et al., 2019). Higher values of **rho_c** indicate high levels of reliability where values between 0.60 and 0.70 are acceptable in exploratory research and values between 0.70 and 0.90 satisfactory to good. Values that are definitely above 0.95 are considered problematic as they indicate the redundant nature of the measurement, hence causing the overall reduction of the construct validity along with non-desirable response patterns (Hair et al., 2021). All the values reported in models are below the 0.95 and above the 0.60 threshold for both models.

Next, the average variance extracted values (AVE) were checked to check if they were above the 0.50 suggested threshold that signifies that the convergent validity is achieved (Hair et al., 2017). Both in DPETO model – no-xAI and DPETO model – xAI, some of the constructs have reported AVE values less than 0.50. Despite of the general threshold of 0.50, it was not possible for us to delete these constructs and have retained these values as acceptable using the guidance of accepting AVE values less than 0.50 while checking the composite reliability (CR) alongside and if CR is greater than 0.70 (CR > 0.70) which is true in the results (Fornell and Larcker, 1981). Therefore, concluding that overall, the measurement criteria of the digital platform ecosystem – trust model for both AI trust measurement construct types (no explainability and explainability, DPETO model – no-xAI and DPETO model – xAI) are satisfactory.

Table 21 and Table 22 exhibit the results of the convergent validity assessment for the outer measurement model, and the internal consistency reliability.

Table 21: Measurement model for DPETO model - no-xAI measures

Constructs	**Indicators**	**1st order outer loading (λ)**	**2nd order outer loading (λ)**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
	Measurement Model DPETO-no-xAI – No explainable artificial intelligence based measures				
Digital Platform Ecosystem Second order construct				0.843	0.434
Digital Platform Ecosystem Platform AI				0.836	0.561
	DEAI1	0.766	0.697		
	DEAI3	0.667	0.588		
	DEAI4	0.771	0.656		
	DEAI5	0.787	0.691		
Digital Platform Ecosystem Value Creation				0.827	0.614
	DETV3	0.759	0.619		
	DETV4	0.776	0.663		
	DETV5	0.815	0.689		
Digital Platform Ecosystem Collaboration				0.870	0.403
	DECOLB1	0.733			
	DECOLB10	0.680			
	DECOLB2	0.634			
	DECOLB3	0.612			
	DECOLB4	0.621			
	DECOLB5	0.645			
	DECOLB6	0.539			
	DECOLB7	0.663			
	DECOLB8	0.642			
	DECOLB9	0.553			

Constructs	**Indicators**	**1st order outer loading (λ)**	**2nd order outer loading (λ)**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
Digital Platform Ecosystem Trust				0.923	0.431
	DEHCTM10	0.573			
	DEHCTM11	0.618			
	DEHCTM12	0.722			
	DEHCTM4	0.626			
	DEHCTM5	0.659			
	DEHCTM6	0.591			
	DEHCTM7	0.673			
	DEHCTM8	0.729			
	DEHCTM9	0.705			
	DETIO1	0.703			
	DETIO2	0.658			
	DETIO3	0.706			
	DETIO4	0.669			
	DETIO5	0.654			
	DETIO6	0.607			
	DETIO7	0.577			
Digital Platform Ecosystem Willingness to Transact				0.925	0.804
	DEWTT1	0.911			
	DEWTT2	0.874			
	DEWTT3	0.904			
Digital Platform Ecosystem Network Coopetition				0.845	0.647
	DENCPT1	0.850			
	DENCPT2	0.728			
	DENCPT3	0.829			

Table 22: Measurement model for DPETO model - xAI measures

Constructs	Indicators	1st order outer loading (λ)	2nd order outer loading (λ)	Composite Reliability (CR)	Average Variance Extracted (AVE)
	Measurement Model DPETO-xAI – explainable artificial intelligence based measures				
Digital Platform Ecosystem Second order construct				0.843	0.434
Digital Platform Ecosystem Platform AI				0.836	0.561
	DEAI1	0.767	0.699		
	DEAI3	0.668	0.593		
	DEAI4	0.770	0.655		
	DEAI5	0.786	0.690		
Digital Platform Ecosystem Value Creation				0.827	0.614
	DETV3	0.759	0.617		
	DETV4	0.776	0.661		
	DETV5	0.815	0.689		
Digital Platform Ecosystem Collaboration				0.870	0.402
	DECOLB1	0.732			
	DECOLB10	0.674			
	DECOLB2	0.634			
	DECOLB3	0.616			
	DECOLB4	0.622			
	DECOLB5	0.655			
	DECOLB6	0.534			
	DECOLB7	0.662			
	DECOLB8	0.641			
	DECOLB9	0.546			

Constructs	**Indicators**	**1st order outer loading (λ)**	**2nd order outer loading (λ)**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
Digital Platform Ecosystem Trust				0.930	0.454
	DEHCTMXAI10	0.599			
	DEHCTMXAI11	0.632			
	DEHCTMXAI12	0.754			
	DEHCTMXAI4	0.722			
	DEHCTMXAI5	0.690			
	DEHCTMXAI6	0.615			
	DEHCTMXAI7	0.739			
	DEHCTMXAI8	0.755			
	DEHCTMXAI9	0.685			
	DETTIOXAI1	0.647			
	DETTIOXAI2	0.679			
	DETTIOXAI3	0.669			
	DETTIOXAI4	0.615			
	DETTIOXAI5	0.654			
	DETTIOXAI6	0.662			
	DETTIOXAI7	0.641			
Digital Platform Ecosystem Willingness to Transact				0.925	0.804
	DEWTT1	0.912			
	DEWTT2	0.873			
	DEWTT3	0.904			
Digital Platform Ecosystem Network Coopetition				0.845	0.646
	DENCPT1	0.848			
	DENCPT2	0.724			
	DENCPT3	0.833			

4.4.1.2 Discriminant validity assessment

A discriminant validity assessment was conducted using the Heterotrait-Monotrait (HTMT) ratio of correlation as this has been proven to be a better assessment over others such as the Fornell-Larcker criterion (Hair et al., 2021). Fornell-Larcker criterion is proved to have failed to identify any discriminant validity anomalies and is therefore advised to avoid (Radomir and Moisescu, 2019).

Table **23** and Table **24** shows the values, which are significantly lower than the threshold values of 0.90 as a test for conceptually similar constructs (Henseler, Ringle and Sarstedt, 2015). This research also tested for a more conservative threshold where suggested values are lower than 0.85, in the case of where constructs of the study are conceptually more distinct, as is in this research. Additionally, this research used the bootstrap confidence intervals to test if the HTMT values are significantly different from 1.0 (Henseler, Ringle and Sarstedt, 2015) or a lower threshold value of 0.90 or 0.85, defined on the basis of the context of the study (Franke and Sarstedt, 2019). Also, used the suggested 5000 bootstrap samples which when run as a complete bootstrapping took some time to process (Hair et al., 2017). The BCa Bootstrap was used, which stands for Bias Corrected and Accelerated Bootstrap, selecting the 0.05 significance level two-tailed testing. Analysing the results, no HTMT confidence interval values correspond to the value of 1, which indicates that all HTMT values are significantly different from 1.0 as highlighted above and neither of the confidence intervals include the value of 1.0. Hence concluding that the discriminant validity has been established for all constructs of the study and all model evaluation criteria have been met. The discriminant validity was checked by checking the indicator construct cross loadings, and Table 25 and Table 26 presents the values with highest values in bold.

Table 23: Discriminant validity assessment (HTMT) for DPETO model - no-xAI

	DPE Collaboration	DPE Network Coopetition	DPE Trust	DPE Willingness To Transact	Digital Platform Ecosystem HO
DPE Collaboration	-	-	-	-	-
DPE Network Coopetition	0.625 [0.506; 0.739]*	-	-	-	-
DPE Trust	0.571 [0.479;0.673]*	0.570 [0.447;0.689]*	-	-	-
DPE Willingness To Transact	0.639 [0.546; 0.726]*	0.453 [0.321;0.586]*	0.720 [0.641;0.789]*	-	-
Digital Platform Ecosystem HO	0.560 [0.454; 0.664]*	0.555 [0.427;0.678]*	0.661 [0.567;0.748]*	0.606 [0.489;0.711]*	-

*Values in the brackets represent the lower (2.5%) and upper (97.5%) bounds of the 95% confidence intervals.

Table 24: Discriminant validity assessment (HTMT) for DPETO model-xAI

	DPE Collaboration	DPE Network Coopetition	DPE Trust	DPE Willingness To Transact	Digital Platform Ecosystem HO
DPE Collaboration	-	-	-	-	-
DPE Network Coopetition	0.625 [0.506;0.739]*	-	-	-	-
DPE Trust	0.651 [0.572;0.728]*	0.623 [0.512;0.727]*	-	-	-
DPE Willingness To Transact	0.639 [0.546;0.726]*	0.453 [0.321;0.586]*	0.747 [0.677;0.807]*	-	-
Digital Platform Ecosystem HO	0.560 [0.454;0.664]*	0.555 [0.427;0.678]*	0.712 [0.628;0.789]*	0.606 [0.489;0.711]*	-

*Values in the brackets represent the lower (2.5%) and upper (97.5%) bounds of the 95% confidence intervals.

Table 25: Discriminant validity assessment (cross loadings) for DPETO model - no-xAI

	DPE Collaboration	Network Coopetition	DPE Platform AI	DPE Trust	DPE Value Creation	DPE Willingness To Transact	Digital P Ecosystem HO
DEAI1	0.291	0.263	**0.766**	0.308	0.411	0.365	0.697
DEAI3	0.327	0.251	**0.667**	0.204	0.325	0.259	0.588
DEAI4	0.216	0.231	**0.771**	0.368	0.332	0.293	0.656
DEAI5	0.266	0.240	**0.787**	0.409	0.373	0.346	0.691
DECOLB1	**0.733**	0.381	0.342	0.335	0.312	0.404	0.381
DECOLB10	**0.680**	0.345	0.231	0.387	0.232	0.349	0.270
DECOLB2	**0.634**	0.326	0.237	0.358	0.306	0.353	0.312
DECOLB3	**0.612**	0.355	0.228	0.291	0.266	0.323	0.286
DECOLB4	**0.621**	0.287	0.221	0.360	0.268	0.376	0.282
DECOLB5	**0.645**	0.289	0.325	0.385	0.367	0.406	0.400
DECOLB6	**0.539**	0.214	0.077	0.163	0.161	0.239	0.136
DECOLB7	**0.663**	0.297	0.182	0.381	0.261	0.433	0.254
DECOLB8	**0.642**	0.373	0.101	0.292	0.288	0.341	0.220
DECOLB9	**0.553**	0.285	0.261	0.251	0.249	0.250	0.296
DEHCTM10	0.226	0.344	0.221	**0.573**	0.264	0.364	0.280
DEHCTM11	0.268	0.301	0.330	**0.618**	0.308	0.363	0.371
DEHCTM12	0.379	0.353	0.324	**0.722**	0.341	0.534	0.385
DEHCTM4	0.266	0.279	0.298	**0.626**	0.376	0.406	0.387
DEHCTM5	0.336	0.318	0.299	**0.659**	0.286	0.395	0.340
DEHCTM6	0.306	0.326	0.278	**0.591**	0.320	0.417	0.345

	DPE Collaboration	Network Coopetition	DPE Platform AI	DPE Trust	DPE Value Creation	DPE Willingness To Transact	Digital P Ecosystem HO
DEHCTM7	0.344	0.303	0.369	**0.673**	0.462	0.459	0.479
DEHCTM8	0.434	0.323	0.330	**0.729**	0.423	0.548	0.432
DEHCTM9	0.338	0.340	0.281	**0.705**	0.337	0.470	0.357
DENCPT1	0.469	**0.850**	0.273	0.402	0.384	0.321	0.377
DENCPT2	0.298	**0.728**	0.241	0.283	0.269	0.221	0.295
DENCPT3	0.418	**0.829**	0.276	0.434	0.320	0.333	0.344
DETIO1	0.365	0.287	0.303	**0.703**	0.384	0.472	0.397
DETIO2	0.396	0.363	0.260	**0.658**	0.399	0.492	0.378
DETIO3	0.433	0.320	0.253	**0.706**	0.396	0.456	0.371
DETIO4	0.382	0.261	0.292	**0.669**	0.422	0.415	0.411
DETIO5	0.370	0.298	0.222	**0.654**	0.359	0.366	0.332
DETIO6	0.258	0.264	0.238	**0.607**	0.340	0.294	0.332
DETIO7	0.295	0.270	0.248	**0.577**	0.313	0.296	0.323
DETV3	0.368	0.317	0.330	0.421	**0.759**	0.373	0.619
DETV4	0.318	0.273	0.398	0.435	**0.776**	0.345	0.663
DETV5	0.343	0.365	0.403	0.436	**0.815**	0.335	0.689
DEWTT1	0.535	0.332	0.383	0.601	0.413	**0.911**	0.462
DEWTT2	0.468	0.317	0.402	0.582	0.394	**0.874**	0.462
DEWTT3	0.499	0.343	0.354	0.570	0.393	**0.904**	0.432

Table 26: Discriminant validity assessment (cross loadings) for DPETO model - xAI

	DPE Collaboration	DPE Network Coopetition	DPE Platform AI	DPE Trust	DPE Value Creation	DPE Willingness To Transact	Digital P Ecosystem HO
DEAI1	0.292	0.263	**0.767**	0.371	0.411	0.365	0.699
DEAI3	0.326	0.251	**0.668**	0.309	0.325	0.259	0.593
DEAI4	0.217	0.231	**0.770**	0.387	0.332	0.292	0.655
DEAI5	0.266	0.240	**0.786**	0.409	0.373	0.346	0.690
DECOLB1	**0.732**	0.381	0.342	0.398	0.312	0.404	0.382
DECOLB10	**0.674**	0.344	0.231	0.400	0.232	0.349	0.270
DECOLB2	**0.634**	0.326	0.237	0.398	0.306	0.353	0.312
DECOLB3	**0.616**	0.356	0.228	0.350	0.266	0.323	0.285
DECOLB4	**0.622**	0.288	0.221	0.399	0.268	0.376	0.281
DECOLB5	**0.655**	0.289	0.325	0.495	0.367	0.406	0.400
DECOLB6	**0.534**	0.214	0.077	0.167	0.161	0.240	0.136
DECOLB7	**0.662**	0.297	0.182	0.418	0.261	0.433	0.255
DECOLB8	**0.641**	0.373	0.101	0.336	0.288	0.341	0.220
DECOLB9	**0.546**	0.284	0.261	0.277	0.249	0.250	0.297
DEHCTMXAI10	0.246	0.279	0.299	**0.599**	0.271	0.394	0.332
DEHCTMXAI11	0.247	0.329	0.311	**0.632**	0.259	0.412	0.333
DEHCTMXAI12	0.432	0.427	0.406	**0.754**	0.410	0.563	0.473
DEHCTMXAI4	0.324	0.358	0.327	**0.722**	0.364	0.447	0.398
DEHCTMXAI5	0.365	0.366	0.301	**0.690**	0.327	0.460	0.363
DEHCTMXAI6	0.311	0.357	0.326	**0.615**	0.273	0.459	0.349
DEHCTMXAI7	0.402	0.414	0.433	**0.739**	0.420	0.502	0.495

	DPE Collaboration	DPE Network Coopetition	DPE Platform AI	DPE Trust	DPE Value Creation	DPE Willingness To Transact	Digital P Ecosystem HO
DEHCTMXAI8	0.416	0.407	0.371	**0.755**	0.429	0.563	0.462
DEHCTMXAI9	0.378	0.426	0.311	**0.685**	0.387	0.425	0.402
DENCPT1	0.467	**0.848**	0.273	0.440	0.384	0.321	0.377
DENCPT2	0.298	**0.724**	0.241	0.313	0.269	0.221	0.295
DENCPT3	0.420	**0.833**	0.276	0.481	0.320	0.333	0.344
DETTIOXAI1	0.487	0.297	0.280	**0.647**	0.425	0.405	0.403
DETTIOXAI2	0.507	0.344	0.372	**0.679**	0.469	0.485	0.484
DETTIOXAI3	0.454	0.305	0.318	**0.669**	0.416	0.456	0.422
DETTIOXAI4	0.440	0.369	0.327	**0.615**	0.419	0.344	0.429
DETTIOXAI5	0.452	0.317	0.302	**0.654**	0.418	0.458	0.413
DETTIOXAI6	0.451	0.324	0.285	**0.662**	0.361	0.400	0.372
DETTIOXAI7	0.459	0.270	0.328	**0.641**	0.377	0.450	0.407
DETV3	0.370	0.317	0.330	0.419	**0.759**	0.373	0.617
DETV4	0.318	0.274	0.398	0.435	**0.776**	0.345	0.661
DETV5	0.346	0.365	0.403	0.472	**0.815**	0.335	0.689
DEWTT1	0.536	0.333	0.383	0.624	0.413	**0.912**	0.462
DEWTT2	0.469	0.318	0.402	0.599	0.394	**0.873**	0.462
DEWTT3	0.501	0.343	0.354	0.589	0.393	**0.904**	0.432

4.4.2 Multicollinearity – structural model collinearity assessment

Multicollinearity was tested for using the variance inflation factor (VIF) values and found that all values are below 5. This indicates that collinearity is not a concern among the constructs (Hair et al., 2017). (see Table 27)

Table 27: Multicollinearity assessment (VIF values) for DPETO model -no-xAI

	DPE Collaboration	DPE Network Coopetition	DPE Trust	DPE Willingness To Transact	Digital P Ecosystem HO
DPE Collaboration	-	-	-	-	-
DPE Network Coopetition	-	-	-	-	-
DPE Trust	1.474	1.474	-	1.474	-
DE Willingness To Transact	-	-	-	-	-
Digital Ecosystem HO	1.474	1.474	1	1.474	-

Table 28: Multicollinearity assessment (VIF values) for DPETO model - xAI

	DPE Collaboration	DPE Network Coopetition	DPE Trust	DPE Willingness To Transact	Digital P Ecosystem HO
DPE Collaboration	-	-	-	-	-
DPE Network Coopetition	-	-	-	-	-
DPE Trust	1.597	1.597	-	1.597	-
DPE Willingness To Transact	-	-	-	-	-
Digital Ecosystem HO	1.597	1.597	1	1.597	-

4.4.3 Testing direct and mediated relationships

Next, the bootstrapping procedure was conducted using 5000 subsamples with 95% confidence intervals, bias corrected and accelerated BCa based to test the direct and mediation relationships in the model. This is a two-tailed test and a significance level is set to 0.05 (Hair et al., 2017). Mediation analysis was then performed to assess the mediating role of DPE Trust on the linkage between Digital Platform Ecosystem Higher Order construct and three outcome variables – Willingness to Transact, Collaboration and Network Coopetition. It was found that all indirect effects are significant since neither of the 95% confidence intervals include zero (Hair et al., 2017). Although not necessary, the t-value and p values of the indirect effects were then checked in both models which are all reported as significant (Table 29). It was concluded that DPE Trust partially mediates the relationships between Digital Platform Ecosystem Higher Order construct and three outcome variables – Willingness to Transact, Collaboration and Network Coopetition since both direct and the indirect effects are significant for both sets of models. To further investigate the type of partial mediation, the computation of the product of direct effect and indirect effect was reviewed. Analysing the direct and indirect effect signs, it was found that since both are positive, the sign of their product is also positive in all cases. Therefore, it was concluded that DPE Trust represents complementary (partial mediation) mediation of the relationships in this study (Zhao, Lynch and Chen, 2010). These results also suggest that in the DPETO model – xAI, DPE Trust is likely to have more impact on the three outcome variables, Willingness to Transact, Collaboration and Network Coopetition because it has more significant mediated paths than the model with DPE Trust in the absence of explainable artificial intelligence. Additionally, when looking at both models, the (DPE Trust) mediated relationships between Digital Platform Ecosystem Higher Order construct and three outcome variables –Willingness to Transact (β=0.357), Collaboration (β =0.306)and Network Coopetition (β =0.256) in the model with explainable artificial intelligence DE Trust is stronger than that of the model without explainable artificial intelligence DPE Trust, Willingness to Transact (β=0.306), Collaboration (β = 0.216) and Network Coopetition (β =0.194). This implies that the potential effect of explainable artificial intelligence included DPE Trust on digital platform ecosystem outcomes of willingness to transact, collaboration and network coopetition.

Table 29: Structural model assessment for direct and indirect effect

DPETO model – no - xAI	**Total Effect**			**BCa Bootstrap CI**		**Direct Effect**			**BCa Bootstrap CI**		**Indirect Effect**				**BCa Bootstrap CI**	
	β	**SE**	**t-Value**	**LB**	**UB**	**β**	**SE**	**t-Value**	**LB**	**UB**		**β**	**SE**	**t-Value**	**LB**	**UB**
Digital Ecosystem HO -> DPE Collaboration	0.463	0.048	9.722 *** (p=0.000)	0.370	0.557	0.247	0.060	4.124 *** (p=0.000)	0.129	0.363	Digital Ecosystem HO -> DPE Trust -> DPE Collaboration	0.216	0.038	5.701 *** (p=0.000)	0.149	0.297
Digital Ecosystem HO -> DPE Network Coopetition	0.424	0.049	8.612 *** (p=0.000)	0.330	0.521	0.230	0.062	3.740 *** (p=0.000)	0.112	0.353	Digital Ecosystem HO -> DPE Trust -> DPE Network Coopetition	0.194	0.038	5.100 *** (p=0.000)	0.121	0.270
Digital Ecosystem HO -> DPE Willingness To Transact	0.505	0.049	10.297*** (p=0.000)	0.404	0.599	0.199	0.064	3.093 * (p=0.002)	0.068	0.321	Digital Ecosystem HO -> DPE Trust -> DPE Willingness To Transact	0.306	0.040	7.590 *** (p=0.000)	0.234	0.390
Total Effect is significant, so there could be mediation																

DPETO model - xAI																
	Total Effect					**Direct Effect**					**Indirect Effect**					
	β	**SE**	**t-Value**	**LB**	**UB**	**β**	**SE**	**t-Value**	**LB**	**UB**		**β**	**SE**	**t-Value**	**LB**	**UB**
Digital Ecosystem HO -> DPE Collaboration	0.464	0.048	9.750 *** (p=0.000)	0.372	0.557	0.158	0.057	2.750 ** (p=0.006)	0.043	0.272	Digital Ecosystem HO -> DPE Trust -> DPE Collaboration	0.306	0.038	8.161 *** (p=0.000)	0.240	0.386
Digital Ecosystem HO -> DPE Network Coopetition	0.424	0.049	8.597 *** (p=0.000)	0.329	0.521	0.168	0.066	2.558 * (p=0.011)	0.040	0.299	Digital Ecosystem HO -> DPE Trust -> DPE Network Coopetition	0.256	0.040	6.366 *** (p=0.000)	0.182	0.339
Digital Ecosystem HO -> DPE Willingness To Transact	0.504	0.049	10.265*** (p=0.000)	0.404	0.598	0.147	0.059	2.473 * (p=0.013)	0.030	0.262	Digital Ecosystem HO -> DPE Trust -> DPE Willingness To Transact	0.357	0.038	9.348 *** (p=0.000)	0.286	0.437
Total Effect is significant, so there could be mediation																

Significance levels are Ns $p > 0.05$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$, **** $p \leq 0.0001$ (GraphPad style[6])
β = Coefficient Std Beta, SE = Standard Deviation (STDEV) SE, T Statistics, t-Value

[6] GraphPad style which reports four digits after the decimal point with a leading zero (0.1234). P values less than 0.0001 shown as "< .0001". P values less than 0.001 are summarized with three asterisks, and P values less than 0.0001 are summarized with four asterisks.

4.4.4 Model selection criteria

The results of the PLS-based criteria indicate that the model with X AI for DPE Trust to have a better explanatory power and predictive relevance. But, appropriate model selection cannot be achieved only by reliance on PLS criteria of R2, Adjusted R2 and Q2 (Sharma et al., 2019). Solution to this is to revert to model selection criteria based on the Bayesian information criteria (BIC) and the Geweke-Meese criterion (GM), as they are highly accurate and easy to use (Sharma et al., 2019). The in-sample prediction model selection criteria was used to determine which of the DPETO model variants (DPETO-no-xAI and DPETO-xAI) are asymptotically more efficient and consistent (Sharma et al., 2021). The saturated model is presented in Appendix B.

Table 28 presents the asymptotical efficiency values of AICc, AICu, AIC, FPE and Mallow's Cp) as well as the consistency values of BIC, GM, HQc and HQ criterion used as suggested to identify and select model which is parsimonious and hence consistent with reality and therefore, improves the generalisability of the findings (Sharma et al., 2019). It was noted that the smaller values of the criterion signifies a better model fit and model parsimony (Mcquarrie and Tsai, 1998) and concluded that the results are consistent with the findings so far, DPETO-xAI model with xAI in DPE Trust mediator results in smaller values compared to the DPETO-no-xAI model with no xAI in DPE Trust mediator, see Table 30: Model selection criteria assessment.

Table 30: Model Selection Criteria Assessment

Criteria	DPETO-no-xAI	DPETO-xAI
PLS based criterion[1]		
R^2	0.452	0.468
Adjusted R^2	0.449	0.465
Q^2	0.247	0.246
Asymptotically efficient[2]		
AICc	139.828	129.960
AICu	-192.281	-202.148
AIC	-195.294	-205.162
FPE	0.556	0.540
Mallow's Cp	39.806	29.097
Asymptotically consistent[3]		
BIC	-183.870	-193.737
GM	384.231	373.521
HQc	-190.578	-200.445
HQ	-190.739	-200.606

[1]PLS criterion: coefficient of determination (R^2)Adjusted coefficient of determination (Adjusted R^2) and predictive relevance (Q^2);
[2]Asymptotically efficient: corrected AIC (AICc), unbiased AIC (AICu), information criterion (AIC), final prediction error (FPE) and Mallow's Cp;
[3]Asymptotically Consistent: Bayesian information criterion (BIC), Geweke and Meese's criterion (GM), corrected HQ criterion (HQc) and Hannan and Quinn's criterion (HQ)

4.4.4.1 PLS predict

The model evaluation of PLS-SEM results was continued using the out-of-sample predictions used in PLSpredict as it helps in the evaluation of the predictive capabilities of the model (Shmueli et al., 2019). Table 9 and table 10 show the results of PLSpredict and indicate that xAI mediated Trust on the DPETO-xAI model results in predictions that are better than non-xAI mediated trust in the DPETO-no-xAI model. All $Q^2_{predict} > 0$ values were reported, except for 1 indicator, which was disregarded as a value of zero or less indicates that the predictive power of PLS SEM analysis for that indicator usually does not outperform the most naïve benchmark (Shmueli et al., 2019). As suggested in the methodology of PLSpredict, for the indicators with $Q^2_{predict} > 0$, the comparison of the RMSE (or MAE) values with the naïve LM benchmark was continued. PLS-SEM_RMSE and PLS-SEM_MAE values were found to be lower than LM_RMSE and LM_MAE values for the majority of indicators as presented in Table **31** and Table **32** respectively for the two models. The PLS-LM RMSE and PLS-LM MAE values to compute the differences were also reported, negatives signifying the PLS-SEM values < LM values. For both models, a majority of indicators with PLS-SEM < LM were reported, hence Medium Predictive Power (Shmueli et al., 2019), however, to compare the two models, PLS-LM RMSE negative counts (25 for DPETO-no-xAI model, 27 for DPETO-xAI model) and PLS-LM MAE negative counts (21 for DPETO-no-xAI model, 25 DPETO-xAI model) were calculated respectively. It was reported that the DPETO-xAI model using xAI influenced, mediated DPE Trust is an efficient and consistent system to foster value outcomes of Willingness to Transact, Collaboration and Network Coopetition in digital ecosystem platforms in financial services domain.

Table 31: PLSpredict assessment for DPETO-no-xAI model

	Q²predict	**PLS-SEM_RMSE**	**PLS-SEM_MAE**	**LM_RMSE**	**LM_MAE**	**PLS-LM RMSE**	**PLS - LM MAE**
DECOLB1	0.139	0.900	0.721	0.915	0.724	-0.015	-0.003
DECOLB10	0.065	0.934	0.726	0.949	0.734	-0.015	-0.008
DECOLB2	0.093	0.909	0.727	0.922	0.734	-0.013	-0.007
DECOLB3	0.078	0.882	0.705	0.904	0.721	-0.022	-0.016
DECOLB4	0.076	0.943	0.759	0.966	0.767	-0.023	-0.008
DECOLB5	0.146	1.002	0.785	1.006	0.784	-0.004	0.001
DECOLB6	0.001	1.216	0.955	1.208	0.956	0.008	-0.001
DECOLB7	0.057	1.008	0.796	1.015	0.797	-0.007	-0.001
DECOLB8	0.037	0.945	0.758	0.902	0.720	0.043	0.038
DECOLB9	0.083	1.240	0.980	1.243	0.988	-0.003	-0.008
DENCPT1	0.135	0.964	0.738	0.969	0.732	-0.005	0.006
DENCPT2	0.081	0.993	0.778	1.004	0.786	-0.011	-0.008
DENCPT3	0.112	0.935	0.748	0.949	0.750	-0.014	-0.002
DEHCTM10	0.073	1.411	1.169	1.424	1.184	-0.013	-0.015
DEHCTM11	0.134	1.143	0.887	1.169	0.905	-0.026	-0.018
DEHCTM12	0.142	0.983	0.744	1.001	0.761	-0.018	-0.017
DEHCTM4	0.145	1.201	0.947	1.189	0.939	0.012	0.008
DEHCTM5	0.109	1.168	0.891	1.181	0.908	-0.013	-0.017
DEHCTM6	0.115	1.224	0.929	1.235	0.942	-0.011	-0.013
DEHCTM7	0.216	0.927	0.705	0.930	0.700	-0.003	0.005
DEHCTM8	0.183	0.921	0.713	0.922	0.718	-0.001	-0.005
DEHCTM9	0.120	1.042	0.816	1.060	0.828	-0.018	-0.012
DETIO1	0.152	1.005	0.798	1.011	0.799	-0.006	-0.001
DETIO2	0.138	1.002	0.783	0.983	0.756	0.019	0.027
DETIO3	0.133	0.997	0.770	0.999	0.770	-0.002	0.000
DETIO4	0.164	1.200	0.933	1.193	0.913	0.007	0.020
DETIO5	0.105	1.008	0.788	1.008	0.782	0.000	0.006
DETIO6	0.106	1.108	0.836	1.086	0.830	0.022	0.006
DETIO7	0.100	1.112	0.872	1.127	0.871	-0.015	0.001
DEWTT1	0.205	1.022	0.790	1.032	0.791	-0.010	-0.001
DEWTT2	0.207	1.042	0.805	1.061	0.813	-0.019	-0.008
DEWTT3	0.178	0.952	0.745	0.969	0.755	-0.017	-0.010
DEAI1	0.483	0.761	0.573	0.000	0.000	0.761	0.573
DEAI3	0.343	0.983	0.725	0.000	0.000	0.983	0.725
DEAI4	0.427	0.918	0.699	0.000	0.000	0.918	0.699
DEAI5	0.476	0.828	0.621	0.000	0.000	0.828	0.621
DETV3	0.380	0.731	0.563	0.000	0.000	0.731	0.563
DETV4	0.436	0.755	0.564	0.000	0.000	0.755	0.564
DETV5	0.471	0.711	0.551	0.000	0.000	0.711	0.551
	6.844	**39.026**	**30.393**	**33.532**	**26.158**	**5.494**	**4.235**

† PLS-LM RMSE: 25 Negative Sign Counts, PLS-LM MAE: 21 Negative Sign Counts

Table 32: PLSpredict assessment for DPETO-xAI model

	Q^2predict	**PLS-SEM_RMSE**	**PLS-SEM_MAE**	**LM_RMSE**	**LM_MAE**	**PLS-LM RMSE**	**PLS – LM MAE**
DECOLB1	0.140	0.900	0.721	0.915	0.724	-0.015	-0.003
DECOLB10	0.066	0.934	0.725	0.949	0.734	-0.015	-0.009
DECOLB2	0.093	0.909	0.727	0.922	0.734	-0.013	-0.007
DECOLB3	0.077	0.882	0.705	0.904	0.721	-0.022	-0.016
DECOLB4	0.076	0.943	0.759	0.966	0.767	-0.023	-0.008
DECOLB5	0.147	1.001	0.785	1.006	0.784	-0.005	0.001
DECOLB6	0.002	1.216	0.955	1.208	0.956	0.008	-0.001
DECOLB7	0.057	1.008	0.796	1.015	0.797	-0.007	-0.001
DECOLB8	0.037	0.945	0.758	0.902	0.720	0.043	0.038
DECOLB9	0.083	1.240	0.980	1.243	0.988	-0.003	-0.008
DENCPT1	0.136	0.964	0.738	0.969	0.732	-0.005	0.006
DENCPT2	0.081	0.993	0.778	1.004	0.786	-0.011	-0.008
DENCPT3	0.112	0.935	0.748	0.949	0.750	-0.014	-0.002
DEHCTMXAI10	0.105	1.372	1.113	1.396	1.124	-0.024	-0.011
DEHCTMXAI11	0.105	1.166	0.916	1.187	0.934	-0.021	-0.018
DEHCTMXAI12	0.220	0.957	0.720	0.977	0.734	-0.020	-0.014
DEHCTMXAI4	0.153	1.208	0.934	1.206	0.933	0.002	0.001
DEHCTMXAI5	0.124	1.133	0.859	1.152	0.874	-0.019	-0.015
DEHCTMXAI6	0.117	1.213	0.934	1.228	0.947	-0.015	-0.013
DEHCTMXAI7	0.240	0.852	0.643	0.873	0.656	-0.021	-0.013
DEHCTMXAI8	0.207	0.937	0.732	0.953	0.736	-0.016	-0.004
DEHCTMXAI9	0.157	0.962	0.740	0.979	0.750	-0.017	-0.010
DETTIOXAI1	0.158	0.960	0.718	0.953	0.703	0.007	0.015
DETTIOXAI2	0.227	0.879	0.689	0.888	0.688	-0.009	0.001
DETTIOXAI3	0.175	0.917	0.712	0.933	0.716	-0.016	-0.004
DETTIOXAI4	0.178	1.026	0.792	1.026	0.791	0.000	0.001
DETTIOXAI5	0.166	0.939	0.738	0.949	0.748	-0.010	-0.010
DETTIOXAI6	0.133	0.908	0.723	0.926	0.734	-0.018	-0.011
DETTIOXAI7	0.163	0.980	0.767	0.996	0.776	-0.016	-0.009
DEWTT1	0.205	1.022	0.790	1.032	0.791	-0.010	-0.001
DEWTT2	0.207	1.043	0.805	1.061	0.813	-0.018	-0.008
DEWTT3	0.177	0.952	0.746	0.969	0.755	-0.017	-0.009
DEAI1	0.485	0.759	0.571	0.000	0.000	0.759	0.571
DEAI3	0.349	0.979	0.722	0.000	0.000	0.979	0.722
DEAI4	0.427	0.919	0.700	0.000	0.000	0.919	0.700
DEAI5	0.474	0.829	0.623	0.000	0.000	0.829	0.623
DETV3	0.378	0.733	0.564	0.000	0.000	0.733	0.564
DETV4	0.434	0.757	0.566	0.000	0.000	0.757	0.566
DETV5	0.470	0.712	0.551	0.000	0.000	0.712	0.551
	7.341	**37.984**	**29.543**	**32.636**	**25.396**	**5.348**	**4.147**

† PLS-LM RMSE: 27 Negative Sign Counts, PLS-LM MAE: 25 Negative Sign Counts

4.5 Stage 2: Complimenting PLS-SEM with necessary condition analysis

Goal of necessary condition analysis in this research is to help identify the must-have factors that are required for the outcomes in accordance with the necessary logic, complementary to the partial least square structural equation modelling (PLS-SEM) analysis that this research has conducted (Richter et al., 2020). After running the PLS-SEM and the relevant analysis of the measurement models including the quality of the reflective measurement model, checking internal consistency reliability, indicator reliability, convergent validity and discriminant validity(Hair et al., 2017) the latest variable scores were exported to a CSV file. This file did not have the single indicators integrated in it as all the constructs in the model are measured using the reflective measurement models (Richter et al., 2020). Necessary condition analysis was carried out on the DPETO-xAI model where xAI mediates DPE Trust as it has been established that that variant of the model is the one with the most predictive power based on the previous sections of the analysis. The above is a key consideration while complementing the PLS-SEM analysis with NCA (Richter et al., 2020). The xAI influenced DPE trust mediated DPETO-xAI model consists of three endogenous constructs, Willing to Transact, Collaboration, Network Coopetition, several NCAs were run, where in each analysis all exogenous constructs were entered including, "DPE Trust", "Digital Platform Ecosystem HO", "DPE Platform AI", "DPE Value Creation".

4.5.1 Necessary condition analysis – Set A

These NCA effect sizes for the first set of NCA (Set A) on the endogenous constructs, with all exogenous constructs presented in Table 33: NCA Set A Effect Sizes, along with bottleneck tables (see Table 33) and scatter plots for each construct (see figures 29 to 40). Based on the accuracy of the CE-FDH (Ceiling Envelopment – Free Disposal Hull) and reference ceiling line being a 100% by definition, the ceiling line accuracy for CR-FDH (Ceiling Regression - Free Disposal Hull) for both NCA Set A and NCA Set B has not been reported.

The results of NCA Set A (see Table 33) indicate that DPE Trust is a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for Collaboration (medium effect) and DPE Willingness to Transact (medium effect) (Richter et al., 2020). It was also reported that DPE platform AI appears to me a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for Collaboration and DPE Willingness to Transact. Furthermore, we analyse each necessary condition in detail with the bottleneck tables (see Table 34).

From the bottleneck tables (see Table 34), it was highlighted that in order to reach up to 50% level of DPE Network Coopetition, both DPE Trust and DPE Platform AI are not necessary and in order to reach up to 80% through to 100% level DPE Trust is a necessary condition that need to be in place at no less than 43.5%. Similarly, to reach up to 80% through to 100% Digital Ecosystem Higher Order construct at 49.5%, DPE Platform AI at 57.1 % (for 80%) ; 71.5 (for 100%) and DPE Value Creation at 45.8% - 46.2% are the necessary but insufficient conditions that need to be in place.

Table 33: NCA Set A effect sizes

	CE-FDH Effect size *d*	**p-Value**	**CE-FDH Effect size *d***	**p-Value**	**CE-FDH Effect size *d***	**p-Value**
Construct	DPE Collaboration		DPE Willingness To Transact		DPE Network Coopetition	
DPE Trust	**0.204**	**0.004**	**0.198**	**0.000**	0.100	0.582
Digital P Ecosystem HO	**0.124**	**0.019**	0.071	0.002	**0.117**	**0.029**
DPE Platform AI	**0.240**	**0.036**	**0.224**	**0.001**	0.183	0.273
DPE Value Creation	**0.163**	**0.003**	**0.147**	**0.000**	0.107	0.225

Note: d ranges between $0 \leq d \leq 1$, where $0 < d < 0.1$ signifies small effect, $0.1 \leq d < 0.3$ medium effect,

$0.3 \leq d < 0.5$ large effect and $d \geq 0.5$ as very large effect. (Richter et al., 2020).

Statistically significant at $p < 0.05$ (Dul, van der Laan and Kuik, 2020).

Table 34: NCA Set A bottleneck table (percentages)

(CE-FDH)	DPE Trust	Digital P Ecosystem HO	DPE Platform AI	DPE Value Creation
Bottleneck DPE Network Coopetition				
0	NN	NN	NN	NN
10	NN	NN	NN	NN
20	NN	NN	NN	NN
30	NN	NN	NN	NN
40	NN	3.4	NN	NN
50	NN	3.4	NN	NN
60	NN	3.4	27.3	NN
70	NN	3.4	27.3	7.1
80	43.5	49.5	57.1	45.8
90	43.5	49.5	57.1	46.2
100	43.5	49.5	71.5	46.2
	DPE Trust	**Digital P Ecosystem HO**	**DPE Platform AI**	**DPE Value Creation**
Bottleneck DPE Collaboration				
0	NN	NN	NN	NN
10	NN	NN	NN	NN
20	NN	NN	NN	NN
30	NN	NN	16.7	NN
40	9.0	4.7	27.2	NN
50	23.2	4.7	27.3	NN
60	31.8	4.7	27.3	22.7
70	32.3	18.0	27.3	30.2
80	32.3	18.0	40.8	30.2
90	33.8	37.2	49.2	53.9
100	81.6	59.5	57.1	61.3
Bottleneck DPE Willingness To Transact	**DPE Trust**	**Digital P Ecosystem HO**	**DPE Platform AI**	**DPE Value Creation**
0	NN	NN	NN	NN
10	9.0	NN	NN	NN
20	9.0	4.0	27.2	NN
30	9.0	4.0	27.2	NN
40	9.0	4.0	27.3	NN
50	21.5	4.7	27.3	22.7
60	21.5	4.7	27.3	22.7
70	21.5	4.7	27.3	22.7
80	32.3	4.7	27.3	22.7
90	40.6	32.6	27.3	45.8
100	49.2	32.6	27.3	46.2

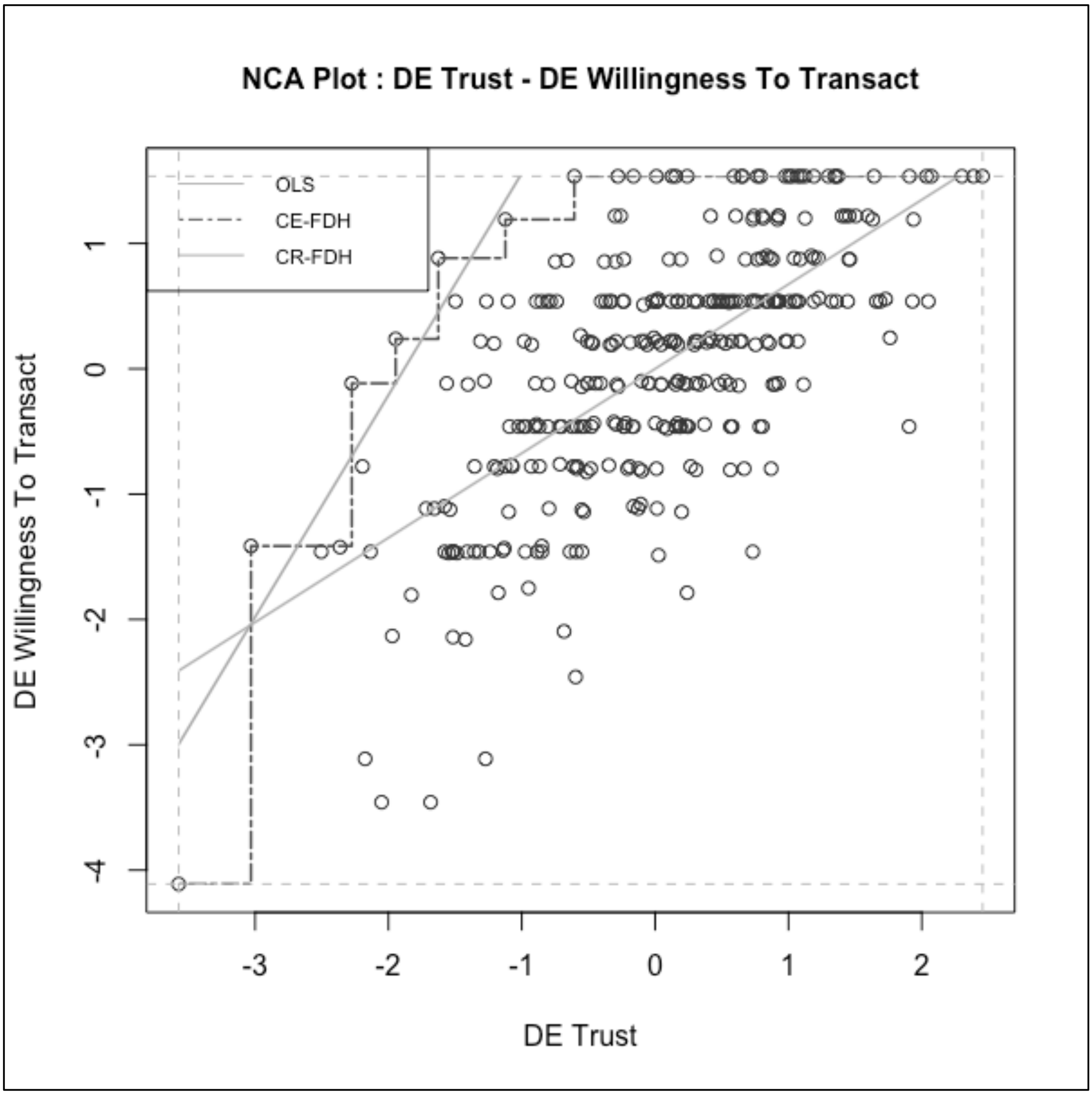


Figure 29: Scatter plot of NCA - Trust and Willingness To Transact

Visual inspection of the scatter plot (Figure 29) confirms the empty space in the upper left corner. It is noticeable that a ceiling envelopment with free disposal hull (CE-FDH)., with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 6.757 and has 100% ceiling accuracy. The presence of cases mainly in the centre to the upper right corner suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016).

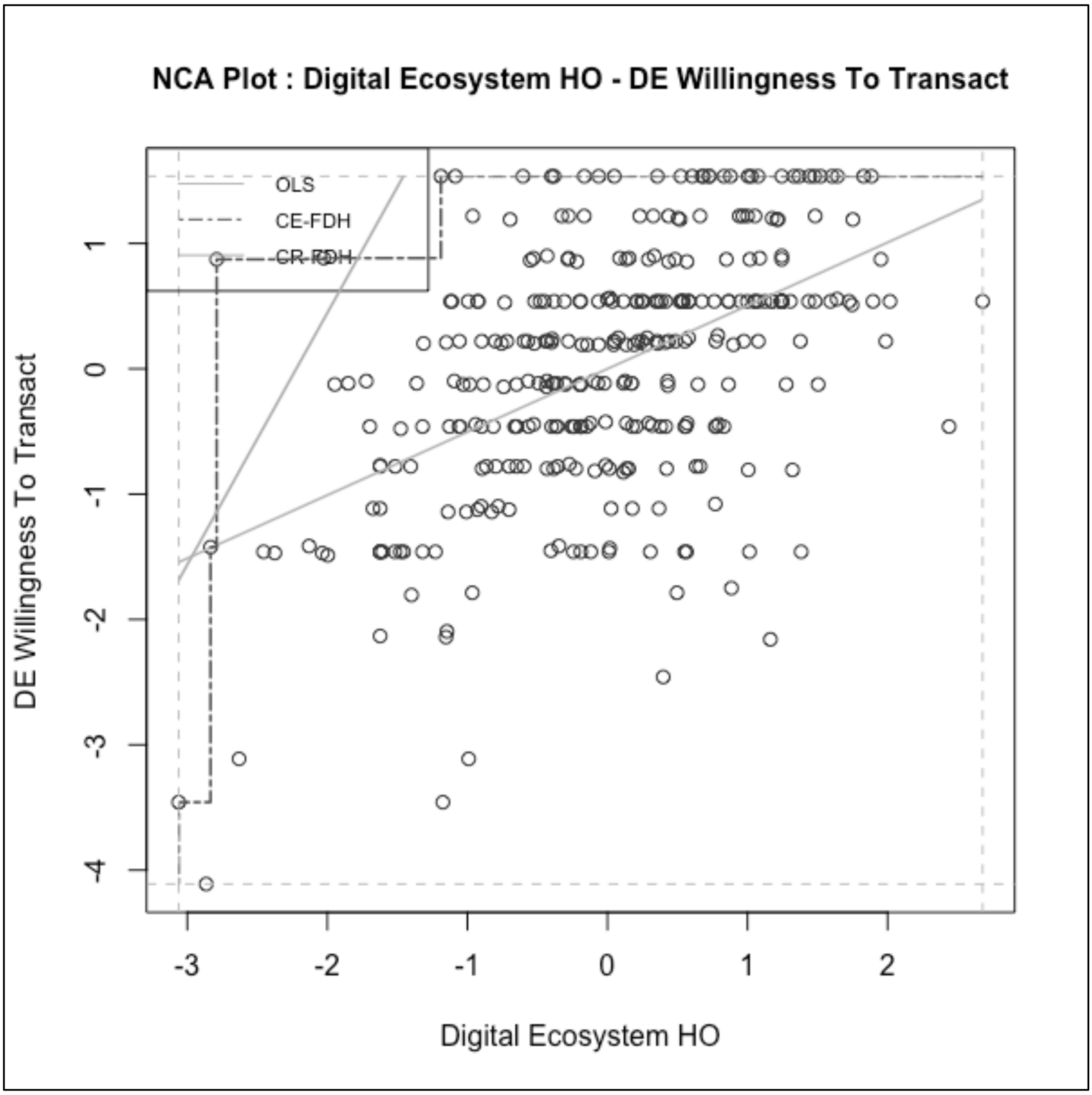


Figure 30: Scatter plot of NCA – DPE HO and Willingness To Transact

The visual inspection of the scatter plot (Figure **30**) confirms minimum empty space in the upper left corner. It is hence concluded that a necessary condition is not observed. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 2.317 and has 100% ceiling accuracy. The presence of cases is scattered in a random order and suggests minimum evidence for the necessary condition hypothesis in this case (Dul, 2016).

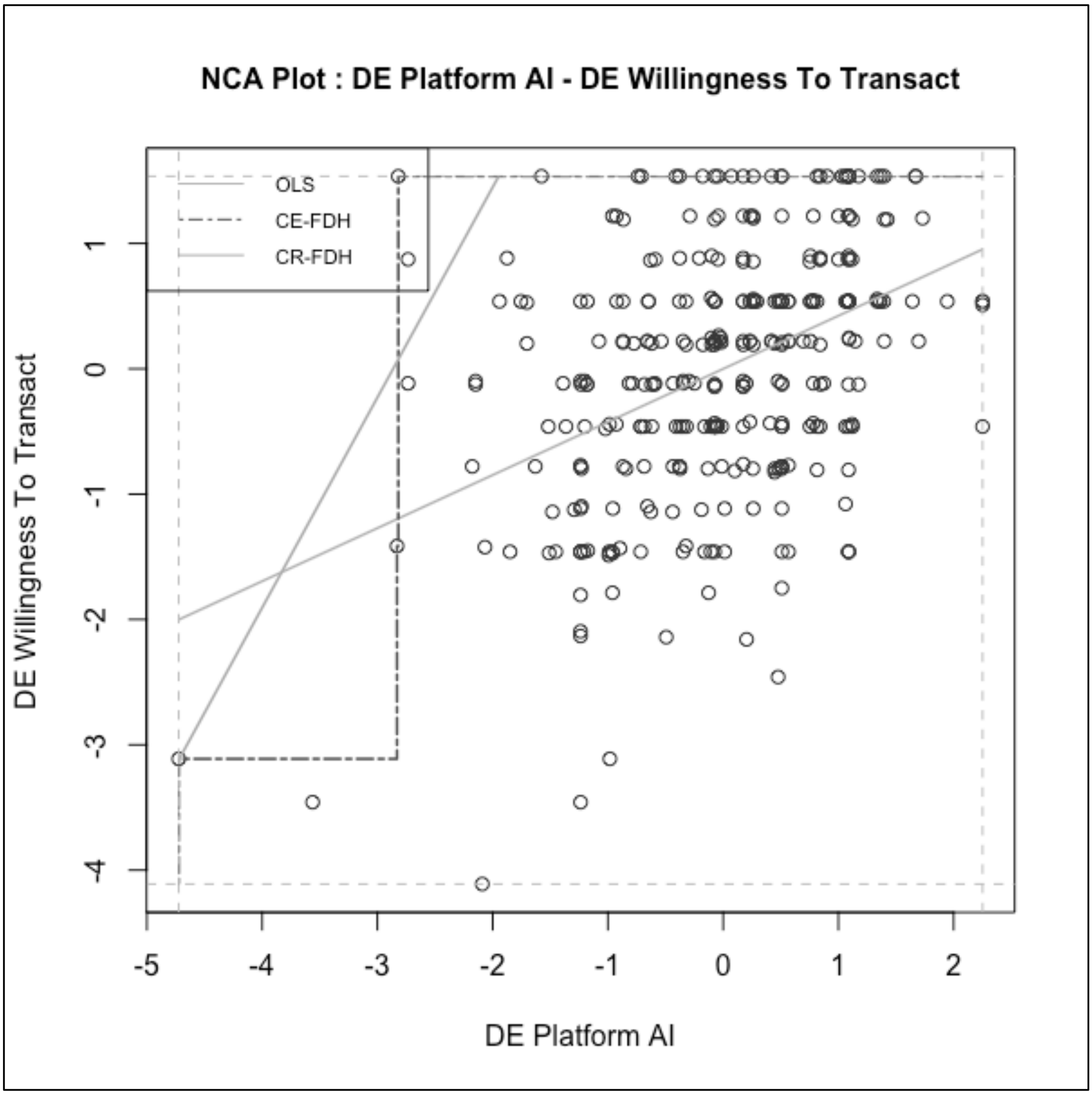


Figure 31: Scatter plot of NCA – DPE Platform AI and Willingness To Transact

The visual inspection of the scatter plot (Figure **31**) confirms the empty space in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 8.836 and has 100% ceiling accuracy. The presence of cases towards the upper right corner suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016).

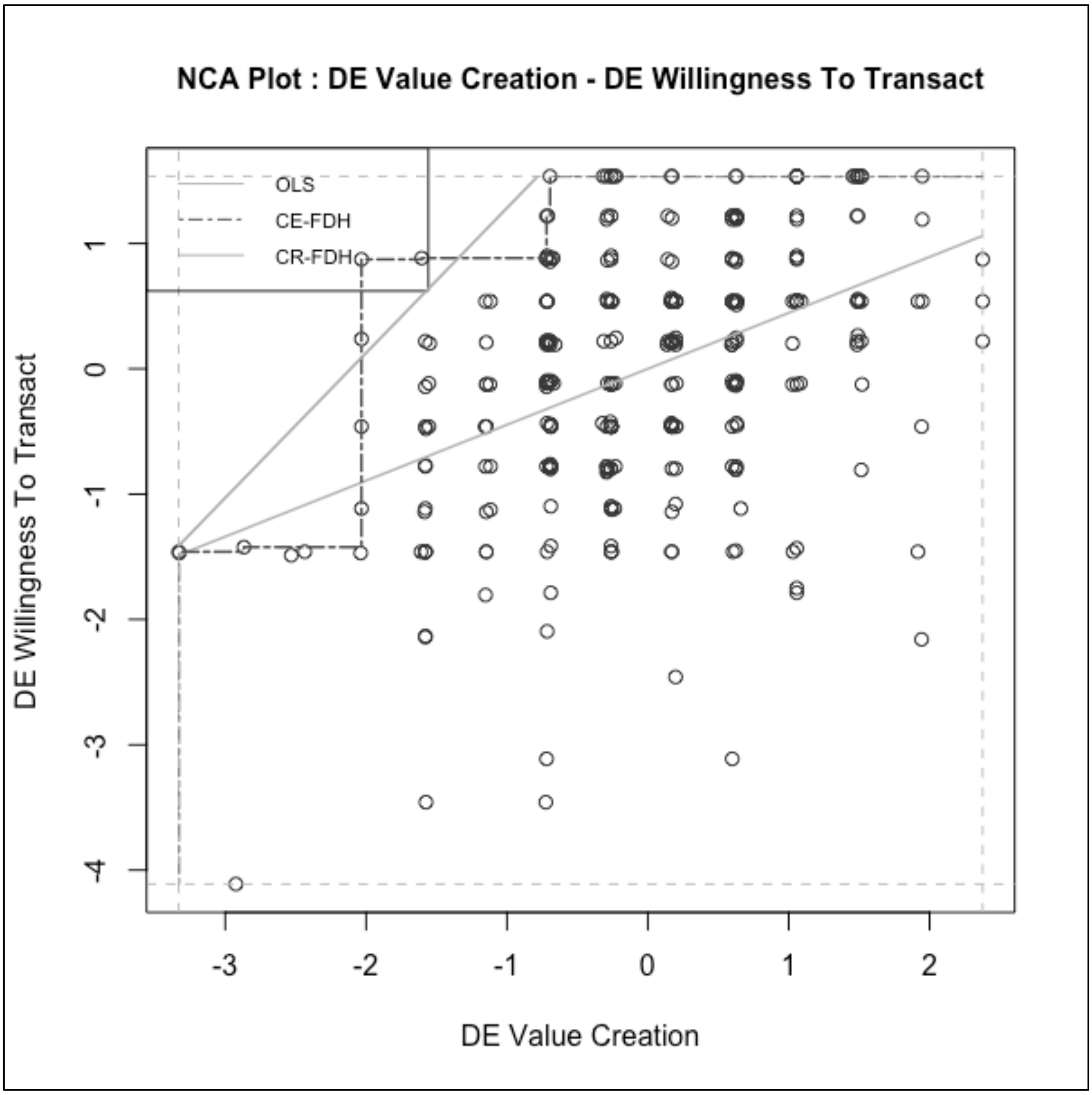


Figure 32: Scatter plot of NCA – DPE Value Creation and Willingness To Transact

The visual inspection of the scatter plot (Figure **32**) confirms minimum empty space (small effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 4.725 and has 100% ceiling accuracy. The presence of cases in a scattered fashion suggests non- supportiveness for the necessary condition hypothesis in this case (Dul, 2016).

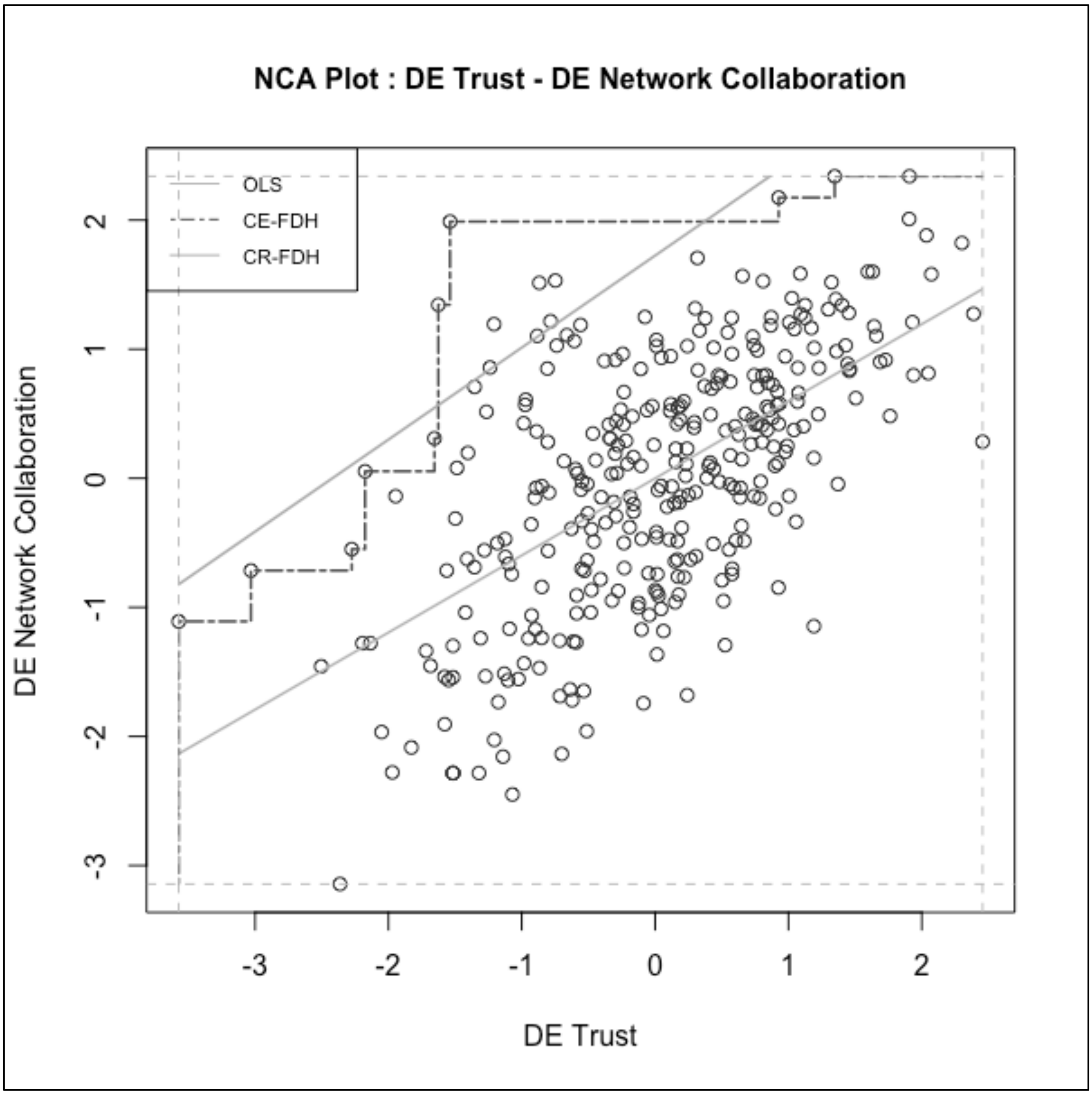


Figure 33: Scatter plot of NCA – DPE Trust and Collaboration

The visual inspection of the scatter plot (Figure **33**) confirms empty space (medium effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 6.738 and has 100% ceiling accuracy. The presence of cases scattered towards the top right corner suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016).

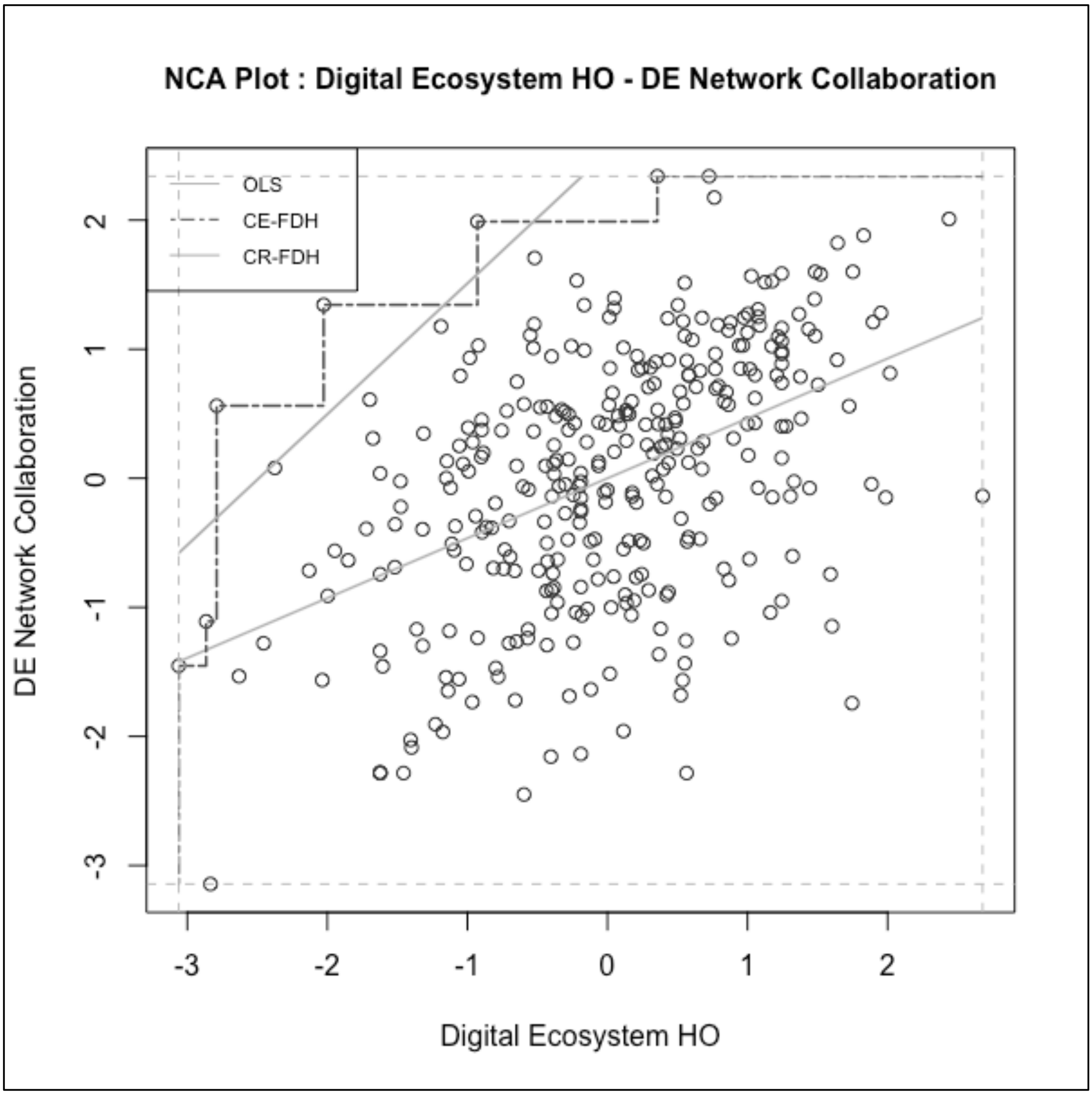


Figure 34: Scatter plot of NCA – DPE HO and Collaboration

The visual inspection of the scatter plot (Figure **34**) confirms some empty space (near to small effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 3.905 and has 100% ceiling accuracy. The presence of some cases scattered towards the centre to top right corner suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016).

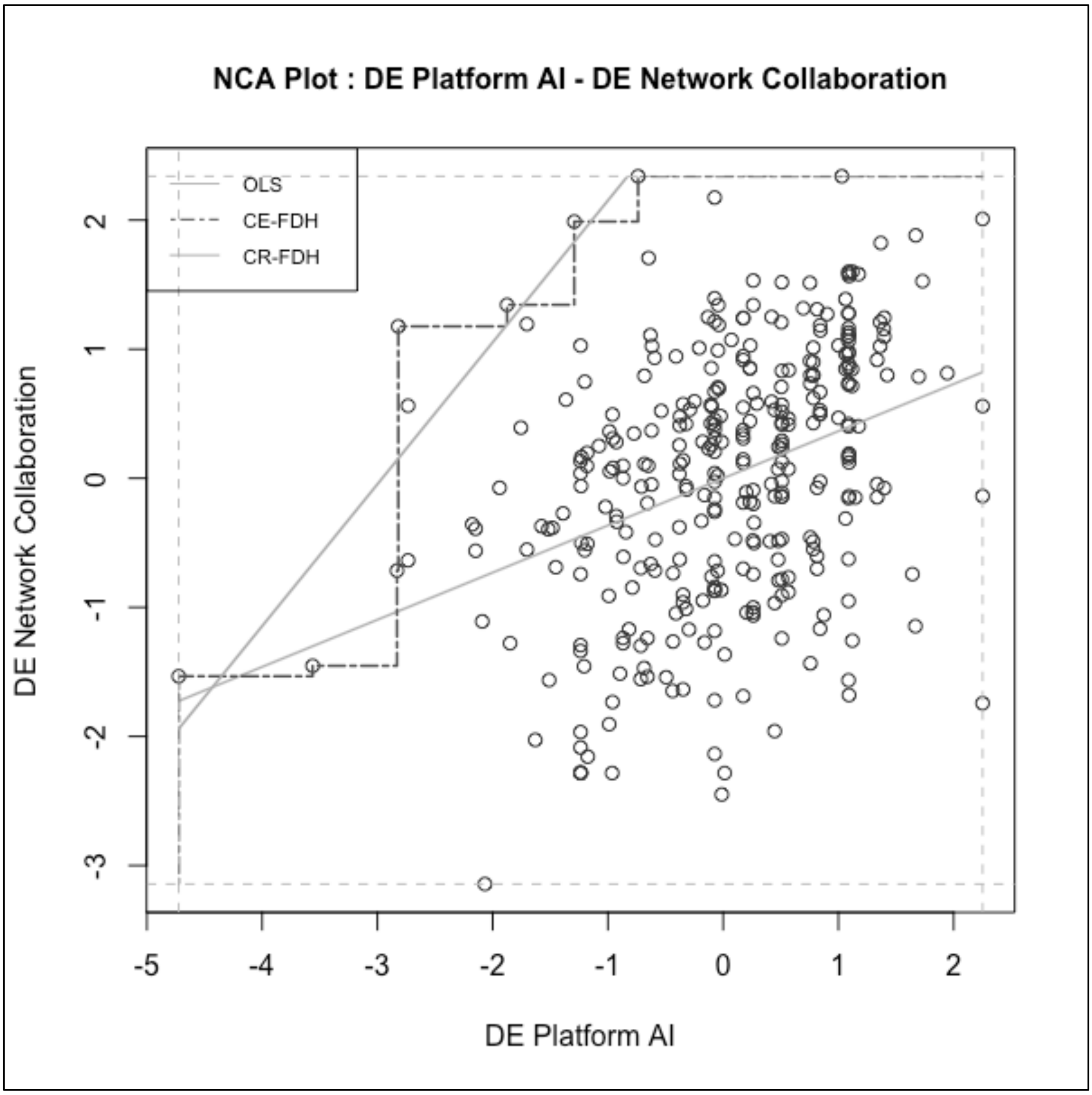


Figure 35: Scatter plot of NCA – DPE Platform AI and Collaboration

The visual inspection of the scatter plot (Figure **35**) confirms large empty space (med-high effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 9.185 and has 100% ceiling accuracy. The presence of cases scattered towards the centre to top right corner suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016).

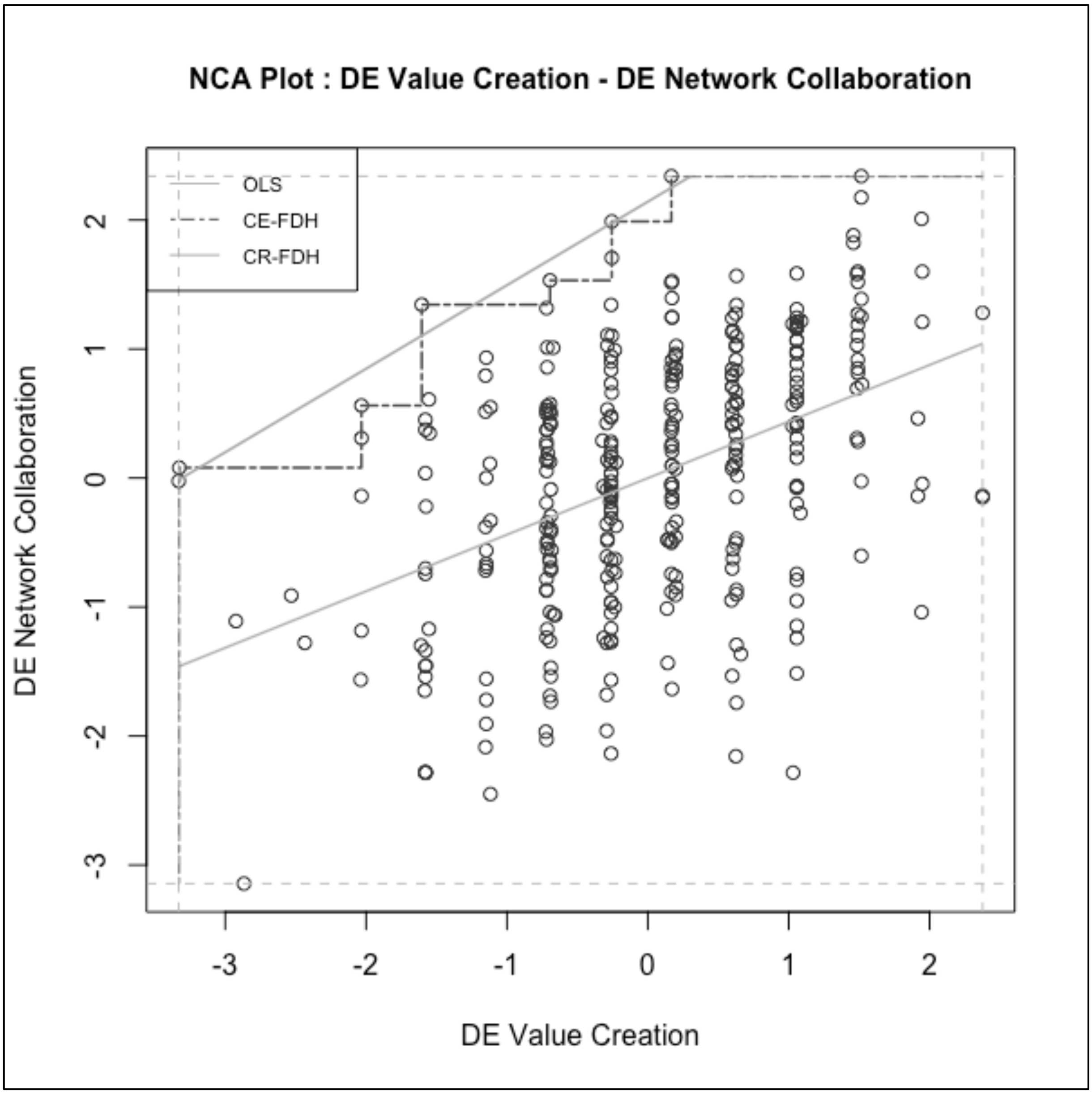


Figure 36: Scatter plot of NCA – DPE Value Creation and Collaboration

The visual inspection of the scatter plot (Figure 36) confirms empty space (med effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 5.102 and has 100% ceiling accuracy. The presence of some cases scattered towards the centre to top right corner suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016).

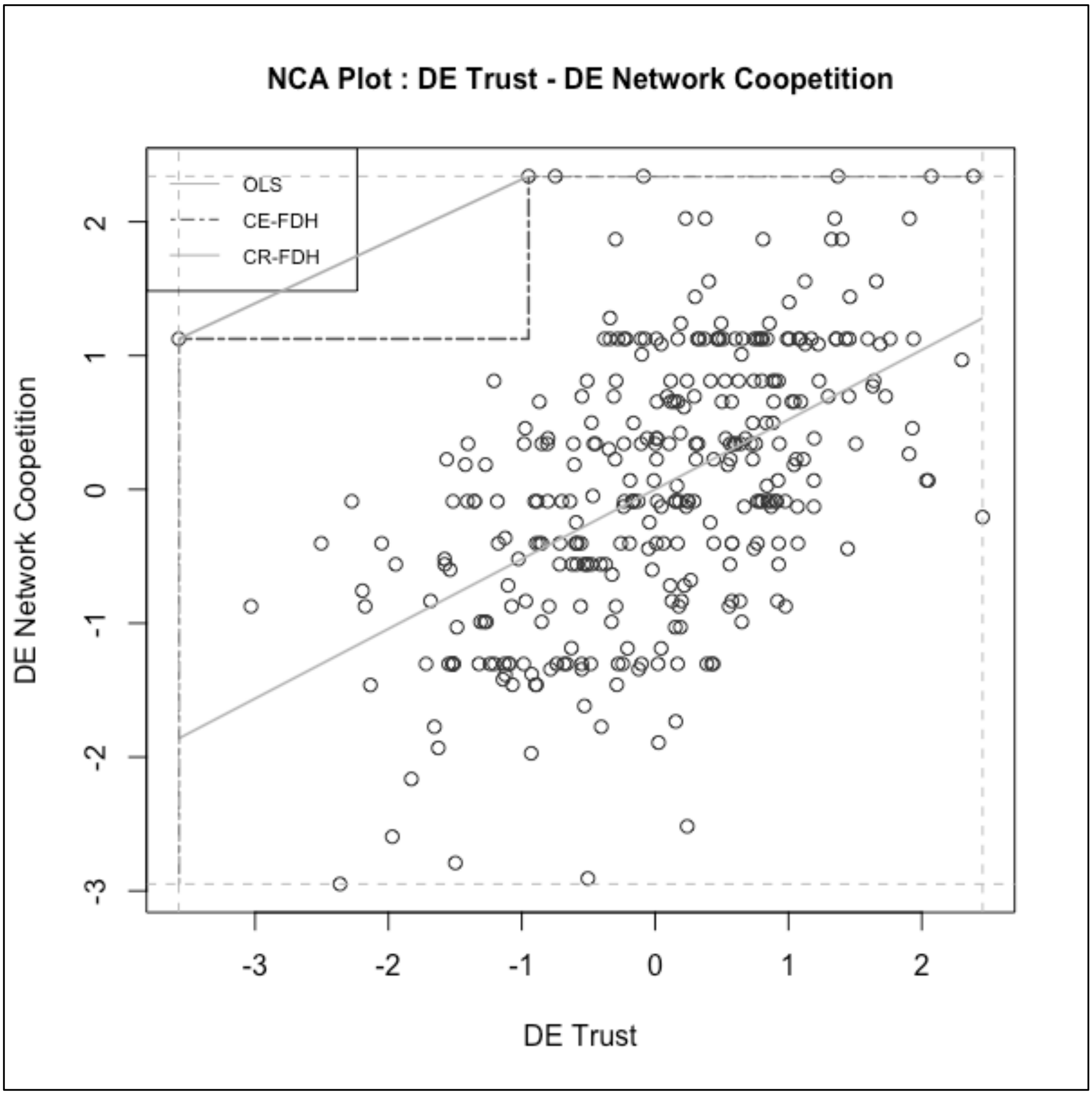


Figure 37: Scatter plot of NCA – DPE Trust and Network Coopetition

The visual inspection of the scatter plot (Figure **37**) confirms small empty space (low effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 3.188 and has 100% ceiling accuracy. The presence of some cases scattered towards the centre to top right corner suggests low supportiveness for the necessary condition hypothesis in this case (Dul, 2016) and p-value is greater than 0.05.

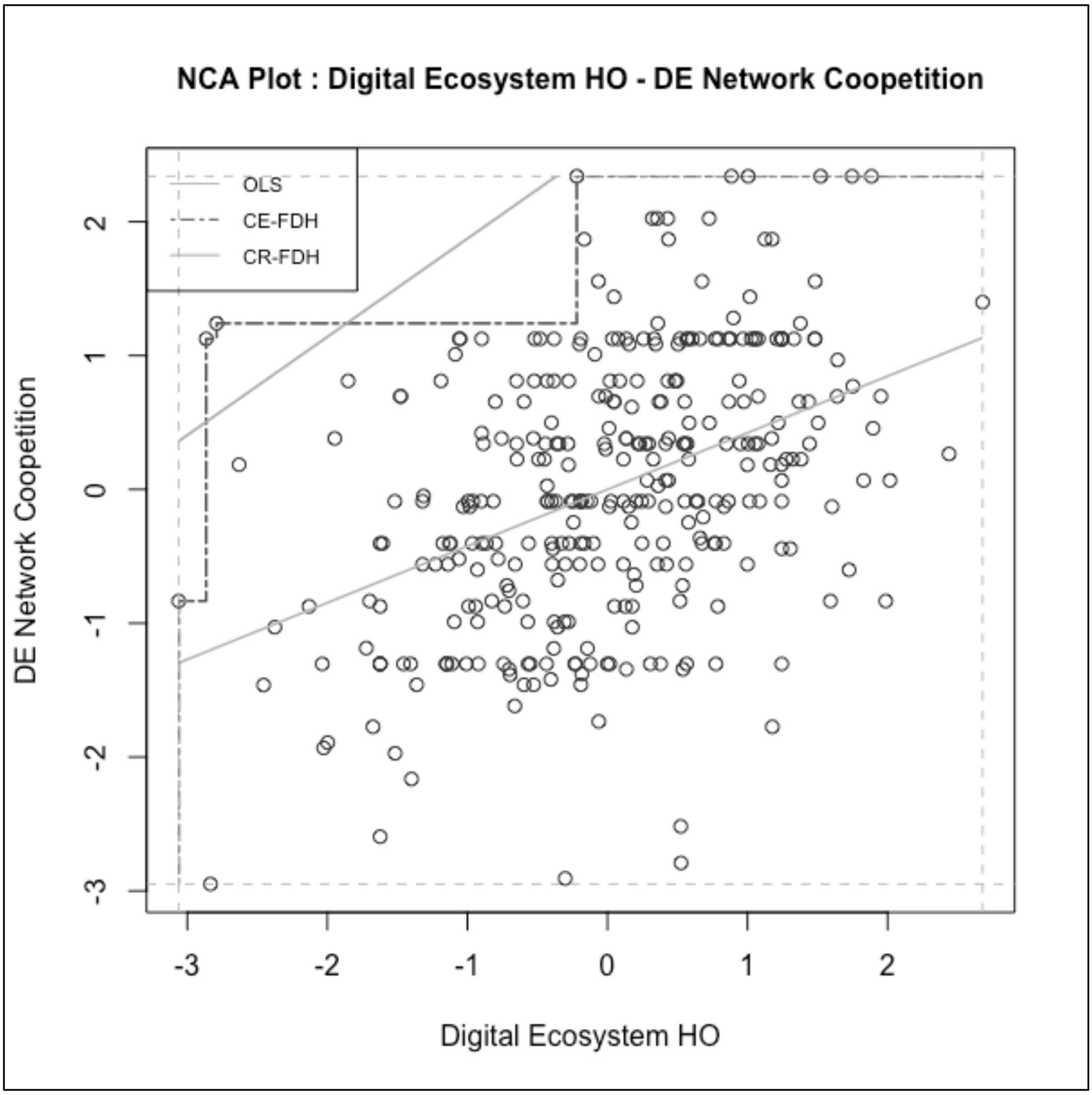


Figure 38: Scatter plot of NCA – DPE HO and Network Coopetition

The visual inspection of the scatter plot (Figure **38**) confirms small empty space (low effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 3.539 and has 100% ceiling accuracy. The presence of most cases scattered towards the centre suggests low supportiveness for the necessary condition hypothesis in this case (Dul, 2016).

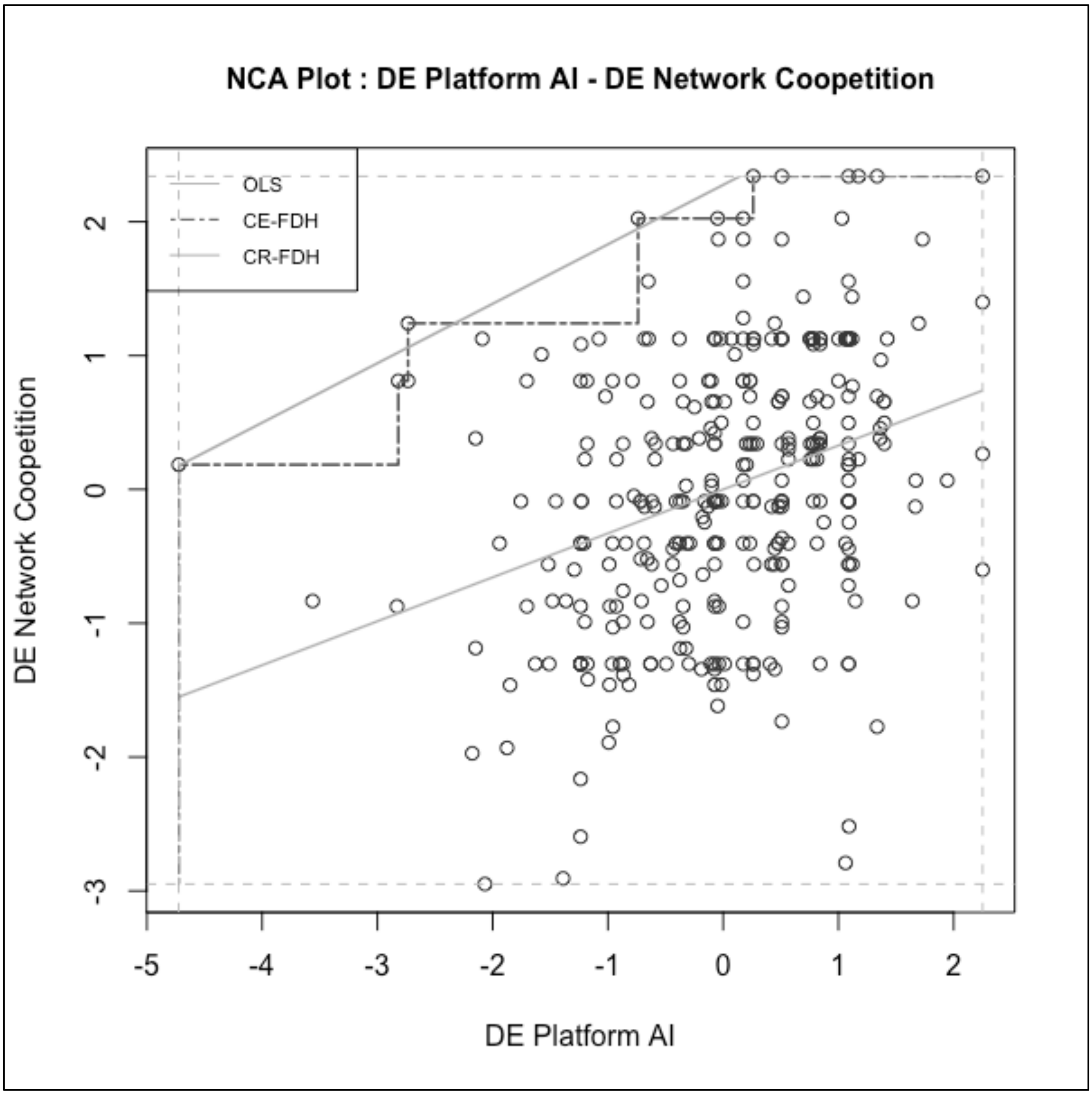


Figure 39: Scatter plot of NCA – DPE Platform AI and Network Coopetition

The visual inspection of the scatter plot (Figure **39**) confirms empty space (med effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 6.744 and has 100% ceiling accuracy. The presence of most cases scattered towards the centre right suggests low supportiveness for the necessary condition hypothesis in this case (Dul, 2016). Additionally, p-value = 0.273 and is greater than 0.05 therefore is not significant.

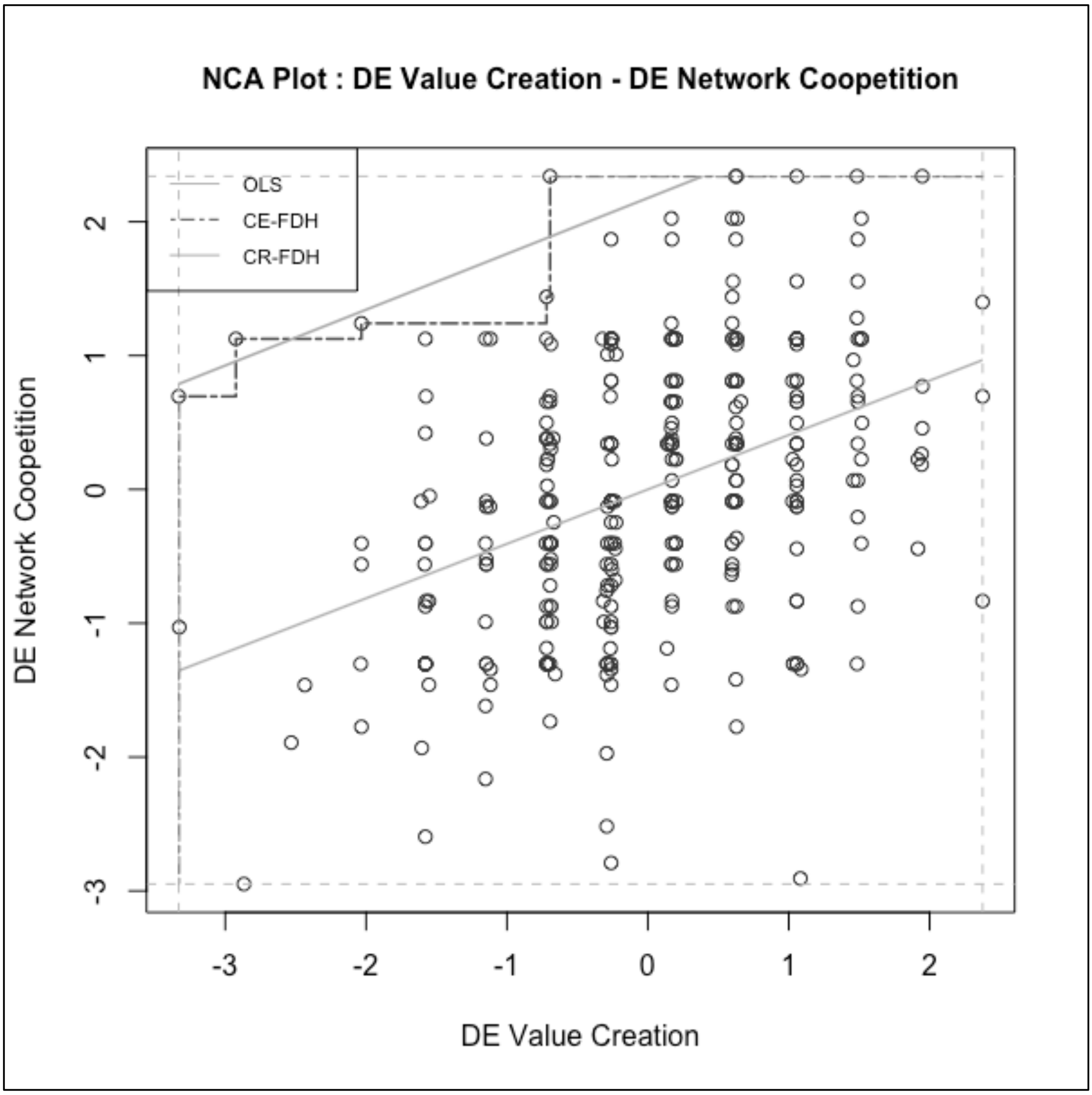


Figure 40: Scatter plot of NCA – DPE Value Creation and Network Coopetition

The visual inspection of the scatter plot (Figure **40**) confirms some empty space (med-low effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 3.217 and has 100% ceiling accuracy. The presence of most cases scattered towards the centre suggests low supportiveness for the necessary condition hypothesis in this case (Dul, 2016). Additionally, p-value = 0.225 and is greater than 0.05 therefore is not significant.

4.5.2 Necessary condition analysis – Set B

Following the NCA Set A, NCA Set B was conducted to test whether DPE Collaboration and DPE Network Coopetition are a necessary condition for DPE Willingness to transact; DPE Network Coopetition and DPE Willingness to transact are a necessary condition for DPE Collaboration; and DPE willingness to transact and DPE Collaboration are a necessary condition for DPE Network Coopetition. The NCA effect sizes for the second set of NCA (Set B) are presented along with bottleneck tables (Table 35 and Table 36) and scatter plot figures for each construct. The results of NCA Set B (see Table 35) indicate that DPE Willingness To Transact (medium effect) and DPE Network Coopetition (medium effect) are meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary conditions for DPE Collaboration (Richter et al., 2020). It was also reported that DPE Collaboration (close to large effect) is a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for DPE Willingness to Transact. Additionally, DPE Collaboration (medium effect) is a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for DPE Network Coopetition.

Furthermore, each necessary condition was analysed in detail with the bottleneck tables. From the bottleneck tables (see Table 36) highlighting that to reach up to 80% level of DPE Network Coopetition, both DPE Collaboration (25.5%) and DPE Willingness to Transact (41.8%) are necessary conditions that need to be in place. For DPE Collaboration to reach up to 60% level, DPE Willingness To Transact (41.2%) and DPE Network Coopetition (19.2%) are necessary conditions. And For DPE Willingness To Transact to be 70% level or above, DPE Collaboration (25.5%) and DPE Network Coopetition (0.8%, very low level) are necessary but insufficient conditions that need to be in place.

Table 35: NCA Set B effect sizes

	CE-FDH Effect Size *d*	**p-Value**	**CE-FDH Effect Size *d***	**p-Value**	**CE-FDH Effect Size *d***	**p-Value**
Construct	DPE Collaboration		DPE Willingness To Transact		DPE Network Coopetition	
DPE Collaboration	-	-	**0.117**	**0.013**	**0.200**	**0.000**
DPE Willingness To Transact	**0.267**	**0.000**	-	-	0.096	0.790
DPE Network Coopetition	**0.158**	**0.001**	0.020	0.536	-	-

Note: d ranges between $0 \leq d \leq 1$, where $0 < d < 0.1$ signifies small effect, $0.1 \leq d < 0.3$ medium effect,

$0.3 \leq d < 0.5$ large effect and $d \geq 0.5$ as very large effect. (Richter et al., 2020).

Statistically significant at $p < 0.05$ (Dul, van der Laan and Kuik, 2020).

Table 36: NCA Set B bottleneck table (percentages)

(CE-FDH)	Collaboration	Willingness To Transact	Network Coopetition
Bottleneck DPE Network Coopetition			
0	NN	NN	-
10	12.7	NN	-
20	12.7	NN	-
30	15.7	NN	-
40	18.4	NN	-
50	18.4	NN	-
60	25.5	NN	-
70	25.5	NN	-
80	25.5	41.8	-
90	25.5	41.8	-
100	25.5	41.8	-
	Collaboration	**Willingness To Transact**	**Network Coopetition**
Bottleneck DPE Collaboration			
0	-	NN	NN
10	-	NN	0.8
20	-	NN	0.8
30	-	NN	0.8
40	-	17.7	0.8
50	-	17.7	0.8
60	-	41.2	19.2
70	-	46.9	19.2
80	-	52.9	19.2
90	-	52.9	44.4
100	-	100.0	94.0
	Collaboration	**Willingness To Transact**	**Network Coopetition**
Bottleneck DPE Willingness To Transact			
0	NN	-	NN
10	NN	-	NN
20	NN	-	NN
30	NN	-	NN
40	NN	-	NN
50	12.7	-	0.8
60	18.4	-	0.8
70	25.5	-	0.8
80	25.5	-	3.0
90	26.7	-	8.1
100	26.7	-	8.1

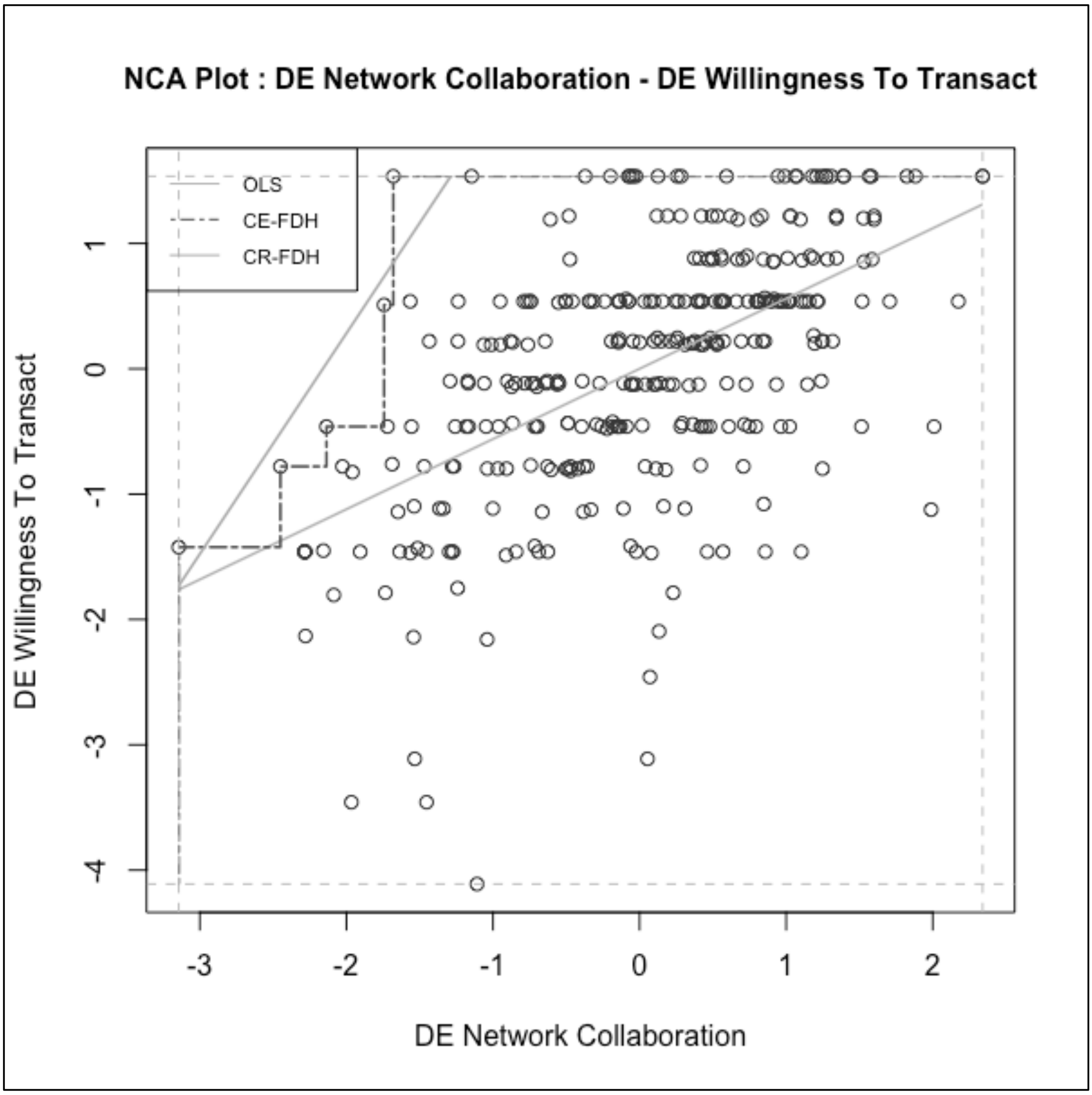


Figure 41: Scatter plot of NCA – Collaboration and Willingness To Transact

The visual inspection of the scatter plot (**Figure 41**) confirms some empty space (med-low effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 3.630 and has 100% ceiling accuracy. The presence of most cases towards the top right suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016). Additionally, p-value = 0.013 and is lower than 0.05 therefore is significant.

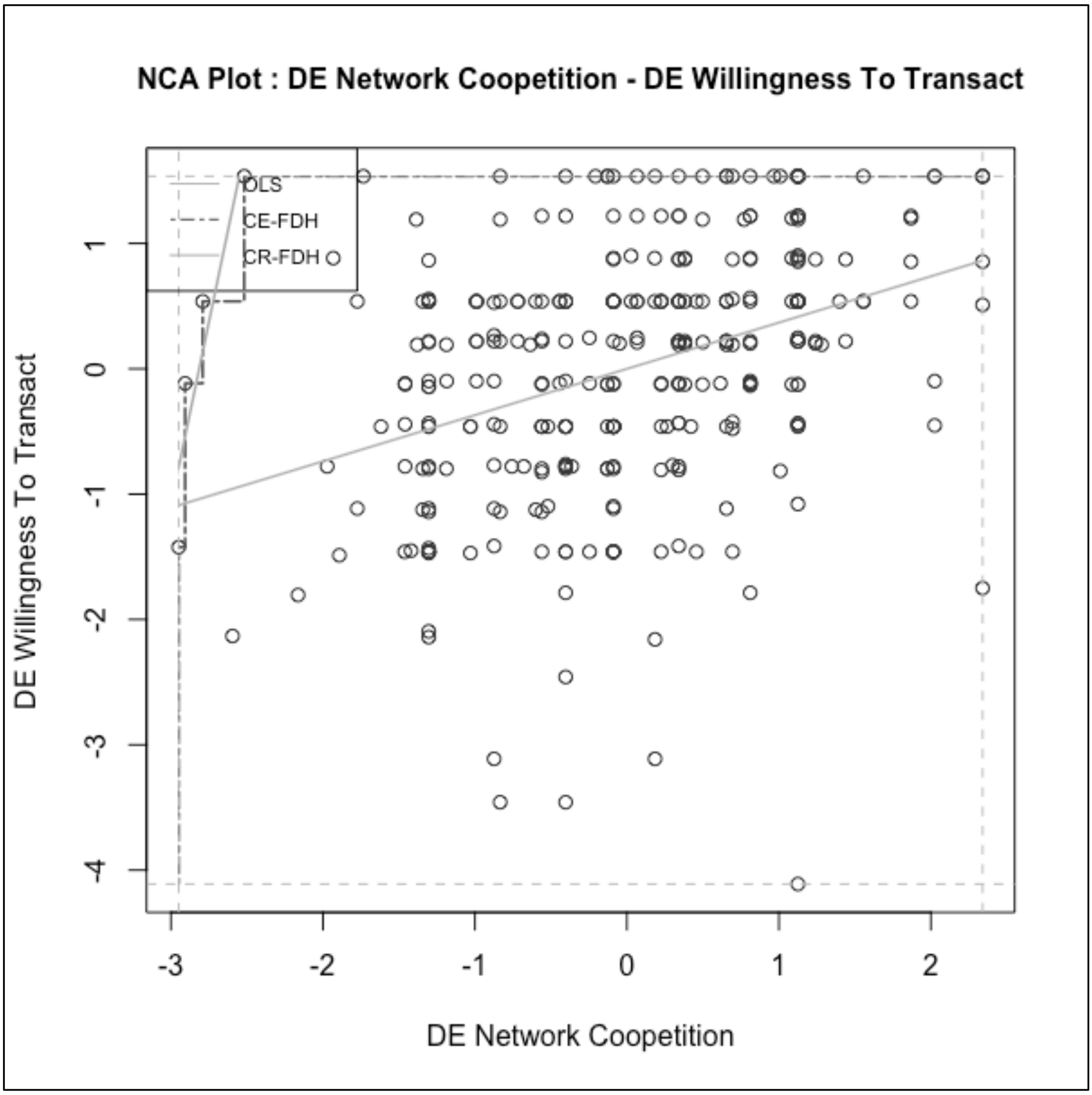


Figure 42: Scatter plot of NCA – Network Coopetition and Willingness To Transact

The visual inspection of the scatter plot (Figure **42**) confirms very little empty space (very low effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 0.588 and has 100% ceiling accuracy. The presence of most cases towards the centre suggests non supportiveness for the necessary condition hypothesis in this case (Dul, 2016). Additionally, p-value = 0.536 and is higher than 0.05 therefore is not significant.

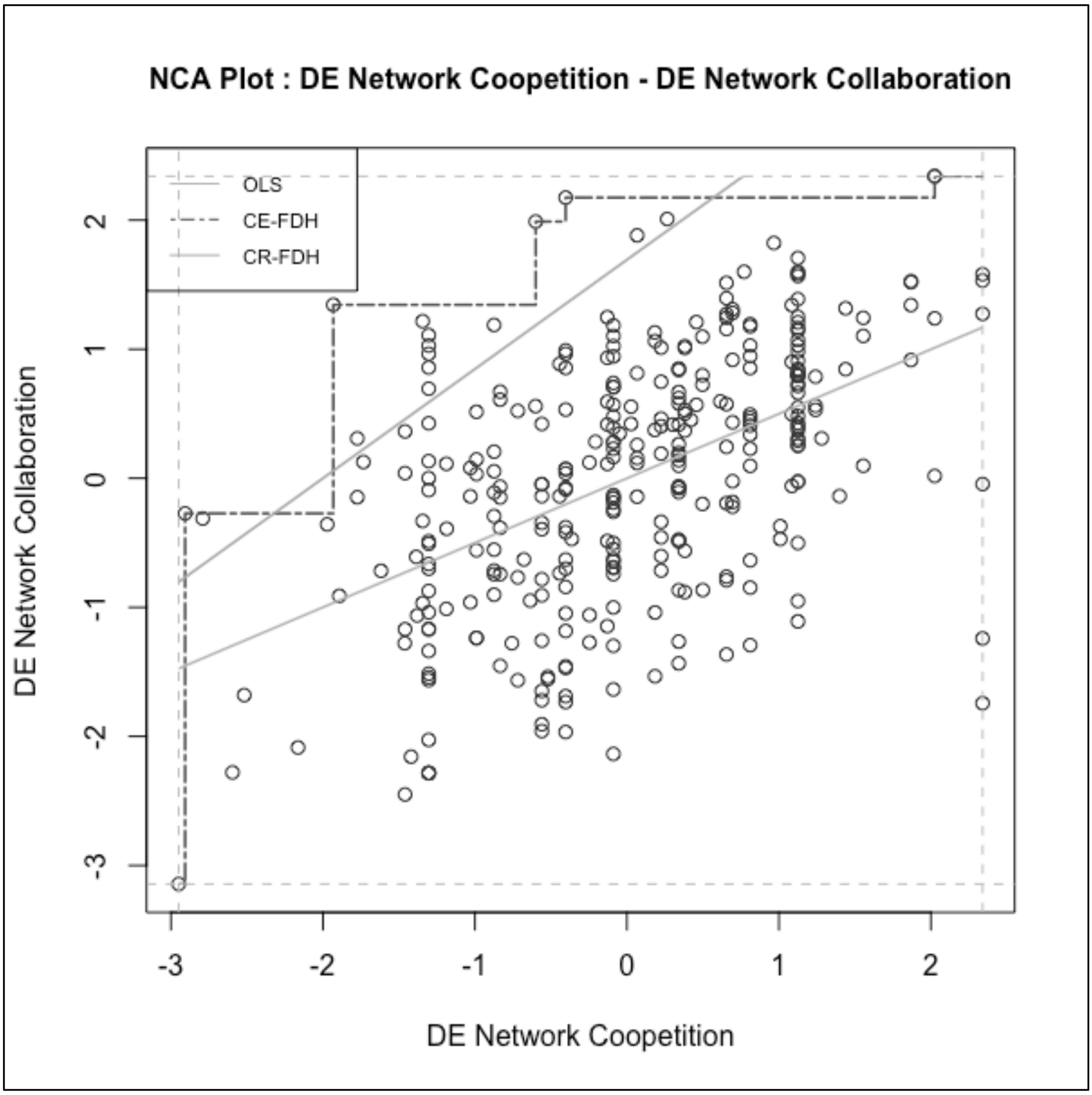


Figure 43: Scatter plot of NCA – Network Coopetition and Collaboration

The visual inspection of the scatter plot (**Figure 43**) confirms empty space (med effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 4.573 and has 100% ceiling accuracy. The presence of some cases towards the centre right suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016). Additionally, p-value = 0.001 and is lower than 0.05 therefore is significant.

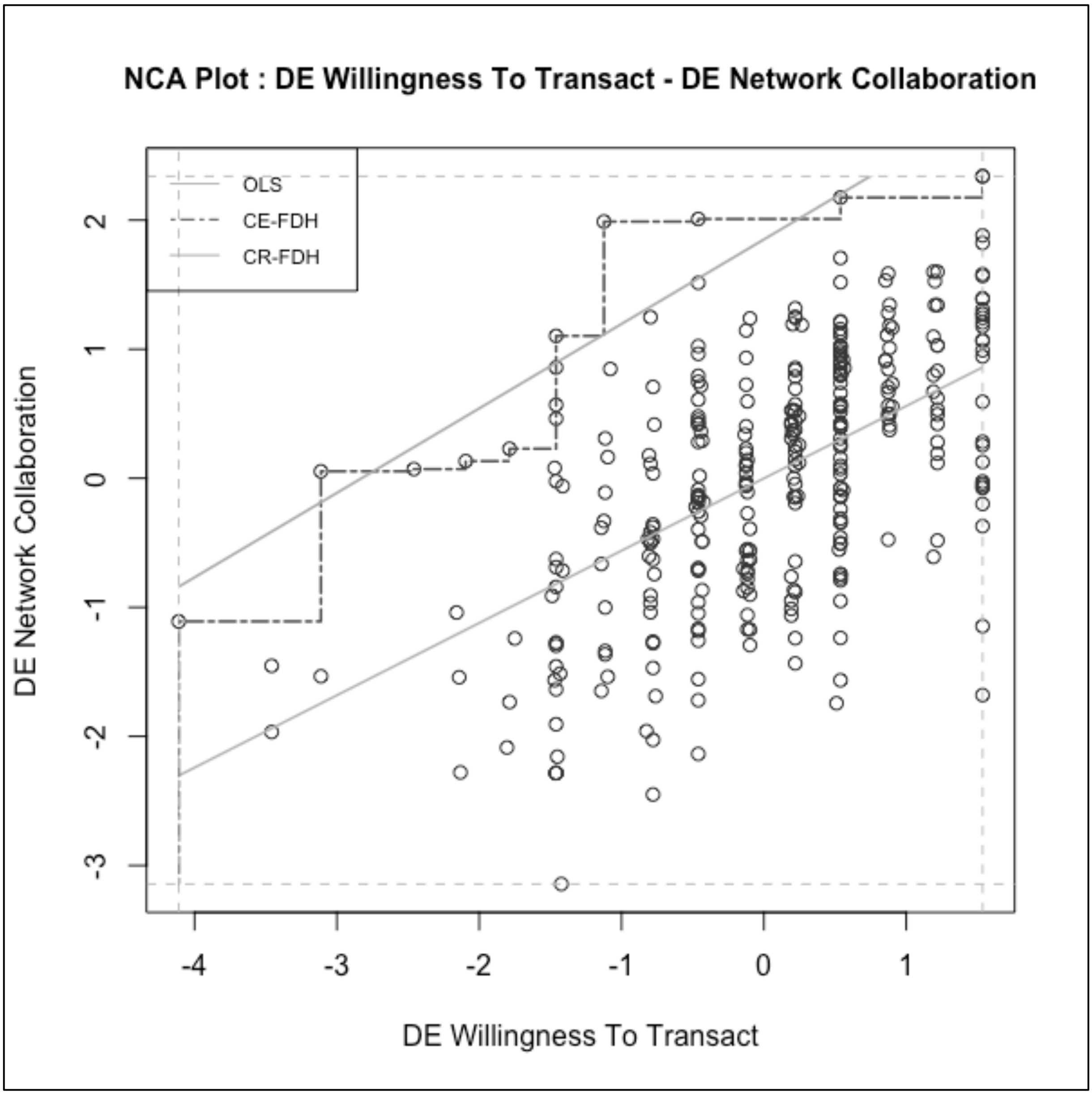


Figure 44: Scatter plot of NCA – Willingness To Transact and Collaboration

The visual inspection of the scatter plot (**Figure 44**) confirms empty space (med-large effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 8.278 and has 100% ceiling accuracy. The presence of some cases towards the right corner suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016). Additionally, p-value = 0.000 and is lower than 0.05 therefore is significant.

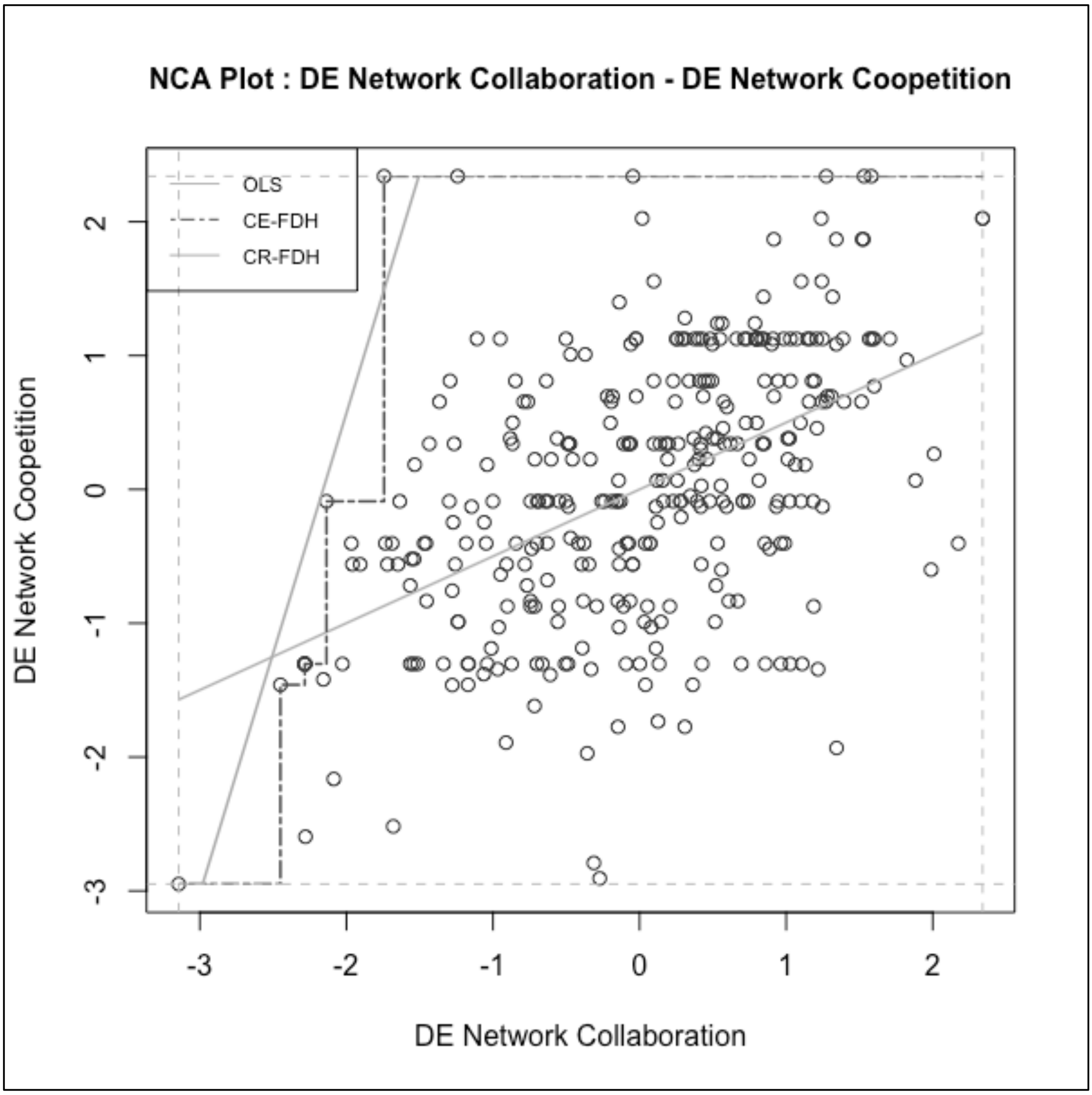


Figure 45: Scatter plot of NCA – Collaboration and Network Coopetition

The visual inspection of the scatter plot (Figure **45**) confirms empty space (med-large effect size d) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 5.795 and has 100% ceiling accuracy. The presence of some cases towards the centre suggests supportiveness for the necessary condition hypothesis in this case (Dul, 2016). Additionally, p-value = 0.000 and is lower than 0.05 therefore is significant.

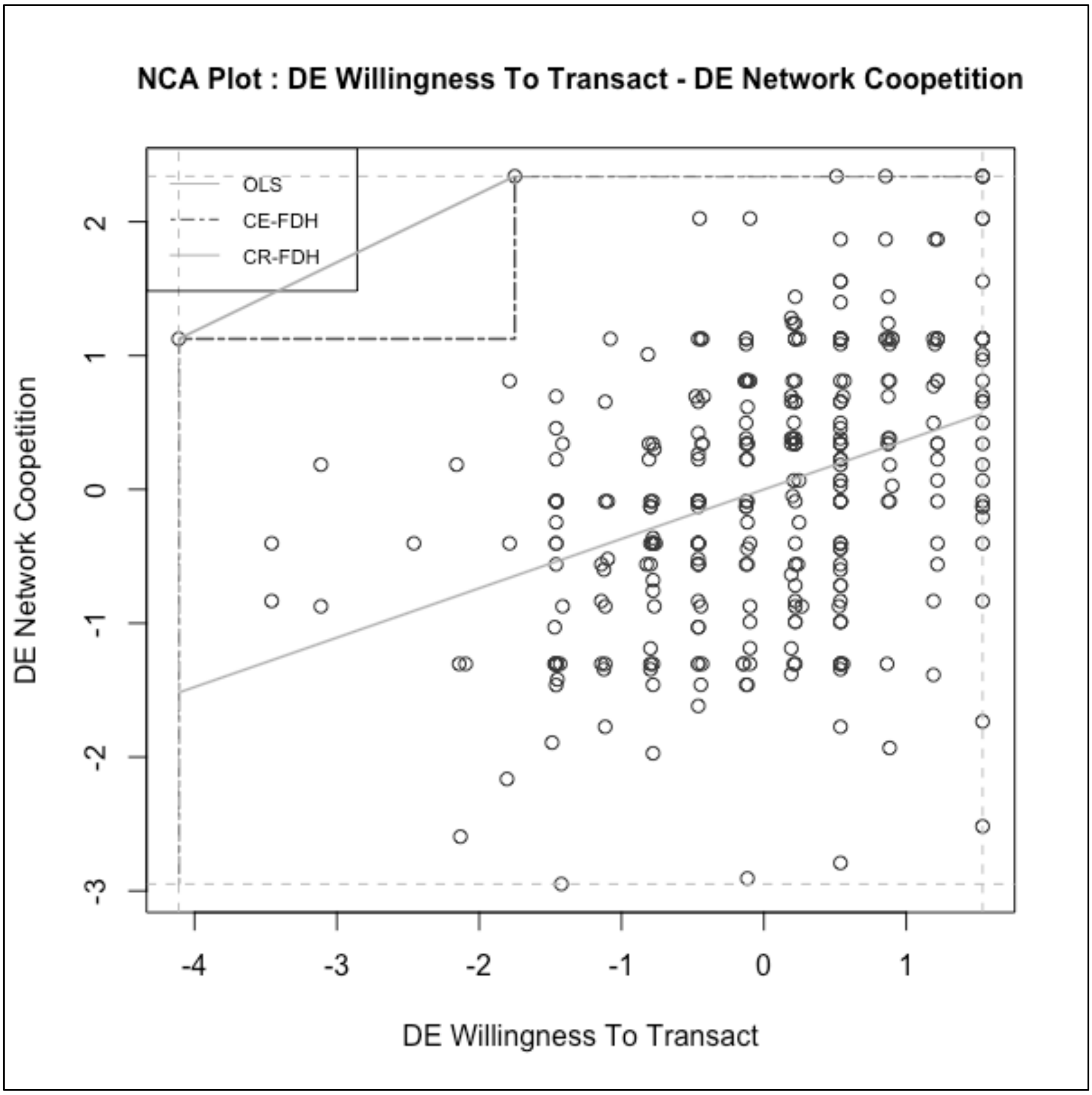


Figure 46: Scatter plot of NCA – Willingness To Transact and Network Coopetition

The visual inspection of the scatter plot (Figure 46) confirms low empty space (low effect size) in the upper left corner. It is noticeable that a ceiling envelope with free disposal hull (CE-FDH), with a piecewise linear function fits the data points. CE-FDH is selected as the outcomes have few levels and are discrete. The size of the empty space ceiling zone for CE-FDH is 2.869 and has 100% ceiling accuracy. The presence of most cases towards the centre right and bottom right suggests non supportiveness for the necessary condition hypothesis in this case (Dul, 2016). Additionally, p-value = 0.790 and is higher than 0.05 therefore is not significant.

4.6 Summary of hypotheses results and validity

Below, the results of the hypotheses that were detailed within the initial chapters of this research thesis are summarised. Highlighting the key results associated with each hypothesis, along with the type of analysis that were conducted to confirm if the hypotheses are supported or not supported based on the analysis.

A post hoc analysis was also conducted to check if the sample of 333 respondents was sufficient – using the values of willingness to transact digital ecosystem outcomes in DPETO with (β = 0.357) and without (β = 0.306) explainable AI-influenced trust mediator, at 0.05 error probability and three predictors. This revealed that the sample used for this study was sufficient and of high statistical power close to 1.0, hence sufficient to detect significant effects in the DPETO model.

Table 37: Hypotheses results summary

Hypothesis	**Validity**	**Result**	**Type of analysis**	**Reference**
H1: Digital platform ecosystem will have positive effect on digital platform ecosystem outcomes of willingness to transact.	Supported	A statistically significant positive relationship exists between the Digital Platform Ecosystem and Willingness To Transact, with a path coefficient of 0.199 ($t = 3.093$, $p = 0.002$).	PLS -SEM on DPETO-no-xAI	Table 29
H2: Digital platform ecosystem will have positive effect on digital platform ecosystem outcomes of network coopetition.	Supported	A statistically significant and positive relationship exists between the Digital Platform Ecosystem and Network Coopetition, as indicated by a path coefficient of 0.230 ($t = 3.740$, $p < 0.000$).	PLS -SEM on DPETO-no-xAI	Table 29
H3: Digital platform ecosystem will have positive effect on digital ecosystem outcomes of collaboration.	Supported	A statistically significant positive relationship is observed between the Digital Platform Ecosystem and	PLS -SEM on DPETO-no-xAI	Table 29

Hypothesis	Validity	Result	Type of analysis	Reference
		Collaboration, supported by a path coefficient of 0.247 ($t = 4.124$, $p < 0.000$).		
H1	Supported	A statistically significant positive relationship between Digital Platform Ecosystem and Willingness To Transact, with a path coefficient of 0.147 ($t = 2.473$, $p = 0.013$).	PLS -SEM on DPETO-xAI	Table 29
H2	Supported	A statistically significant positive relationship is found between Digital Platform Ecosystem and Network Coopetition, with a path coefficient of 0.168 ($t = 2.558$, $p = 0.011$).	PLS -SEM on DPETO-xAI	Table 29
H3	Supported	There is a statistically significant positive relationship between Digital Platform	PLS -SEM on DPETO-xAI	Table 29

Hypothesis	Validity	Result	Type of analysis	Reference
		Ecosystem and Collaboration, with a path coefficient of 0.158 (t = 2.750, p = 0.006).		
H4: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of willingness to transact will be mediated by digital platform ecosystem trust.	Supported	A highly significant and positive indirect relationship between the Digital Platform Ecosystem and Willingness To Transact, mediated by Digital Platform Ecosystem Trust, with a path coefficient of 0.306 (t = 7.590, p < 0.000).	PLS-SEM Mediation Analysis on DPETO-no-xAI	Table 29
H5: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of network coopetition will be mediated by digital platform ecosystem trust.	Supported	A significant and positive indirect relationship is observed between the Digital Platform Ecosystem and Network Coopetition, mediated by Digital Platform Ecosystem Trust, with a path coefficient of 0.194 (t = 5.100, p < 0.000)	PLS-SEM Mediation Analysis on DPETO-no-xAI	Table 29

Hypothesis	Validity	Result	Type of analysis	Reference
H6: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of collaboration will be mediated by digital platform ecosystem trust.	Supported	A significant and positive indirect relationship between the Digital Platform Ecosystem and Collaboration, mediated by Digital Platform Ecosystem Trust, with a path coefficient of 0.216 ($t = 5.701$, $p < 0.000$).	PLS-SEM Mediation Analysis on DPETO-no-xAI	Table 29
H7: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of willingness to transact will be mediated by artificial influence explainability influenced digital platform ecosystem trust.	Supported	A significant and positive indirect relationship is observed, where the Digital Platform Ecosystem exerts influence on individuals' Willingness To Transact through the mediator of Digital Platform Ecosystem Trust. The path coefficient for this indirect effect is 0.357 ($t = 9.348$, $p = 0.000$).	PLS-SEM Mediation Analysis on DPETO-xAI	Table 29

Hypothesis	Validity	Result	Type of analysis	Reference
H8: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of network coopetition will be mediated by artificial influence explainability influenced digital platform ecosystem trust.	Supported	A significant and positive indirect connection from the Digital Platform Ecosystem to Network Coopetition, mediated by Digital Platform Ecosystem Trust. The path coefficient for this indirect effect is 0.256 (t = 6.366, p = 0.000).	PLS-SEM Mediation Analysis on DPETO-xAI	Table 29
H9: Digital platform ecosystem's positive effects on digital platform ecosystem outcomes of collaboration will be mediated by artificial influence explainability influenced digital platform ecosystem trust.	Supported	A significant and positive indirect relationship in which the Digital Platform Ecosystem influences Collaboration through the mediator of Digital Platform Ecosystem Trust. The path coefficient for this indirect effect is 0.306(t = 8.161, p = 0.000).	PLS-SEM Mediation Analysis on DPETO-xAI	Table 29

Hypothesis	Validity	Result	Type of analysis	Reference
H10: Digital platform ecosystem trust when mediated with artificial intelligence explainability influenced digital platform ecosystem trust is a stronger predictor model of digital platform ecosystem outcomes in comparison to non-explainability influenced digital platform ecosystem trust.	Supported	DPETO-xAI model with xAI in DPE Trust mediator results in smaller values, hence a better predictor model. DPETO-xAI model is an efficient and consistent system to foster value outcomes of Willingness to Transact, Collaboration and Network Coopetition in Digital Platform Ecosystem	• Model selection criterion: Asymptotically efficient & Asymptotically Consistent • PLSPredict	Table 30 Table 31 Table 32
H11: Digital platform ecosystem trust mediator is a meaningful and a necessary condition for collaboration.	Supported	DPE Trust is a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for DPE Collaboration (medium effect)	NCA Set A	Table 33

Hypothesis	Validity	Result	Type of analysis	Reference
H12: Digital platform ecosystem trust mediator is a meaningful and a necessary condition for willingness to transact.	Supported	DPE Trust is a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for DPE Willingness to Transact (medium effect)	NCA Set A	Table 33
H13: Digital platform ecosystem trust mediator is a meaningful and a necessary condition for network coopetition.	Not Supported	DPE Trust is a not meaningful (d=0.100) and not a significant ($p > 0.05$) necessary condition for DPE Network Coopetition (small effect)	NCA Set A	Table 33
H14: Digital platform ecosystem Platform AI is a meaningful and a necessary for collaboration.	Supported	DPE platform AI appears to me a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for DPE Collaboration and DPE Willingness to Transact	NCA Set A	Table 33

Hypothesis	Validity	Result	Type of analysis	Reference
H15: Digital platform ecosystem Platform AI is a meaningful and a necessary for willingness to transact.	Supported	DPE platform AI appears to me a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for DPE Willingness to Transact	NCA Set A	Table 33
H16: Digital platform ecosystem Platform AI is a meaningful and a necessary network coopetition.	Not Supported	DPE platform AI is not a meaningful ($d = 0.183$, med effect) and not a significant ($p > 0.05$) necessary condition for DPE Coopetition	NCA Set A	Table 33
H17: Digital platform ecosystem outcome of collaboration is a meaningful and a necessary condition for willingness to transact.	Supported	DPE Collaboration (close to large effect) is a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for DPE Willingness to Transact	NCA Set B	Table 35

Hypothesis	Validity	Result	Type of analysis	Reference
H18: Digital platform ecosystem outcome of network coopetition is a meaningful and a necessary condition for willingness to transact.	Not supported	DPE Network coopetition is not a meaningful ($d=0.020$) and not a significant ($p > 0.05$) necessary condition for Willingness to Transact	NCA Set B	Table 35
H19: Digital platform ecosystem outcome of network coopetition is a meaningful and a necessary condition for collaboration.	Supported	DPE Network Coopetition (medium effect) is meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary conditions for DPE Collaboration	NCA Set B	Table 35
H20: Digital platform ecosystem outcome of willingness to transact is a meaningful and a necessary condition for collaboration.	Supported	DPE Willingness To Transact (medium effect) is a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary conditions for DPE Collaboration	NCA Set B	Table 35

Hypothesis	**Validity**	**Result**	**Type of analysis**	**Reference**
H21: Digital platform ecosystem outcome of collaboration is a meaningful and a necessary condition for network coopetition.	Supported	DPE Collaboration (medium effect) is a meaningful ($d \geq 0.1$) and significant ($p < 0.05$) necessary condition for DPE Network Coopetition.	NCA Set B	Table 35
H22: Digital platform ecosystem outcome of willingness to transact is a meaningful and a necessary condition for network coopetition.	Not Supported	DPE Willingness to Transact is not a meaningful ($d=0.096$, nearing small effect) and not a significant ($P > 0.05$) necessary condition for DPE Network Coopetition.	NCA Set B	Table 35

4.7 Chapter summary

In this chapter, an overall analysis of the research components was undertaken. The chapter examined response rates and presented descriptive statistics on the survey respondents. Utilising Partial Least Squares Structural Equation Modelling (PLS-SEM), the chapter analysed the conceptual DPETO model's path relationships. This analysis examined two distinct models (with and without artificial intelligence explainability influenced trust mediator), each involving its set of measurement items and corresponding PLS-SEM analysis results. The chapter also delved into measurement model assessments, encompassing measurement scale validation and model loadings.

The chapter then evaluated the internal consistency, reliability, and convergent validity. Discriminant validity using the Heterotrait-Monotrait (HTMT) ratio and cross-loadings. Multicollinearity was assessed through the structural model's variance inflation factor (VIF) calculations. Thereafter, the testing of direct and mediated relationships was conducted, which revealed significant insights into the relationships of variables. A critical part of the chapter was in the model selection process, which involved the selection criteria to identify the most suitable model representation out of the two DPETO models. This included prediction assessments, including out-of-sample predictions.

Furthermore, the chapter introduced the use of Necessary Condition Analysis (NCA) as a complementary approach to PLS-SEM analysis. NCA was applied to two distinct sets of variables (Set A & Set B analysis), answering the hypotheses that were designed to understand the conditions associated with the examined constructs.

Finally, the chapter covered the analysis and testing of the hypotheses, answering their statistical significance and contribution to the research's broader objectives. Through the comprehensive analysis, the chapter also provided a holistic understanding of the overall empirical landscape of this research and the associated practical implications.

5 Discussion and contributions

"Research is creating new knowledge"
– Neil Armstrong

This chapter covers the key dimensions of this research, explaining its contributions at various levels – theoretical, methodological, and practical. Through the detailed synthesis of the analysis, this chapter highlights the emerging novel insights, across theory, advanced research methods, and practical applications. Ultimately, this chapter provides a comprehensive understanding of the overarching implications of this research study.

5.1 Discussion

The key gaps within the extant scholarly work and practical applications in the domain of digital platform ecosystems establish the necessary groundwork for this research. Central issues such as the foundational trust in the digital platform ecosystem, the increased use of artificial intelligence within these platforms and the lack of understanding of the impact of trust on value outcomes are focal aspects. These issues serve as the basis of this research which intends to refine the academic progress and provide pragmatic approaches to embedding trust methodologies in alignment with the advancing technological landscape.

The primary aim of this study was to conceptually understand the existence of 'ecosystem trust' and how it impacts digital platform ecosystem outcomes. This study aimed to contribute to the literature on digital platform ecosystems and associated topics of digital platform ecosystem outcomes by developing a uniquely posited conceptual model, referenced as the Digital

Platform Ecosystem Trust Outcomes (DPETO) model. A thorough review of the existing literature on digital ecosystems concluded that digital platform ecosystems are emerging in various contexts. These ecosystems are taking a variety of shapes and forms to address their value outcomes, defined broadly by their underlying organising principles. Taking a view of these ecosystems, namely, digital platform ecosystems, where digital platforms (often owned and operated by a non-hierarchical authority) (Adner, 2017) are becoming relevant in all spheres. This is raising critical issues of propagation and permeability of trust, broadly as and for those participating (and/or transacting) on these ecosystems while they are collaborating, negotiating within and beyond the network boundaries - co-creating and capturing value. The problem of trust, hence, becomes of critical mass, needing addressing by emerging mechanisms, technologies and architectures that resonate with those of the digital platform ecosystems and the pace of their evolution. These are the issues that are explored in this research by quantifying the relationships and the factors that influence them and were developed into the key research questions answered in this research. The question RQ1 included understanding how the digital platform ecosystem does itself affect the associated participation outcomes and is discussed in section 5.1.1. The question RQ2 included understanding how the presence of trust affects the associated participation outcomes and is discussed in section 5.1.2. Section 5.1.2 also discusses RQ3 and RQ4. RQ3 explored digital platform ecosystem trust, involving artificial intelligence explainability, and its impact on digital platform ecosystem participation outcomes. RQ4 explored the absence of artificial intelligence explainability. Furthermore, section 5.1.3 further discusses the overall effects of trust and the role of explainability. Section 5.1.4 discusses RQ5**,** conditions that are meaningful and necessary.

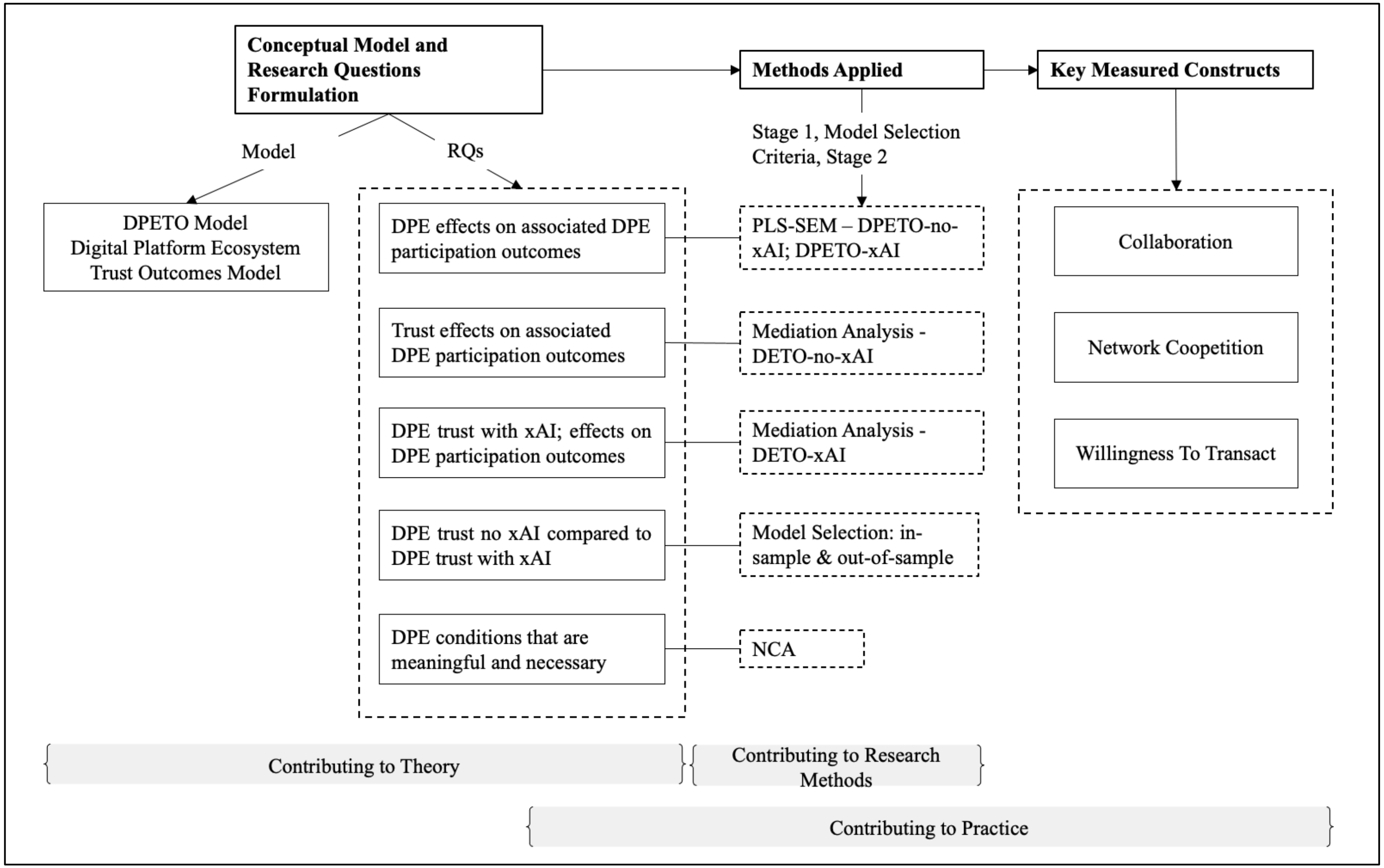


Figure 47: Research synthesis framework

As such, to answer the key questions set out the main purpose of this study (see 1.4 and Figure 47) was to first establish by examining if there is a relationship between digital platform ecosystem composition aspects of platform AI, value creation drivers, the digital platform ecosystem trust and digital platform ecosystem outcomes of Collaboration, Network Coopetition and Willingness To Transact. Furthermore, this study explored the effect of explainable artificial intelligence (xAI) on digital platform ecosystem trust and how it mediates the digital platform ecosystem outcomes.

5.1.1 Effects of digital platform ecosystem principles on participation outcomes

This study conducted a comprehensive analysis on understanding the effects of digital platform ecosystem principles and how they influence the participation outcomes. This was an essential step to operationalise and validate initially, the novel DPETO framework. Following the DPETO conceptual framework development, a detailed analysis was conducted using PLS-SEM methodology both on DPETO-no-xAI and on DPETO-xAI variations of the model. Firstly, the hypothesis H1 was tested to answer this question about the outcome of willingness to transact. This was reported as positive and statistically significant for both DPETO models (see Table 37). Secondly, the hypothesis H2 was tested to answer this question about the outcome of network coopetition and was reported as positive and statistically significant for both DPETO models. Thirdly, the hypothesis H3 was tested to answer this question about the outcome of collaboration and was reported as positive and statistically significant for both DPETO models. Not many research studies have conceptualised the digital platform ecosystem in exact terms as the DPETO model and with the quantitative evaluation of the significance of these relationships. Additionally, the newly developed scales and measurement items required validation and this initial PLS-SEM analysis established the validity of these measurement items. These findings confirm the presence of a meaningful relationship between the digital platform ecosystems' composition principles of platform AI and value creation and the vital role that they play with regards to the digital platform ecosystem outcomes of willingness to transact, network coopetition and collaboration. This is a novel finding as no known previous studies have empirically tested this relationship. The evidence from the analysis also highlights the role of digital platform ecosystem composition itself, such as the presence of artificial intelligence and the associated transaction behaviours concerning businesses across the financial services digital platform ecosystem domain. This evidence additionally advances digital platform ecosystems outcomes related research related to network-level behaviours such as collaboration and coopetition and their importance in shaping digital platform ecosystem transactional behaviours.

5.1.2 Effects of trust on digital platform ecosystem participation outcomes – without and with AI explainability

Critical to the proposed DPETO model in this research and after the validation of the digital platform composition principles, the effects of trust on the digital platform ecosystem were studied. This was essential to advance research regarding the theories of trust with regards to digital platform ecosystems and establish the validity of the conceptual framework. The hypothesis H4, H5 and H6 were tested for the effects of the digital platform ecosystem on the outcomes of willingness to transact, network coopetition and collaboration respectively and in the presence of trust as a mediator. Additionally, as noted in this research thesis earlier, artificial intelligence poses issues related to black box and artificial intelligence explainability is a potential way to understand this behaviour. Therefore, the effects of trust as a mediator was measured with (H4, H5, H6) and without (H7, H8, H9) the presence of xAI. Applying a PLS-SEM mediation approach, the results reported a highly significant and positive indirect relationship in all cases confirming the vital role of trust in facilitating transactional and cooperative behaviours within the digital platform ecosystem landscape. The analysis results also confirm the mediation effects to be stronger when trust was mediating the digital platform ecosystem outcomes in the influence of xAI, confirming the need to explain black box behaviours of platform AI as a composition principle of the digital platform ecosystem.

5.1.3 Effects of trust – Further validation of the model

The DPETO model as discussed in the sections so far, through a comprehensive analysis utilising the PLS-SEM methodology confirms that digital platform ecosystem strongly influences the outcomes of willingness to transact, network coopetition and collaboration when mediated by digital platform ecosystem trust. The role of explainability of the artificial intelligence principles used within the digital platform ecosystem however warranted further investigation and validation. To determine whether Digital Platform Ecosystem Trust, when mediated by Artificial Intelligence Explainability (xAI), is a more robust predictor model of digital platform ecosystem outcomes than non-explainability influenced Digital Platform Ecosystem Trust, a further analysis utilising the two DPETO models and model selection criteria of Asymptotically efficient and Asymptotically Consistent was conducted. Hypothesis H10 confirmed that the DPETO-xAI model, incorporating explainability influenced Digital Platform Ecosystem Trust, yielded smaller values, indicating superior predictive performance. These results suggested that the DPETO-xAI model is efficient and consistent for predicting digital platform ecosystem outcomes, specifically Willingness to Transact, Collaboration, and Network Coopetition. These findings are a critical contribution of this research and highlight the significance of integrating artificial intelligence explainability into trust models within the digital platform ecosystem and demonstrate the available potential to enhance predictive accuracy and model effectiveness.

5.1.4 Conditions that are meaningful and necessary

To further the understanding of the required levels of digital platform ecosystem trust for achieving the digital platform ecosystem outcomes, this research conducted a necessary condition analysis. Firstly, the digital platform ecosystem composition principles, ecosystem platform ecosystem AI serve as both a meaningful and necessary condition for achieving the outcomes of collaboration and willingness to transact. This confirms the role of artificial intelligence as an enabler in the digital platform ecosystem. Secondly, it was reported that the digital platform ecosystem trust servers as both a meaningful and necessary condition for achieving the digital platform ecosystem outcomes of collaboration and willingness to transact. Trust is critical consideration in digital platform ecosystems and these findings validate and advance research frameworks proposed in this thesis. Similarly, as hypothesised, the outcomes of digital platform ecosystems have influence over other outcomes. To understand these effects, a necessary condition analysis was conducted on the digital platform ecosystem outcomes. Firstly, for achieving the outcome of collaboration, both willingness to transact and network coopetition was a meaningful and necessary condition. This indicates that to achieve higher levels of collaboration (100% level) within the digital platform ecosystem participants should be willing and transact (at a 100% level) and exhibit traits of network co-opetition (at a 94% level). Secondly, for achieving higher levels of willingness to transact (100% level), some levels of collaboration (27%)and network coopetition (8%) are required. Lastly, for high levels of network coopetition (100%), some collaboration (25.5%) and some willingness to transact (41.8%) is required. These findings help understand and prioritise the digital platform ecosystem outcomes dependent on the scenario which require these outcomes at a certain expected level.

5.2 Contributions to theory

This research contributes to theory in multiple ways by answering the critical questions of this research. The Digital Platform Ecosystem Trust Outcomes (DPETO) model, a conceptual framework developed herein, integrates key theoretical constructs of digital platforms ecosystem and their associated transactional, value creating, outcomes. This model specifically delineates the role of trust within digital platform ecosystems and its mediating effect on associated outcomes. By addressing this, the model progresses with previously identified research gaps, particularly those highlighting the lack of frameworks incorporating trust and artificial intelligence within digital ecosystems (Senyo, Liu and Effah, 2019; Lillie et al., 2020). While examining the first research question, the DPETO model provides insights into how various components of the digital ecosystem foster participation. The empirical evidence suggests that these components have a positive influence on outcomes such as the willingness to engage in transactions, network coopetition, and collaboration. This finding is pivotal, as it highlights the importance of ecosystem components in enhancing active participation, a facet that has not been fully explored in existing literature (Adner, 2017).

The study also addresses a second research question regarding the existence of trust within digital platform ecosystems and its consequential impact on participation outcomes. The DPETO model is instrumental in illustrating that trust indeed serves as a mediating factor, enhancing the literature on digital platform ecosystems, trust frameworks, and participation outcomes. This contribution is particularly critical in light of the identified gaps that suggest a need for a deeper understanding of trust's role in these environments (Jacobides et al., 2019; Söllner et al., 2018).

Furthermore, the research probes into the effects of explainable artificial intelligence on the mediation of trust within the DPETO model. The analysis confirms that the presence of explainable AI significantly strengthens the trust mediator within the framework as compared to the absence of explainable AI. This is a unique and novel attempt to examine the effects of explainable artificial intelligence and how it affects trust in the digital platform ecosystem. This investigation into the influence of explainable AI on trust in digital platform ecosystems, contributes to an emerging area of research that marries complex technological advancements with human-centric factors such as trust.

The study's methodological approach, particularly the use of PLS-SEM analysis, facilitated a comparison of the DPETO model's efficacy with and without the inclusion of explainable AI's influence on trust. This comparison not only establishes the model's robustness but also accentuates the role of AI in shaping the dynamics of trust within digital platform ecosystems. Additionally, this research examines the emerging domain of necessary conditions within the digital platform ecosystem trust outcomes model. It explores the essentiality of relevant phenomena existing within digital ecosystems and their outcomes, as framed by primary literature on the subject (Dul, 2021). In terms of contributions, there are three possible formulations of a contributions with necessary condition analysis (Dul, 2021):

- Contributions in terms of a conversation on causal relationships of a phenomenon
- Contributions in terms of a conversation on if the factors are complementary to each other or substitutes
- Contributions in terms of a conversation on the necessity relationship of a phenomenon.

This research did not employ necessity logic when empirically testing these related relationships as it was primarily based on PLS-SEM analysis, and it is now known if these are a true necessity relationship. It was explored if these digital platform ecosystem relationships are necessary relationships, as they make a key difference in building theoretical understanding and practical actions. This research contributes by providing additional empirical evidence of digital ecosystems necessity relationships.

It concludes that digital platform ecosystem trust is a meaningful necessary condition for the digital ecosystem outcomes of Collaboration and Willingness to Transact.

In terms of artificial intelligence, the research ascertains its role as a critical and indispensable condition for fostering Collaboration and Willingness to Transact within the ecosystem. It further elaborates that willingness to transact and network coopetition are meaningful and significant necessary conditions for collaboration. Furthermore, Collaboration is a meaningful and significant necessary condition for Willingness to Transact, and Collaboration is a meaningful (and significant necessary condition) for Network Coopetition. This highlights that collaboration in turn is essential for fostering willingness to transact and nurture network coopetition within the ecosystem. This finding contributes a novel perspective to literature on the causal interplay between these elements, suggesting a reciprocal and necessary relationship amongst them.

Finally, this research advanced theoretical understanding by designing and implementing a new measurement instrument that adds to the rigour in testing requirements for the advanced analytical techniques employed in this study, specifically PLS-SEM. This methodological contribution ensures a more comprehensive analysis, reinforcing the validity and reliability of the research findings. The introduction of this instrument establishes a methodological advancement, advancing future research efforts in studying the complexities of digital platform ecosystems.

5.3 Contributions to advanced research methods

This research contributes to advanced research analytical methods by utilising PLS-SEM in this study to further strengthen the possibilities of the adoption of this in the domain of IS research. It has leveraged the PLS-SEM guidelines and standard best practices but has carefully adjusted the methodological approach where appropriate by combining it with other relevant research considerations and recommendations.

Furthermore, it has leveraged the PLS-SEM technique alongside the necessary condition analysis (NCA) technique (Richter et al., 2020), a newer method of analysis. No previous studies in the digital ecosystem platform domain have leveraged this technique. IS research and particularly in the emerging research in the area of digital platform ecosystems, is complex. Adding to the complexity are the newer conceptual models that could include many determinants and constructs that have not been studied previously. Necessary conditional analysis addresses the complexity by additionally qualifying the critical levels that are necessary for these constructs. This also helps with the creation of parsimonious research models that are value driven and are of utility to researchers and practitioners (Richter and Hauff, 2022). By utilising a mixed methodology, combining the PLS-SEM and NCA, researchers can test both necessity and sufficiency relationships. With the increased practical value due to these combinations, researchers can further identify critical constructs that relate to the best possible outcomes (using PLS-SEM), such as those tested in this research (Richter et al., 2020). NCA can be complementary to these findings, helping identify factors that are critical to achieve these possible outcomes. This combination, as highlighted in the methodology chapters, helps to derive must-haves and should-haves. This methodology has utility in many research fields, an example being HRM (human resource management) research. Other instances include testing theory-based necessity propositions in manufacturing disciplines. Other studies in IS include analysis of promotion of radical innovation through end user computing satisfaction, highlighting that for innovation it is necessary that employees share information and knowledge (Richter et al., 2020). This research aims to open up and highlight more avenues to future research applying PLS-SEM and NCA combination methodology. This combination method also presents opportunities to test existing and established models to advance existing theory. Similar to this research, NCA can also be applied to test mediation models and other PLS-SEM analyses such as those including moderation (Richter et al., 2020).

5.4 Contributions to practice

Integrating trust into the framework of digital platform ecosystems has emerged as a critical aspect in today's technology-driven era of business management. The digital platform ecosystem trust outcomes (DPETO) model, conceptualised in this study, represents a critical step towards embedding trust within these ecosystems. It addresses the necessity of trust for gaining strategic advantage in digital platforms. It also offers a comprehensive framework adaptable to various technological contexts without being limited to specific technologies. This adaptability highlights the model's potential to guide organisations through the changing technological landscape, establishing a trust-centric approach to managing digital platform ecosystems.

The practical and managerial implications of the DPETO model are manifold, offering insights into how trust building methodologies can be adopted and implemented within digital platform ecosystems. From a strategic perspective, the model provides a blueprint for organisations to embed trust as a core strategic and operational principle. It allows for the customisation of the framework to fit the unique and changing technological and contextual needs of organisations, ensuring that trust is effectively integrated into their digital ecosystem strategies.

Furthermore, on a managerial level (from an owner persona perspective), the DPETO model provides considerations for the adoption process, such as the identification of associated risks areas and the development of strategies for their mitigation. This is critical for practitioners and decision-makers who are responsible for designing these complex digital platform ecosystems. The model also serves as a guide for embedding trust into the ecosystem's architecture, ensuring that technological advancements, such as artificial intelligence (AI), are leveraged in a manner that enhances trust among end-users and participants / actors.

Empirical validation of the DPETO model through the testing of hypotheses (H1, H2, H3) using the PLS-SEM methodology has confirmed the positive influence of digital ecosystem principles on participation outcomes. These outcomes – willingness to transact, network coopetition, and collaboration, are critical for the success of creating these ecosystems from an ecosystem owner's perspective. The findings also highlight the significance of trust in enhancing these outcomes, thereby providing a strong rationale for organisations, particularly owners, to prioritise trust-building in their strategic planning.

Moreover, the investigation into the role of trust as a mediator, especially in the context of explainable AI (xAI), offers critical insights for all practitioners (owners and participants). Testing hypotheses (H4 through H9) revealed that the mediation effect of trust is strengthened in the presence of xAI, emphasising the importance of operational transparency. For owners, this highlights the need to incorporate xAI features into their digital platforms to explain AI operations, thereby fostering trust amongst ecosystem participants.

The DPETO model's application offers actionable strategies for organisations aiming to enhance their digital platform ecosystems. For ecosystem owners, the model provides a strategic framework to conceptualise integration of trust-building features systematically. This could include not only the technological considerations but perhaps also the cultural and operational adjustments they need to think about to embed trust as a foundational value within their organisations.

End-users and participants benefit from a more transparent, trustworthy digital platform ecosystem, encouraging more active engagement and collaboration. This creates the dynamics where increased participation leads to richer interactions and more value creating activities within the ecosystem.

Additionally, the model's emphasis on the role of AI and its explainability offers a forward-looking perspective for organisations. It suggests that the future of digital ecosystems lies not just in the complexity of technologies utilised, but in how these technologies are presented and understood by users. By adopting xAI, organisations can ensure that their digital platforms are not only technologically advanced but also accessible and trustworthy.

The DPETO model thus represents a paradigm shift in how organisations approach the integration of trust in digital platform ecosystems. It provides a comprehensive framework for understanding and implementing trust mechanisms in a way that aligns with technological advancements and user expectations. This approach is essential for fostering a digital ecosystem where trust acts as a catalyst for participation, collaboration, and value creation.

In conclusion, the DPETO model's practical contributions provide actionable insights into the strategic and managerial aspects of trust integration. This also highlights the importance of transparency in areas of user and multi-party engagement, ensuring digital platform ecosystems are equipped to foster creation of trust and collaboration.

5.5 Chapter summary

In this chapter, a comprehensive exploration of the research's implications unfolds. The chapter commences by describing the contributions to theory, unveiling new perspectives and frameworks that enrich the existing bodies of knowledge. The originality and depth of these theoretical contributions provide the foundation for further scholarly exploration in the field.

The chapter delves into the contributions to advanced research methods, showcasing innovative methodologies and approaches employed throughout the study. These methodological insights advance the current research paradigm and offer a blueprint for future investigations in similar domains.

Finally, the chapter elucidates the tangible contributions to practice that originate from the research. By bridging the gap between theoretical constructs and real-world applications, the study offers actionable insights that practitioners and their stakeholders can leverage. These contributions extend the boundaries of traditional academia and offer immediate value to professionals in relevant fields.

In essence, the chapter "Discussion and Contributions" summarises the comprehensive impact of the research, spanning theory, advanced research methods, and practice. It emphasises the significance of the study in shaping the field's theoretical relevance and its role as a catalyst for future explorations and practical implementations.

6 Conclusions, limitations, and future research

"As for the future, your task is not to foresee it, but to enable it."

– *Antoine de Saint Exupery*

6.1 Conclusions

Digital platform ecosystems are new ways of creating and delivering value across the network of actors, participants, and owners of these ecosystems. The key to this digital platform ecosystem' success depends on how trustworthy these value-creating activities are in engaging with these platforms for a set of expectations and associated outcomes. Newly formed conceptual models are a way forward in creatively questioning existing research. This was the aim of this research, where researchers were able to build a critical view on new propositions and frameworks derived from market environment dynamics, such as the COVID-19 pandemic, the rise in the adoption of artificial intelligence in platforms, etc.

This research leverages the relevance of trust theories and mechanisms and emerging technologies and their potential application in the control-trust nexus. A focus on value creation is maintained throughout. Therefore, this study emphasised the need for these digital platform ecosystems to exhibit, foster and channel trust and suggested that leveraging technologies such as explainable artificial intelligence within these platforms is beneficial to create high trust value in platform artificial intelligence.

This study first created a novel conceptual 'DPETO model' to bring the disciplines of digital platform ecosystems and underlying enabler technologies such as artificial intelligence, which are increasingly used to power these platforms and the theories of trust in technological contexts. The DPETO model was then tested for multiple iterations, where the digital platform ecosystem outcomes of collaboration, willingness to transact and network coopetition are mediated by the trust with and without the influence of explainable artificial intelligence.

When it comes to meaningful and necessary conditions, digital platform ecosystem trust was found not to be a meaningful and not significant necessary condition for digital ecosystem network coopetition. Similarly, the digital platform ecosystem AI was reported as not a meaningful and not a significant necessary condition for digital platform ecosystem network coopetition. Additionally, it was found that digital platform ecosystem network coopetition is not a meaningful and not a significant necessary condition for willingness to transact. These findings highlight that network coopetition is an outcome that is mostly independent of other digital platform ecosystem outcomes but has some influence (medium effect) on digital platform ecosystem collaboration.

This research concludes that the digital platform ecosystem outcomes are significantly mediated by digital platform ecosystem trust and provide perspectives on necessary conditions that are necessary but insufficient for these outcomes.

6.2 Limitations and future research

This research is limited to the context and boundaries of the financial services digital platform ecosystem. This is evident from the demographics of the respondents of the research data collection instruments and the scope of this research. Other limitations exist around the newly developed scales and the limited empirical testing of the ‘novel’ constructs of the DPETO model developed in this research. The methodology around literature review is limited to studies included to form the theoretical basis and grounding. Due to the inconsistent behaviour of the search keywords and string operators in academic databases, there may be instances where some specific topics might be missing. However, attempts were made to minimise this by conducting both broad searches and specific searches on all major databases selected. Furthermore, searching specific databases is a bias-based limitation itself, as the research is limited to the content repositories. This research relies on the IS research best practices to avoid such bias. Therefore, the results of this research should be considered alongside these limitations and the scope of the research. However, as appropriate, the research contributions can be generalised further to advance theory and practice in the digital platform ecosystems and trust research domains.

Additionally, researchers in this area can benefit from future advancements by understanding the transforming role of the digital platform ecosystem as organisational structures and the governance and managerial aspects of these platforms and their implications for the discipline of business management. There are traces of such work beginning to surface (Kretschmer et al., 2022; Gawer, 2023). Future research should be conducted to test the DPETO model for multiple technologies, the associated trust, and how it mediates digital ecosystem outcomes. This research focused only on the digital platform ecosystem context. Future research in the digital platform ecosystems can focus on exploring several of the questions beyond the scope of this research (Table 36).

Table 38: Future research agenda for Digital Platform Ecosystems, Trust, External Factors and DPE Outcomes

Body of knowledge	**Future research agenda**
Digital Platform Ecosystems	• Explore detailed contextual components of digital platform ecosystem • Define digital platform ecosystem modularity and explore other technologies • Explore the dynamics of digital platform ecosystem as an organisational form
Trust	• Further validation of trust definitions and how they evolve in the context of digital platform ecosystems • Explore and validate trust acquisition and loss in the digital platform ecosystem • Explore and validate technological factors that affect trust in digital platform ecosystems
Factors	• Explore and validate environmental factors influencing the digital platform ecosystems and trust interplay and how policies influence the development in this field Explore and validate newer emerging technologies influencing digital platform ecosystem dynamics
Outcomes	• Explore and validate other outcomes such as those related to willingness to transact, collaboration and network coopetition

Furthermore, a demonstration can be conducted involving the DPETO model as an artefact in experimentation, simulations, case studies and other activities appropriate to the context. Evaluation of these DPETO as an artefact would overall measure aspects such as support provided as a solution to the problem. This will further require other relevant metrics and analysis dependent on the nature of the problem being explored. Using the conceptual model design evaluation methods (Hevner et al., 2004), these evaluations would iterate back to the conceptual model design and observe the effectiveness and efficiencies of the solutions Table **39**. There is also a need to research methodologies for acquiring and losing trust in the DPETO model. The DPETO model can also be used in future research to understand and measure the effects of environmental factors, such as policy, that may influence trust in digital ecosystems.

Table 39: Proposed design evaluation methods based on Henver et al. 2004

Method	DEPTO model	Future research agenda (FRA) validation
Observational	**Case Study:** Study the conceptual model in depth in digital platform ecosystem environments Field Study: Monitor the use of the conceptual model in multiple projects	**Case Study:** Study the FRAs in-depth in digital platform ecosystem environments Field Study: Monitor the use of the FRAs in multiple projects
Analytical	**Architecture Analysis:** Study the fit of the conceptual model into technical IS architecture.	**Optimisation:** Demonstrate optimal properties of FRAs components. Dynamic Analysis: Study the propositions in use for dynamic qualities (e.g., level of trust)
Experimental	**Controlled Experiment:** Study the conceptual model in a controlled environment for qualities, e.g. user acceptance Simulation: Simulate the conceptual model with artificial data	**Controlled Experiment:** Study the FRAs in a controlled environment for qualities, e.g. trust, security etc.
Descriptive	**Informed Argument:** From the knowledgebase (e.g. knowledge from a literature review conducted), build a convincing argument for the conceptual model's utility. Scenarios: Construct detailed scenarios around the conceptual model to demonstrate its utility.	**Informed Argument:** From the knowledgebase (e.g. knowledge from a literature review conducted), build a convincing argument for the utility of the future research agenda. Scenarios: Construct detailed scenarios around the FRAs to demonstrate their utility.

This research was inspired by human intelligence and how combining familiarity, exploration and synthesis of unthinkable ideas can generate novel ideas (Boden, 2014). Hopefully, the future will witness trusted AI models that can critique their own ideas, advancing management research in trust in the digital platform ecosystem to the next apex.

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Appendix A: Survey questionnaire

Dear Participant,

You are being asked to take part in a research study that aims to understand “Effects of AI Explainability on Trust in Financial Services Digital Ecosystem Platforms”. This study is part of a PhD research by researcher Tarun Rohilla, Henley Business School, University of Reading, UK. You will be expected to answer the survey questionnaire. The research has received a favourable review by the Business Informatics, Systems and Accounting ethics office, Henley Business School, University of Reading.

Your participation
In this study, you will be asked to carefully review the questions presented in this survey questionnaire and answer these to the best of your knowledge and ability. Please follow the instructions for each question section carefully and select the appropriate option from the scales presented or alternatively enter your response in the text box or select using the alternatives provided. Your participation should not take longer than 15 minutes.
Data Storage
All data is stored in the Qualtrics survey platform and Microsoft OneDrive hosted by the University of Reading (Henley Business School, UK). Backup copies are made on a local hard drive and never shared with anyone outside the research team. Data is destroyed after five years as part of the International data protection act.
Right to withdraw
You can stop being a part of the research study at any time with no need for an explanation. You have the right to ask that any data you have supplied to that point be withdrawn or destroyed, you also have the right to omit or refuse to answer or respond to any question that is asked of you. You have the right to have your questions about the procedures answered, before, or after the experiment.
Risks
There are no foreseeable risks.
Cost, reimbursement, and compensation
Your participation in this study is subject to the policies underpinning the platform where this survey was distributed to you any monetary compensation (if any) would be based on the platform policies.
Confidentiality/anonymity
The data we collect does not contain any personal information and any records of this study (either hard copy or electronic) will be kept private. In any sort of report, we make public we will not include any information that will make it possible to identify you. Research records will be accessed only by the research team.

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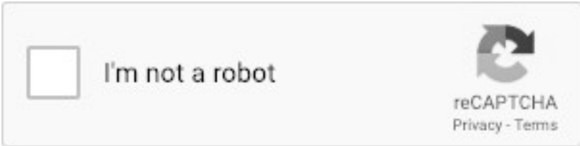
Please confirm that you are a human being



How were you selected to participate in this survey?

- ○ Prolific
- ○ Other Please answer how were you selected to participate in this survey?____

I confirm I'm aged 18 year or over and that I have read and understood the information sheet for the above study. I have had the opportunity to consider the information, ask questions, and have had these answered satisfactorily. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason. I agree to take part in the above study.

- ○ Agree
- ○ Disagree

Survey Block: Automatically Capturing Prolific ID
What is your Prolific ID? Please note that this response should auto-fill with the correct ID if you are accessing the survey through Prolific.
If not filled automatically, please enter
manually. ____

Survey Block: Definitions
For this research below are the definitions in use, please spend some time familiarising yourself with these

Digital Ecosystem Platform
"A digital ecosystem platform is a digital / online platform where participants collaborate, consume and complement each other's products and services organised by an overarching goal."
Digital Ecosystem Platform Participant / Actor
"A digital ecosystem platform participant or actor is comprised of either individuals or organisations that participate in a digital ecosystem either as a provider or as a consumer."
Digital Ecosystem "Platform" Owner / Provider
"A digital ecosystem platform owner / provider is the responsible party for maintaining and

managing the digital platform without taking the role of a hierarchical authority."

Digital Ecosystem Platform End-User

"A digital ecosystem platform end-user is a digital ecosystem participant or actor often only interested in consuming products and services available on the ecosystem platform."

AI Explainability (xAI)

"Artificial intelligence explainability or xAI or Explainable AI is the principle of explaining AI to humans, contrasting the idea of AI Black Box where AI behaviour cannot be explained."

Network Coopetition

"Multiple participants on the digital ecosystem interacting, often collaborating with direct competition that bring benefits to both."

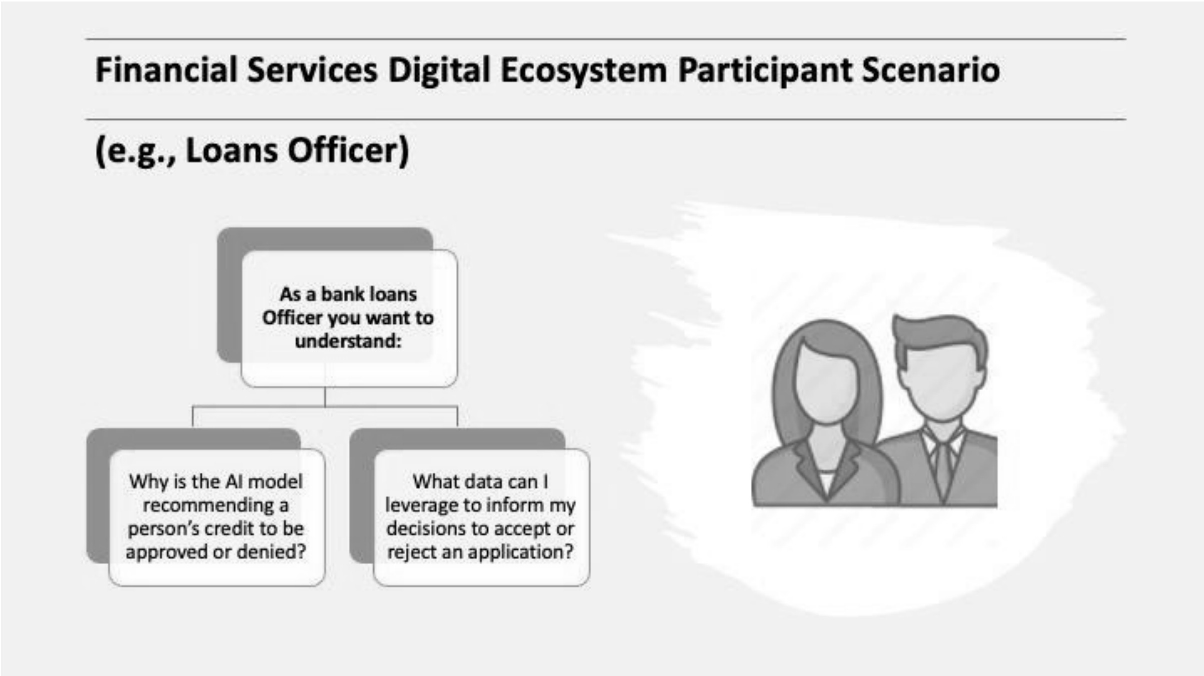
Start of Block: Digital Ecosystem Qualify

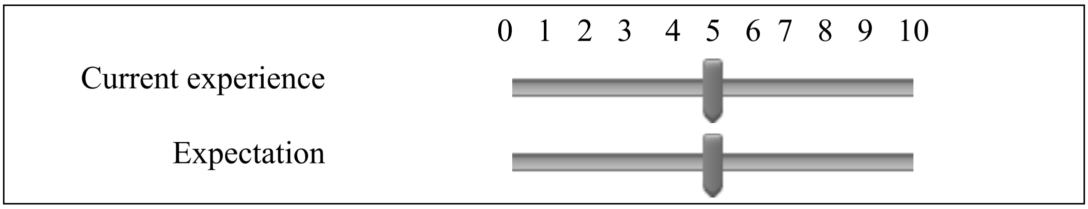
Please review the statements below and select the responses that best matches your persona. Please complete the survey with your experience of a financial services digital ecosystem platform

Select your predominant persona(role) in the financial services digital ecosystem platform

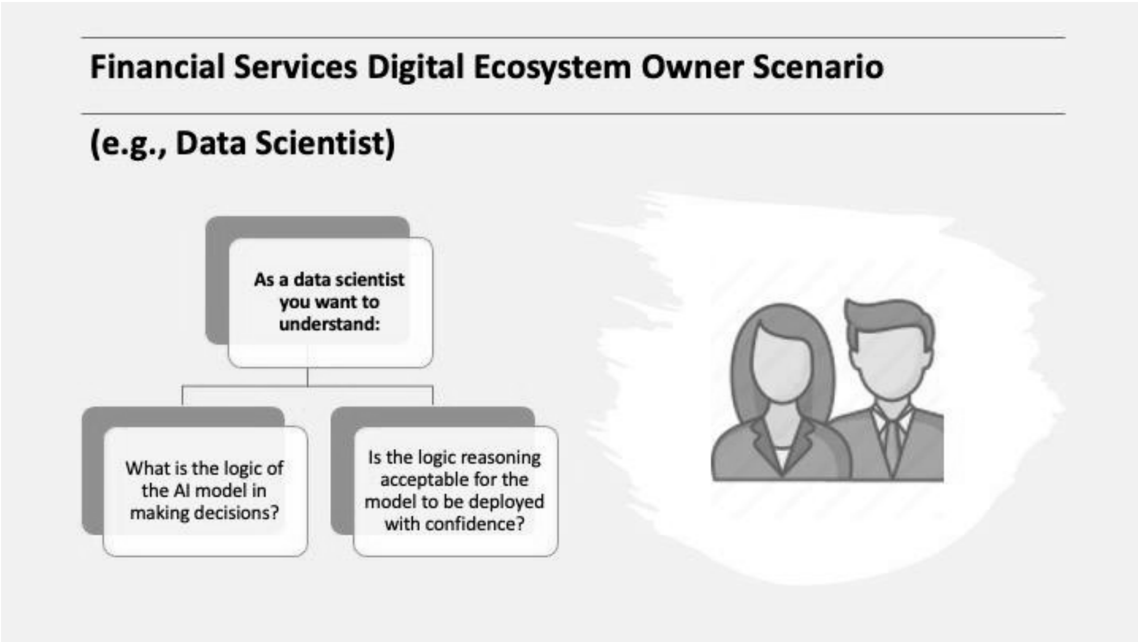
- ○ A Digital Ecosystem Platform End-User in the financial services domain
- ○ A Digital Ecosystem platform Owner in the financial services domain
- ○ A Digital Ecosystem Platform Participant in the financial services domain

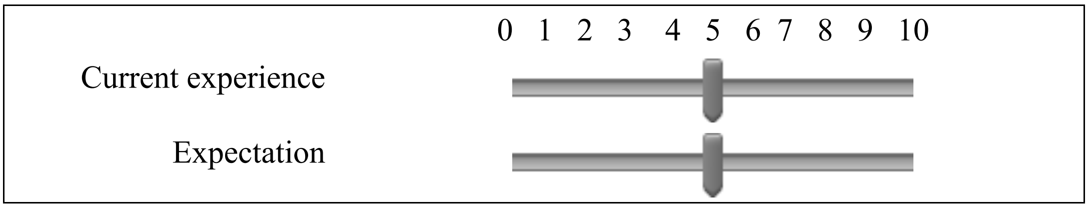
Digital Ecosystem Participant Persona Scenario
Based on the below scenario, please rate the current and ideal level of explanations to the best of your experience of the financial services digital ecosystem



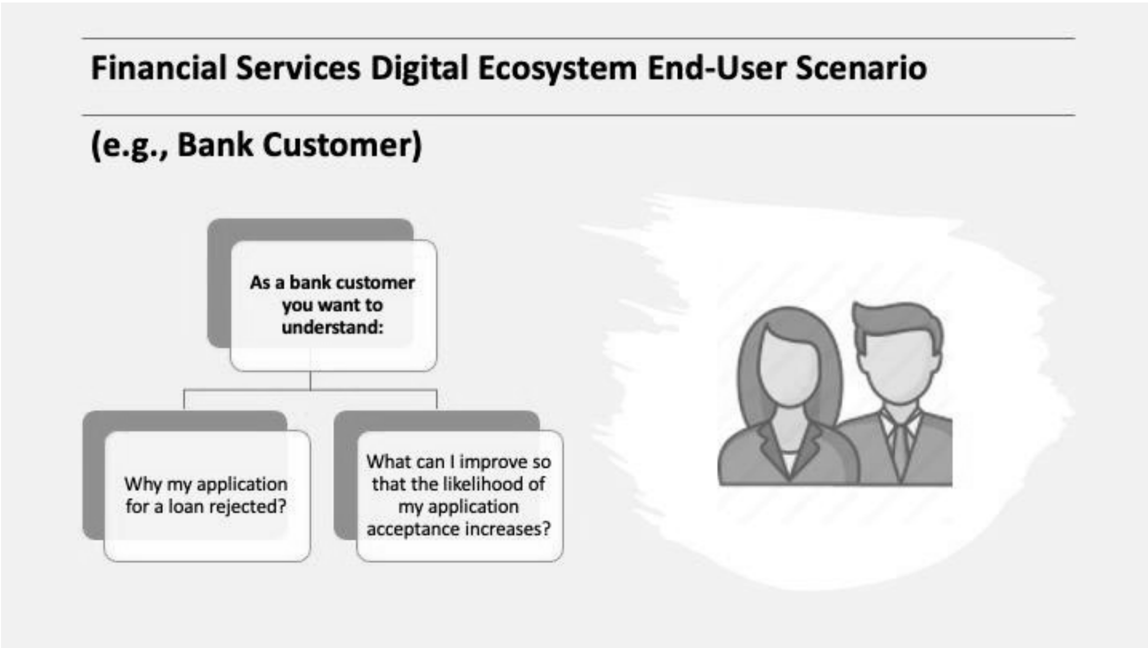


Digital Ecosystem Owner Persona Scenario
Based on the below scenario, please rate the current and ideal level of explanations to the best of your experience of the financial services digital ecosystem





Digital Ecosystem End-User Persona Scenario
Based on the below scenario, please rate the current and ideal level of explanations to the best of your experience of the financial services digital ecosystem



	0 1 2 3 4 5 6 7 8 9 10
Current experience	
Expectation	

Rate the importance of each level of explanation as per the below outline:

	0 1 2 3 4 5 6 7 8 9 10
Level 1 Some indicators of explanation	
Level 2 Provides further insights into explanations	
Level 3 Provides details information into level 2 explanations	

Generally about AI Explainability and algorithmic explanations please assess the below statements:

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Explanations at systems level within digital ecosystem platforms are:	○	○	○	○	○
Machine/Systems understandable explanations are:	○	○	○	○	○

Generally about AI Explainability and algorithmic explanations please assess the below statements

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Explanations at user level within digital ecosystem platforms are:	○	○	○	○	○
User / human understandable explanations are:	○	○	○	○	○

Generally about AI Explainability and algorithmic explanations please assess the below statements

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Persona specific explanations within digital ecosystem platforms are:	○	○	○	○	○
User / human understandable explanations are:	○	○	○	○	○

Please provide the description of the financial services digital ecosystem platform that you are experienced / familiar with (Add example URL)____

Please assess the digital ecosystem platform's technological features based on the statements presented below:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Artificial intelligence is an enabler of digital ecosystem platform	○	○	○	○	○	○	○
Digital ecosystem platform exhibit black box behaviour	○	○	○	○	○	○	○
Digital ecosystem platform employ artificial intelligence enabled (algorithmic) decision making	○	○	○	○	○	○	○
AI-enabled automated outcomes within digital ecosystem platforms are explained	○	○	○	○	○	○	○
AI-enabled automated outcomes within digital ecosystem platforms are understandable	○	○	○	○	○	○	○

Please assess the below statements related to value features in digital ecosystem platform:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Explanations foster trust within digital ecosystem platforms	○	○	○	○	○	○	○
Digital ecosystem platforms are trustworthy	○	○	○	○	○	○	○
Digital ecosystem platforms enables interactions between autonomous complementors and consumers	○	○	○	○	○	○	○
Trust enabling technologies offered by technological modularity are integrated within digital ecosystems	○	○	○	○	○	○	○
Technological modularity within digital ecosystems enables trust generation technologies	○	○	○	○	○	○	○

Based on your experience in financial services digital ecosystem platforms,
Please assess the below statements about Explanation Methods for machine learning models

	Not at all important	Low importance	Slightly important	Neutral	Moderately important	Very important	Extremely important
Structure of the explanation method	○	○	○	○	○	○	○
Reliance on looking into the machine learning model	○	○	○	○	○	○	○
Number of machine learning models covered in the explanation method	○	○	○	○	○	○	○
Time taken for the generation of explanations	○	○	○	○	○	○	○

Based on your experience in financial services digital ecosystem platforms,
Please assess the below statements about Individual Explanations

	Not at all important	Low importance	Slightly important	Neutral	Moderately important	Very important	Extremely important
Accuracy when fidelity is essential	○	○	○	○	○	○	○
Prediction of the black box machine learning model	○	○	○	○	○	○	○
Extent of consistency among explanations for different machine learning models on the same job	○	○	○	○	○	○	○
Extent of similarity of explanations for similar instances	○	○	○	○	○	○	○
Extent to which the recipient of explanation understands the explanation	○	○	○	○	○	○	○
The probability of the target class of the machine learning model	○	○	○	○	○	○	○
Coverage of the important features or how well the explanation reflects parts of the explanations	○	○	○	○	○	○	○

Please assess the below presented statements regarding your experience of digital ecosystem platform usage

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Digital ecosystem platform has the skills and expertise to perform transactions in an expected manner	○	○	○	○	○	○	○
Digital ecosystem platform has access to the information needed to handle transactions appropriately	○	○	○	○	○	○	○
Digital ecosystem platform is fair in its conduct of transactions	○	○	○	○	○	○	○
Digital ecosystem platform is fair in its use of private user data collected	○	○	○	○	○	○	○
Digital ecosystem platform is fair in its transactional policies	○	○	○	○	○	○	○
Digital ecosystem platform is open and receptive to participants/actors needs	○	○	○	○	○	○	○
Digital ecosystem platform makes good-faith efforts to address most participants concerns	○	○	○	○	○	○	○
Overall, digital ecosystem platform is trustworthy	○	○	○	○	○	○	○

Please assess the below presented statements regarding your experience of interacting with digital ecosystem platform

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I believe that there could be negative consequences when using the digital ecosystem platform	○	○	○	○	○	○	○
I feel I must be cautious when using the digital ecosystem platform	○	○	○	○	○	○	○
It is risky to interact with the digital ecosystem platform	○	○	○	○	○	○	○
I believe that the digital ecosystem platform will act in my best interest	○	○	○	○	○	○	○
I believe that the digital ecosystem platform will do its best to help me if I need help	○	○	○	○	○	○	○
I believe that the digital ecosystem platform is interested in understanding my needs and preferences	○	○	○	○	○	○	○
I think that the digital ecosystem platform is competent and effective in its AI algorithms and outcomes	○	○	○	○	○	○	○
I think that the digital platform ecosystem performs its role as a digital platform very well	○	○	○	○	○	○	○
I believe that digital ecosystem platform has all the functionalities I would expect from a digital platform	○	○	○	○	○	○	○
If I use the digital ecosystem platform, I think I would be able to depend on it completely	○	○	○	○	○	○	○
I can always rely on the digital ecosystem platform for AI algorithms and outcomes	○	○	○	○	○	○	○
I can trust the information presented to me by the digital ecosystem platform	○	○	○	○	○	○	○

Please assess the below statements regarding the network coopetition and trust within digital ecosystem platform

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Decision to join network coopetition is fostered by reputation based trust	○	○	○	○	○	○	○
Decisions to join network coopetition is fostered by third party legitimisation	○	○	○	○	○	○	○
Trust-based coordination techniques for operating procedures facilitate effectiveness vs traditional contracts	○	○	○	○	○	○	○

Please assess the below statements regarding collaboration in financial services digital ecosystem platforms

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Digital ecosystem platform participants engage in collaboration for value creation	○	○	○	○	○	○	○
Technological modularity facilitates collaboration in digital ecosystem platform	○	○	○	○	○	○	○
Collaboration in the digital ecosystem platform is achieved by leveraging technological modularity	○	○	○	○	○	○	○
Digital ecosystem platform empowers participants with value creation opportunities	○	○	○	○	○	○	○
Artificial intelligence in digital ecosystem platform fosters collaboration between participants	○	○	○	○	○	○	○
Weak trust may erode cooperation within digital ecosystems	○	○	○	○	○	○	○
High trust allows stronger partnering	○	○	○	○	○	○	○
Trust is essential to develop a partnering strategy	○	○	○	○	○	○	○
Partnering with competitors is likely if perceived to be honest and reliable	○	○	○	○	○	○	○
Trust facilitates knowledge exchange	○	○	○	○	○	○	○

Please assess the below statements regarding willingness to transact in financial services digital ecosystem platforms

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I intend on using digital ecosystem platform for some of my future transactions (financial services transactions)	○	○	○	○	○	○	○
I am inclined to procure digital ecosystem platform's offered goods and services	○	○	○	○	○	○	○
I am likely to utilise the services offered by the digital ecosystem platform	○	○	○	○	○	○	○

Please assess the below statements regarding Artificial Intelligence Explainability (xAI) and your trust in financial services digital ecosystem platforms

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Enables digital ecosystem platform to perform transactions in an expected manner	○	○	○	○	○	○	○
Aids digital ecosystem platforms access to the information needed to handle transactions appropriately	○	○	○	○	○	○	○
Aids digital ecosystem platforms to be fair in its conduct of transactions	○	○	○	○	○	○	○
Aids digital ecosystem platform fairness in its use of private user data collected	○	○	○	○	○	○	○
Aids digital ecosystem platform fairness in its transactional policies	○	○	○	○	○	○	○
Aids digital ecosystem platform to be open and receptive to participant/actor needs	○	○	○	○	○	○	○
Aids digital ecosystem platform to make good-faith efforts to address most participant concerns	○	○	○	○	○	○	○

Please assess the below statements regarding your perception of Artificial Intelligence Explainability (xAI) within financial services digital ecosystem platforms

When Artificial Intelligence Explainability (xAI) is included in the financial services digital ecosystem platform:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I believe that there could be negative consequences when using the digital ecosystem platform	○	○	○	○	○	○	○
I feel I must be cautious when using the digital ecosystem platform	○	○	○	○	○	○	○
It is risky to interact with the digital ecosystem platform	○	○	○	○	○	○	○
I believe that the digital ecosystem platform will act in my best interest	○	○	○	○	○	○	○
I believe that the digital ecosystem platform will do its best to help me if I need help	○	○	○	○	○	○	○
I believe that the digital ecosystem platform is interested in understanding my needs and preferences	○	○	○	○	○	○	○
I think that the digital ecosystem platform is competent and effective in its AI algorithms and outcomes	○	○	○	○	○	○	○
I think that the digital platform ecosystem performs its role as a digital platform very well	○	○	○	○	○	○	○
I believe that the digital ecosystem platform has all the functionalities I would expect from a digital platform	○	○	○	○	○	○	○
I use the digital ecosystem platform, I think I would be able to depend on it completely	○	○	○	○	○	○	○
I can always rely on the digital ecosystem platform for AI algorithms and outcomes	○	○	○	○	○	○	○
I can trust the information presented to me by the digital ecosystem platform	○	○	○	○	○	○	○

In which country do you currently reside in?

- ○ UK
- ○ USA
- ○ Other ____

How old are you?

- ○ 18-24 years old
- ○ 25-34 years old
- ○ 35-44 years old
- ○ 45-54 years old
- ○ 55-64 years old
- ○ 65+ years old

How do you describe yourself

- ○ Male
- ○ Female
- ○ Non-binary / third gender
- ○ Prefer not to say

What is the highest level of school you have completed or the highest degree you have received?

- ○ Less than high school degree
- ○ High school graduate (high school diploma or equivalent including GED)
- ○ Some college but no degree
- ○ Associate degree in college (2-year)
- ○ Bachelor's degree in college (4-year)
- ○ Master's degree
- ○ Doctoral degree
- ○ Professional degree (JD, MD)

What type of organisation do you work for?

- ○ Private Sector
- ○ Public Sector

- ○ Other (Please specify) ____

Based on the number of employees, what is the size of the organisation where you work?

- ○ 1-4
- ○ 5-9
- ○ 10-19
- ○ 20-49
- ○ 50-99
- ○ 100-249
- ○ 250-499
- ○ 500-999
- ○ 1000 or more

Which option below best describes your job role?

- ○ Executive Management
- ○ Senior Director
- ○ Director
- ○ Senior Manager
- ○ Manager
- ○ Specialist (e.g. Engineering services, Software Development etc.)
- ○ Consultant (e.g. External contractor, advisor etc.)
- ○ Other ____

Will you be willing to participate further in an interview for this study on digital ecosystems and trust?

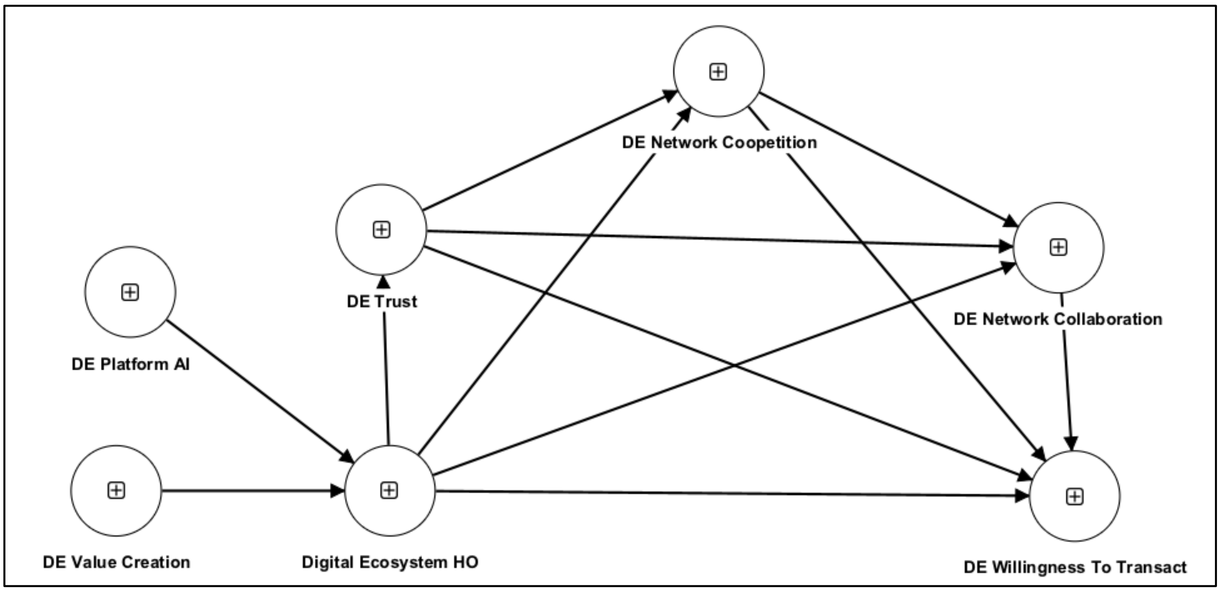
- ○ Yes
- ○ No

Please provide your contact details for further participation

- ○ Name ____
- ○ Work email address ____

Appendix B: The saturated model

The saturated model used to calculate R2 of the target construct. Saturated model with all predictors predicting target construct.



Appendix C: Necessary condition analysis R code

```
install.packages("NCA")
library(NCA)

#NCA1 for Willingness to transact
model1 <- nca_analysis(LVScoresxAINov23, (c("DE Trust", "Digital Ecosystem HO", "DE Platform AI", "DE Value Creation")), "DE Willingness To Transact", test.rep = 10000)
nca_output(model1, plots = TRUE, summaries = TRUE)
nca_output(model1, bottlenecks = TRUE, summaries = FALSE)

#NCA2 for DE Collaboration
model2 <- nca_analysis(LVScoresxAINov23, (c("DE Trust", "Digital Ecosystem HO", "DE Platform AI", "DE Value Creation")), "DE Collaboration", test.rep = 10000)
nca_output(model2, plots = TRUE, summaries = TRUE)
nca_output(model2, bottlenecks = TRUE, summaries = FALSE)

#NCA3 for DE Network Coopetition
model3 <- nca_analysis(LVScoresxAINov23, (c("DE Trust", "Digital Ecosystem HO", "DE Platform AI", "DE Value Creation")), "DE Network Coopetition", test.rep = 10000)
nca_output(model3, plots = TRUE, summaries = TRUE)
nca_output(model3, bottlenecks = TRUE, summaries = FALSE)

#NCA4 for DE Willingness To Transaction , DE Collaboration and DE Network Coopetition
model4 <- nca_analysis(LVScoresxAINov23, (c("DE Collaboration", "DE Network Coopetition")), "DE Willingness To Transact", test.rep = 10000)
nca_output(model4, plots = TRUE, summaries = TRUE)
nca_output(model4, bottlenecks = TRUE, summaries = FALSE)

#NCA5 for DE Willingness To Transaction , DE Collaboration and DE Network Coopetition
model5 <- nca_analysis(LVScoresxAINov23, (c("DE Willingness To Transact", "DE Network Coopetition")), "DE Collaboration", test.rep = 10000)
nca_output(model5, plots = TRUE, summaries = TRUE)
nca_output(model5, bottlenecks = TRUE, summaries = FALSE)

#NCA6 for DE Willingness To Transaction , DE Collaboration and DE Network Coopetition
model6 <- nca_analysis(LVScoresxAINov23, (c("DE Collaboration", "DE Willingness To Transact")), "DE Network Coopetition", test.rep = 10000)
nca_output(model6, plots = TRUE, summaries = TRUE)
nca_output(model6, bottlenecks = TRUE, summaries = FALSE)
```