Trusting the Unknown: The Impact of Artificial Intelligence on Inter-Organisational Trust

Luodi Pan (luodi.pan.16@mail.wbs.ac.uk)
Warwick Business School, University of Warwick, Coventry, UK

Mehmet Chakkol
Warwick Business School, University of Warwick, Coventry, UK

Kostas Selviaridis
Lancaster University Management School, Lancaster, UK

Abstract:

This research explores how Artificial Intelligence (AI) driven digital transformation influences trust in inter-organisational relationships. The study adopts an embedded case study design whereby three AI-driven services, differing in their complexity, were studied within the Chinese e-commerce sector. The wider contribution of the study is towards the OSCM literature by providing insights into the interplay between inter-organisational trust and trust in the AI technology, a timely and emerging research area. Specifically, we contribute to the OSCM literature by exploring theoretically and empirically the relationships between complexity and trust building process in AI-driven digital transformation contexts.

Keywords: Digital transformation, artificial intelligence, technological complexity, trust

1. Introduction

Digital transformation is increasingly changing operations, firms and supply chains by automating jobs, introducing major sources of innovation and creating new service opportunities, thus contributing to market competitiveness (Kache & Seuring, 2017). At the same time, digital transformation threatens jobs, replaces human interactions and entails new mechanisms for governing technology-enabled integration amongst supply chain partners (Huang & Rust, 2018). Importantly, extant research on digital transformation shows trust between organisations is a major driver for technology adoption (Gefen et al., 2003; Choi & Ji, 2015). Trust is vital for effective information sharing, operational linkages, and cooperative norms amongst supply chain partners (Ghosh & Fedorowicz, 2008). However, prior studies offer limited theoretically driven and empirically grounded research exploring the relationship between digital transformation and trust development in inter-organisational relationships. A focus on competence and goodwill trust in these inter-organizational relationships is vital to understand the impact of digital transformation. Specifically, the adoption of artificial intelligence (AI) and its impact on trust development is largely unknown (Hengstler et al., 2016). This is despite many experts consider AI as one of the most disruptive technological innovations of recent times that may fundamentally change how inter-organisational relations are governed.

More specifically, prior work offers limited insights on the impact of different levels of AI complexity on inter-organisational relationship dynamics. This research explores how digital transformation impacts inter-organisational competence and goodwill trust following the adoption of B2B AI services in the Chinese e-commerce sector. Given the importance of trust in governing inter-organisational relationships (Cao and Lumineau, 2015; Ghosh and Fedorowicz, 2008) and especially in relationships in China (e.g. Dobrucali, 2019; Wang, 2007; Yen et al, 2011), the research depicts how the provider of AI-enabled services uses different means of trust building mechanisms successfully to mitigate the black-box handicaps of AI platforms.

2. Literature review

2.1 Digital transformation in supply chains and the role of AI

The literature on digitally-enabled operations and supply chains unanimously recognises the potentially disruptive impact of emerging technologies on processes and practices across the value chain including manufacturing, distribution and logistics, and supply management (e.g. Frank et al., 2019; Min et al., 2019; Ivanov et al., 2019). Digital technologies including AI, robotics, blockchain, internet of things, and additive manufacturing (3D-printing) have the potential to improve productivity, reduce costs and increase customer service levels by increasing efficiency of supply chain processes and enabling effective decision making (KPMG, 2019; Balan, 2018).

The more specific literature on AI-based technologies examines their potential application areas and evaluates its likely effects on operations and supply chains (e.g. Min, 2010; Waller and Fawcett, 2013; Klumpp and Zijm, 2019). AI technologies fundamentally seek to learn from and to mimic human behavioural patterns to replace human beings in decision making and problem-solving activities (Bathaee, 2018; Min, 2010). AI-based technologies transform supply chains as we transition from task automation to (partly) autonomous action of computer programs. In such cases, the division of labour between humans and computers becomes blurred, and human operators need to know when to intervene to override the computers' actions and decisions (Klumpp and Zijm, 2019). Although the adoption of AI in supply chains has been relatively slow, specific sub-disciplines of AI such as expert systems, agent-based systems and genetic algorithms have been applied to inventory management, sourcing, and distribution network design and planning problems (Min, 2010).

Effective implementation of AI technologies in supply chain settings requires consideration of the varying purposes and functionalities of such technologies. Davenport and Ronanki (2018) identify three types of AI-based on how they contribute to meeting business needs: process automation, provision of cognitive insights through data analysis, and cognitive engagement with employees and external organisations such as customers. AI technologies intervene and replace employees at the task level, rather than the job level (Huang and Rust, 2018). Klumpp and colleagues (2019; 2017) identify challenges with respect to the acceptance of AI technologies in supply chains, which is driven by human perceptions regarding the AI technologies' competence and level of autonomous action. They also stress the important role of trust in increasing AI acceptance: developing trust in AI applications entails that employees and managers perceive the machine to be, behave and communicate like a human being (Klumpp and Zijm, 2019). This might also become more complicated when the complexity increase. In this research, we adopt a multifaceted definition of complexity in line with Benedettini and Neely (2011, 2012). As such we conceptualise AI complexity as a synthesis of intelligence difficulty (Huang and Rust, 2018) as well as service complicatedness (Tien, 2008).

Trust issues are particularly pertinent in the case of AI-based technologies because of their 'black-box' properties (Choi and Ji, 2015). Bathaee (2018, p.905) refers to this black-box problem as *"...an inability to fully understand an AI's decision-making process and the inability to predict the AI's decisions or outputs"*. AI technologies are underpinned by deep learning, neural networks, and statistical machine learning methods (Choi, Wallace and Wang, 2018), which provide algorithms for computers or robots to make decisions through learning from large datasets that are beyond the comprehension of the human mind. As such, it is arguably impossible to understand fully how these AI applications turn inputs into decisions. In other words, the decision-making process lacks transparency – even for the designers and software engineers who create such AI systems (Bathaee, 2018). Hence it poses major challenges for providers of AI solutions, as they need to communicate and demonstrate to their customers that AI-enabled decisions and autonomous actions are trustworthy (Hengstler et al., 2016).

2.2 Trust and technology adoption

Research on technology acceptance and adoption has long stressed that trust mediates the interaction between human beings and computers (e.g. Alpcan et al., 2010; Gefen et al., 2003). The notion of trust offers a solid conceptual foundation for understanding the relationship between humans and automation insofar as technology acceptance depends on user beliefs that the technology functions as expected (Ghazizadeh et al., 2012). The existing literature presents two main views with regard to the object(s) of trust – while some studies focus on trust in the technology provider (e.g. Gefen et al., 2003; Yan and Holtmanns, 2008; Sternberg et al., 2020), others emphasise the trustworthiness of the technology itself (e.g. Lee and Moray, 1992; Hengstler et al., 2016).

Research on trust in the technology provider draws on the broader literature on inter-organisational trust. Trust constitutes, "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al., 1995, p. 712). The trust literature draws a distinction between competence and goodwill trust (Das and Teng, 2001; Ireland and Webb, 2007). While competence trust is defined as "*the expectation of technically competent role performance*" towards the supplier (Das and Teng, 2001, p. 256), goodwill trust is defined as *"the expectation that some others in our social relationships have moral obligations and responsibility to demonstrate a special concern for other's interests above their own*" (Das and Teng, 2001, p. 256). This distinction is also relevant for research on the interplay between digital transformation and inter-organisation trust. Sternberg et al. (2020), for instance, highlight a "trust investment paradox": inter-firm trust based on goodwill is a prerequisite for making investments in blockchain technologies whose purpose, in the first place, is to increase transparency and enhance trust among supply chain counterparts.

A separate stream of literature (e.g. Rempel et al., 1985; Lee and Moray, 1992; Hengstler et al., 2016) disentangles trust in the technology from trust in individuals and /or organisations involved in the provision of technological solutions, and focus on trust-related attributes of the technology itself. McKnight et al. (2011) propose that trust in a specific technology relies not only on a user's evaluation of its functionality, helpfulness and reliability, but also depends on perceptions of situational normality, and a person's faith and trusting stance towards technologies more generally.

In a similar vein, Lee and Moray (1992) show that that trust in automation depends on system performance and the occurrence of faults, and that it is also a function of past performance observations. Building on Lee and Moray (1992), Hengstler et al. (2016) suggest that information regarding technology performance, process, and purpose form the basis of trust in applied AI solutions. Since understanding the purpose entails effective communication on behalf of the AI provider, the trustworthiness of the provider is equally important to trust in the AI solution itself (Hengstler et al. 2016). In this study, we consider both aspects in seeking to understand the impact of AI on inter-organisational trust.

3. Methods

An in-depth case study approach (Siggelkow, 2007) was adopted, as it enables an in-depth understanding of the complex and contemporary phenomenon in its context. Multiple research cases are typically welcomed, which is considered to augment external validity and lessen observer bias (Voss et al., 2002; Yin, 2009). We conducted an embedded case study design whereby three AI-driven platform services, differing in their complexity level, were studied in an inter-organisational context within the Chinese e-commerce sector. The focal case organisation mainly provides transaction platform with information services such as search portals, data processing and hosting activities. The three embedded cases represent three different AI classes (mechanical, analytical, and intuitive) corresponding to increasing levels of AI complexity respectively (Huang & Rust, 2018).

Overall, 27 semi-structured interviews were conducted face-to-face plus five interviews which were conducted as video meetings. These interviews were supplemented with documentary evidence, observation notes and additional 24 follow-up interviews, which increased the reliability and validity of the results (Voss et al., 2002). All interviews were transcribed verbatim. Data coding and analysis were aided by NVivo.

In the coding processes, we followed the guideline of Gioia Methodology (cf. Gioia et al., 2013). Emerging data from the different cases were progressively incorporated into the analysis, allowing for the systematic combining of the transpiring issues and the ongoing development of the interview protocol (Dubois and Gadde, 2002). The case study protocol was kept updated iteratively in light of the emergent data and field notes during data collection. As the study was underpinned by abductive reasoning where the researchers iterated between theory and data (Kovács and Spens, 2005). The abductive way to develop the protocol was appropriate, as we investigated a nascent phenomenon (Chakkol et al., 2014). An iterative approach, moving between the emerging data set and the extant literature, will be adopted in order to make sense of the data and place it in the appropriate theoretical context.

4. Findings

4.1 Empirical Context

PlatformGroup (fictional company name) is one of the leading E-commerce companies in China, which is also one of the largest online retailers in 2019. PlatformGroup is a member of the NASDAQ 100 and Fortune 500 with over 220,000 full-time employees. PlatformGroup has many subsidiary companies; three of these are the focus of the study.

DigitalCo operates in the field of digital finance. DigitalCo offers innovative products and services, covering consumer finance, payment, wealth management, crowdfunding, insurance, securities, etc. LogisticsCo is a subsidiary of PlatformGroup which uses the advanced technology and logistics expertise to provide smart supply chain services to businesses across a wide range of industries. RetailerCo is considered China's leading one-stop e-commerce platform. RetailerCo provides over 360 million active customers with direct access to a range of authentic and high-quality products.

4.2 Case Descriptions: AI Platforms

Table 1 - The overview of case organizations, platform services, and related intelligence

Case ID.	Business	Platform Services	AI Service Complexity	Different level of AI intelligence		
				Mechanical	**Analytical**	**Intuitive**
CRobot	*Digital Co*	*Intelligent Customer Service Robot*	*Low*	√	X	X
Smart SCM	*Logistics Co*	*Intelligent Supply Chain System*	*Medium*	√	√	X
MP	*Retailer Co*	*Intelligent Advertisement & Marketing Platform*	*High*	√	√	√

4.2.1 Intelligent customer service robot (CRobot)

This system is an intelligent question answering robot to reply to the frequently asked common questions which were internally developed and being sold to business customers as a platform service. It uses mechanical intelligence "to automatically perform routine, repeated tasks" (Huang & Rust, 2018, p.158). CRobot is planned to replace traditional call centres through the automation of related customer service inquiries. Though the current CRobot lacks empathetic intelligence, it involves mechanic intelligence to automatically conduct routine tasks. Most clients are POP (platform open plan) retailers, who implement this supplementary service to their end-users: *"Most POP (platform open plan) retailers are happy to use our intelligent customer service robot. The customer service robot has served 16.3 million times in 11.11 this year, and 90% of the problems are independently solved by customer service robot. Only 10% still go to human services (Senior Algorithm Engineer II, CRobot).*

CRobot clients have relatively higher trust in this technology platform compared to the other two cases. The technology involved in CRobot is about the application of machine learning, deep learning, and knowledge graph to provide autonomous services with the interactions between computers and human natural language. CRobot has relatively higher transparency and accuracy (around 85%).

Despite the low transparency of AI technology, the responses can be explained to some extent with statistics. This allows customers to better understand the decisions made by CRobot. Meanwhile, a junior algorithm engineer of CRobot explained the accuracy and transparency can be further improved with a better work of annotation and data cleaning*:* *"Though the algorithm of customer service robot is still a black box, at least you can explain some [decisions] based-on statistics. The better the annotation and dirty work you did, the more accuracy and transparency you got" (Junior Algorithm Engineer, CRobot).*

4.2.2 Smart supply chain system (SmartSCM)

This system can visualize and automatically host the management of supply chain to coordinate the warehouse operations with intelligent replenishment and allocation of inventory. This requires mechanical intelligence and analytical intelligence to "*process information for problem-solving and learn from it*" (Huang & Rust, 2018, p.158). The core services of the SmartSCM include an intelligent logistics system based on big data. This system provides retailers and suppliers with omni-channel and full-supply chain data collection, multi-dimensional and customized analysis. It also provides clients with supply chain consulting, customized modelling, and algorithms.

SmartSCM is experiencing an evolution from big data analytics, to business intelligence, and to artificial intelligence. The digital transformation of SmartSCM is centred around the development of the AI-based intelligent prediction system, which firstly accumulated large-scale data of consumer portraits, and then trained by the algorithm of 'random forest'. So that the prediction system can autonomously predict consumer demand for SKU (stock keeping unit), including the type of goods. quantity, pricing, and replenishment solution. The complex workings of the system were briefly explained by an engineer as follows: *"The model is a fixed file as a black box, which is deployed to the prediction system. The daily data from the order system is the input to this black box, and outputs are the predicted sales which will become the input for smart replenishment system. As it's a black box, we can only see the results. However how these results emerge, we don't know and the process can't be explained" (Senior Algorithm Engineer, SmartSCM).*

Importantly, however, there are overarching trust issues amongst the clients when it comes to SmartSCM: *"The trust on the platform depends on the accuracy of the prediction system. Currently, there are no high levels of trust on the platform. As for the smart replenishment system, we need to develop a very complex simulation program to reveal the real-life situation. However, people will regard it as unscientific - if the platform is not well designed and has low accuracy. So we are still working hard on how to reflect the real-life situation of the whole supply chain [into the AI algorithm]" (Senior Algorithm Engineer I, SmartSCM).*

4.2.3 Advanced Marketing platform (MP)

This system is provided to the business clients to help them develop consumer insights, build brands, and provide intelligent advertising and marketing solutions. It involves mechanical intelligence together with analytical intelligence. Moreover, it uses intuitive intelligence to "think creatively and adjust effectively to novel situations" (Huang & Rust, 2018, p.159). MP adopts AI and data-driven advertising to help brand owners with accumulating and managing consumer assets, measuring the incremental effect brought by advertising. The clients of MP are the advertisers, brand owners, vendors, merchants (the POP retailers), and advertising agencies. MP is based on segmented consumer behaviour model to create marketing strategies, execute marketing campaigns, evaluate marketing effectiveness, and enhance marketing initiatives.

In terms of network, MP connects with other large platforms and other connected leading media, reaching almost 100% of all internet users in China, which can be used for multi-scenario marketing such as brand promotion, new sales, and promotions. These are largely delivered with external media network suppliers.

The core platform of MP is independently developed by the advertisement department of RetailerCo. Some supplementary functions were firstly outsourced but then brought in house: *"Previously, we don't have the ability for developing the MTA model, however, [Company A] does. So [Company A] becomes our strategic partner to provide MTA reports. Our VP thinks that we can actually make an (MTA) model by ourselves, so we stop cooperating with [Company A]. Then it happened that our algorithm research and development team in Silicon Valley can develop it" (Product Manager I, MP).*

Several technologies are combined and applied in the MP, such as real-time optimization, deep learning recommendations search ads, programmatic decision making, AI-powered smart bidding, and fully automated advertising. MP has the highest AI service complexity as well as AI difficulties among the three embed cases.

Regarding the trust in technology, there is a mixed picture of MP when comparing small versus large clients. For small clients, relatively higher levels of trust in technology is developed over time due to *"auto-hosting advertising system"* and increased ROI (Return on investment) of advertisement, especially for small POP retailers. This platform is trusted by small to medium sized companies which do not have the dedicated in-house marketing teams. However, large firms like the KA (key account) do not fully trust the platform and even are suspicious of the outcomes produced by the platform. They also have marketing specialists to evaluate the advertising solutions and marketing reports: *"AI algorithm is like a black box operation, which is equivalent to using an unknown tool. With this tool, you give me the money, and I will give you a high return on investment and conversion rate in the advertisement. But you don't know the reasons" (Algorithm Engineer I, MP).*

A product manager pointed out the reasons for lack of trust amongst clients towards the MP service as follows: *"In fact, I think it's a contradiction. MP aims to help clients' advertising become more convenient. However, AI technology can not completely convince the clients, especially for the KA (key account). Because they think the big data analysis for AI is based on the data of the whole industry, which is too general" (Product Manager I, MP).*

4.3 Cross Case Analysis

Table 2 - Cross Case comparisons

	CRobot	**SmartSCM**	**MP**
Service Complexity	*Low (customer service)*	*Medium (Supply chain management)*	*High (Marketing and Advertising)*
AI Difficulty	*Low (Mechanic)*	*Medium (Analytical)*	*High (Intuitive)*
Accuracy	*85%*	*63%*	*NA*
Low Transparency	*Low*	*Lower*	*Lowest*
Trust in Tech	*Relatively High*	*Medium to Low*	*Low*
Competence Trust	*Relatively High*	*Medium to High*	*Medium*
Goodwill trust	*High*	*Very high*	*Very high*
Contractual Governance	*Formal*	*Balanced*	*More flexible*
Relational Governance	*Reduced by self-executing system*	*Norms and commitment*	*More informal and more norms*
Information sharing	*Closed*	*High*	*Higher*
High process visibility	*Not necessary*	*More effort*	*More effort*

Across the cases, the overall trust in AI technology amongst clients can be considered low and the main reason is argued to be around the transparency. Before AI-enabled these three services, the suppliers and customers had already built an abundance of goodwill trust, due to their shared history, leading reputation and online service capability. The goodwill trust in PlatformGroup also contributed to the high IOR trust among the three embedded cases and their clients. All these three cases had high IOR trust amongst their clients before the implementation of the AI-enabled services. However, SmartSCM and MP services required very high levels of goodwill trust since it meant the provider had access to very sensitive supply and demand related customer data. Over the years, due to these high levels of trust, PlatformGroup was able to experiment different AI services with their clients *e.g.: The trust in the organisation needs to be high to adopt the new technology (Senior Algorithm Engineer I, SmartSCM).*

4.4 Trust building mechanisms mitigating for AI uncertainties

All three studied cases introduced AI into traditional business functions to automate business decisions. These novel solutions required additional mechanisms to mitigate for the uncertain, unknown and unpredictable nature of AI-driven decisions. This research empirically identified four key trust building mechanisms employed by the providers in order to enhance the confidence of clients in these platforms. These are displayed in Table 3 below and discussed next.

Table 3 - Trust building mechanisms for clients to mitigate uncertainties related to AI platform

Trust building Mechanisms	**AI Platforms**		
	CRobot	***SmartSCM***	***MP***
Structural	*Using Friendly Response Access Interface.* *Overall Operation Backstage Management: Knowledge base management, Online annotation analysis interface, Response log effect viewing interface.*	*Report displays on Inventory management, Sales Prediction and Plan, Smart Replenishment, and Slow-moving Products Disposal.* *Visualization of the entire supply chain.* *Omni-channel and full-supply chain data collection.* *Simulation of the real-life situation of the whole supply chain.*	*An integrated set of big data, marketing research, branding, and advertainment platforms.* *Detailed and customized report panel with clients' preferred data.* *Developing MTA, shopping path analysis, A/B test systems to increase accountability.* *Visualisation of the effect promoted by the marketing tools.*
Procedural	*Chatbot Product Manual* *Q&A web page* *Standard Operating System* *Policies & Protocol*	*SmartSCM Product Manual* *Help Centre* *Standard & Premium Operating System* *Policies & Protocol* *Communication forum* *Two modes: manual intervention & automatic hosting*	*PM Product Manual* *Help Centre* *Online Self-learning Platform* *Policies & Protocol* *Standard & Premium Operating System* *Self-executing and auto-hosting system* *Standard pricing with Top-up system: CPC, CPD, GSP etc.* *Annual Frame contract for KA*
Interpersonal	*General Operations & Maintenance Team (system bugs & failures).*	*KA helping & service line.* *Boundary Spanners with strategic suppliers.* *Specialised Operations & Maintenance Team.* *Regular Suppliers Meetings.* *Strategic suppliers/partners dinner.*	*KA helping & service line.* *Business Developers act as boundary spanners.* *Specialised Operations & Maintenance Team for KA.* *Free Trial for KA with new tools* *Responding to KA's Feedbacks on new tools with their satisfaction.* *Frequent KA meetings* *Special Discounts for KA with Annual Frame contract*
Informational	*Integrated Info sharing with business clients & desensitisation process.* *Continue to retract user feedback promptly on time.*	*Multi-level inventory dynamic linkage analysis.* *Omni-channel data* *Open Platform with suppliers: deep and extensive synergies on the CPFR model.* *Vertical integration with the strategic suppliers' systems.*	*Real-time integrated information sharing with a wider ecosystem* *Open platform data sharing internally & externally* *Enhancing channels to reach almost 100% of all internet users in China for multi-scenario marketing.*

4.4.1 Structural Mechanisms

Structural mechanisms are activities, applications and modules for building network infrastructure for enhancing user-friendliness and visibility of the AI management system. They are concerned with building the competence trust in the eyes of the clients through additional supplementary and modular functions, increasing the platform and process visibility, and making the results of AI black box more accountable. Structural building mechanisms also laid the basis for enhanced information sharing.

The SmartSCM platform was designed for clear report displays with *"Inventory management", "Sales Prediction and Plan", "Smart Replenishment", and "Slow-moving Products Disposal"*. The SmartSCM**,** as an overall open platform for retail**,** collected and displayed the omni-channel supply chain data and enabled the visualization of the entire supply chain, simulate the real-life situation, and built a shared and networked system. The MP provided advertisers with professional data analysis reports clearly from multiple dimensions, multiple perspectives, and multiple scenarios. Multiple marketing tools were developed for increasing the accountability of the AI black box, such as *MTA (multi-touched attribution), shopping path analysis system, and advertiser A/B test system*.

4.4.2 Procedural Mechanisms

Procedural mechanisms are the procedures employed to establish standards and process norms, which facilitated enhanced transparency of AI systems and contributed to the trust in the system. Procedural mechanisms also created a clearly defined environment for relationships through enhanced coordination, learning, and routinisation. Since there were versatile marketing tools on MP, *"online learning platform"* was established with modules of self-study courses, academy, and forum to better understand and get familiar with different marketing tools. Meanwhile, *"simulation experience centre"* was also introduced to get new clients experiencing different tools. MP created a friendly environment for mutual learning and benefits, which in turn improved IOR trust within the ecosystem: *"The more time we spend on building the self-learning and autonomous system, the better relationship we actually build with our clients. After they are familiar and valued our system, they prefer to spend more time and money to use our platform and try new marketing tools. Well, it's a positive iteration. We create this environment, where even clients can share their experience, communicate through this platform, and make friends and connections" (Junior Engineer Algorithms I, MP).*

4.4.3 Interpersonal Mechanisms

These mechanisms are interpersonal activities conducted by PlatformGroup in communicating and maintaining close relationships with the business clients, especially with key accounts (KA). For example, specialised operations & Maintenance team helped with bugs and system failures and the strategic partners had the VIP helping and service lines with specific boundary spanners. With the increasing levels of AI service complexity, there were more interpersonal activities. Strategic partners of SmartSCM and KA of MP obtained operational privileges and more resources. KA not only had better discounts and chance for a free trial of new marketing tools, but also, the feedbacks from KA influenced the development and launch of the new marketing tool. Interpersonal mechanisms boosted the competence trust in these AI services because they helped with meeting the expectations and requirements from the stakeholders and business clients *e.g. "We will actually allocate boundary spanners as dedicated persons to communicate with KA 1on 1. […] So these boundary spanners are the first to understand the habits of advertisers, as well as their overall placement status" (Product Manager II, MP).*

4.4.4 Informational Mechanisms

Informational mechanism builds the linkages between hub (platform providers) and harbour (business client's ecosystems). Informational mechanisms are different from structural building mechanisms. Because they are focussed on the integration of structures, channels and repositories amongst the ecosystems. They are concerned with the extent to which the AI platforms and ecosystems were vertically and horizontally integrated. The more integrated, timely, and extensive the information sharing is the better it is for the goodwill and competence trust amongst platform providers and clients.

5. Discussion and conclusions

In this research, we set out to investigate the wider implications of AI-driven digital transformation on IOR trust dynamics. The embedded cases suggest these implications are bi-directional emphasizing the interplay between inter-organisational trust and trust in the AI technology. In line with Hengstler et al (2016), the cases showed that low process transparency and visibility of AI services have a detrimental effect on trust in the technology. However, our findings take a step further and demonstrate how the providers invest in *structural, procedural, interpersonal and informational mechanisms* to build acceptable levels of trust in technology so as to enhance the trustworthiness of the respective AI service in the eyes of the customers. Specifically, the findings extend the prior research (Huang and Rust, 2018; Klumpp and Zijm, 2019) by showing that low transparency of AI decision-making process requires higher visibility of backstage management and more intensive efforts to build competence trust in the technology. This is moderated by the complexity of AI services: as for more complex types of AI, we observed increased and overarching investments in communication and information channels hence drastically increasing the breadth and depth of relational exchange to address trust issues. Interestingly, whilst clients were using this technology for autonomous decision making in customer service, supply chain management and marketing, they were simultaneously expanding their technical engineering capabilities with co-location as a common practise amongst providers and clients.

The study also presents implications for IOR trust by investigating the roles of competence and goodwill trust (Das and Teng, 2001; Dyer and Chu, 2003; Ireland and Webb, 2007; Lui and Ngo, 2004) in digital transformation, considering also differing levels of AI complexity. This novel approach allowed the researchers to identify that IOR goodwill trust served as a precondition for the introduction and use of AI services, which was more evident with analytical and intuitive AI types, given also the lower levels of competence trust in these cases. While this finding resonates with the literature (Klumpp and Zijm, 2019), we extend existing research by shedding light on how the trust building process unfolds. In particular, we observed that whilst the goodwill trust was unified and universal across the three different AI platforms, the competence trust was multi-faceted and more evident for the implementation and uptake within the larger customers. This is supported by Connely's et. al (2018) conceptualisation of competence trust across other sectors. In fact, the goodwill trust was a critical necessity for the *introduction* of advanced analytical and intuitive AI services, whilst the provision and further uptake of these services were reliant on how well the providers addressed the competence trust issues related with the black-box problem of the AI technology.

Overall, this study focused on AI service provision to business customers in China. Future research should be needed to extend our theoretical insights into other industries, digital technologies, types of inter-organisations relationships (e.g. alliances or joint ventures) and cultural settings. Future research employing survey and experimental methods could be particularly promising for capturing drivers of trust development at the level of individual managers e.g. job position, and functional roles and responsibilities.

Reference

The full reference list will be provided upon request.