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Case of Dutch Horticulture Industry

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The Role of Ecosystem Data Governance in Adoption of Data Platforms by Internet-of-Things Data Providers: Case of Dutch Horticulture Industry

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***Abstract*—Internet-of-Things (IoT) devices produce massive amounts of data, which are especially valuable when shared between businesses. However, adoption of platforms that facilitate IoT data sharing is still low. Generic literature on interorganizational systems suggests a plethora of adoption factors, but typically focuses on data sharing between pairs of organizations. In a context of ecosystems, data governance becomes important, but its relative importance as an adoption factor is yet unclear. In this article, we examine the perception of IoT data providers regarding the relative importance of ecosystem data governance as an adoption factor, in comparison with generic adoption factors. Our study is situated in the horticulture domain, where data sharing potentially is highly valuable. We conduct a multicriteria decision-analysis survey using the best-worst method, complemented with interviews for interpreting findings. We find that businesses consider a large variety of factors equally important. Ecosystem data governance is in the middle-range, whereas factors like benefits and readiness are most important. At the same time, out of all adoption factors that platform providers can control directly, ecosystem data governance ranks among the highest. Our findings are important for informing data platform operators on what design issues to consider, in order to attract data owners.**

***Index Terms*—Information management.**

I. Introduction

INTERNET-OF-THINGS (IoT) devices in industry are generating large amounts of data on production processes [1]–[3]. Within businesses, IoT data enable monitoring and optimizing business processes, and even radically new business models [1], [3]–[5]. In practice, however, 90% of the data generated by IoT is not being used [6]. IoT data can become even more valuable when businesses share them with other businesses [7], [8]. However, when sharing large amounts of data within an ecosystem of many actors, ecosystem data governance becomes a crucial issue [26]–[28].

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Data platforms are emerging in the market that not only facilitate data sharing, but also enable complementary services and analytics [8]–[10]. For instance, by sharing data with competitors, benchmarks can be created, and sharing data with suppliers may help to optimize supply chains. Yet, most businesses do not share IoT data [11], and it is rarely explored how IoT solutions can generate value beyond the initial use-case scenario [12]–[14]. Little is known about why businesses refuse or fail to share their IoT data [2], [3], [12]–[15]. Although scholars have discussed the importance of ecosystem data governance [26]–[28], its relative importance as an adoption factor has not been explored.

In existing literature on interorganizational information systems (IOS), much research has been done on why companies intend to share data with a partner [16]–[22]. IOS literature has revealed a range of adoption factors, from technological aspects (e.g., security) to organizational aspects (e.g., readiness). Yet, most IOS research focuses on dyadic settings, such as electronic data interchange (EDI) systems in which one company shares data with a specific other company in a predefined use case [23]. In the context of IoT, data sharing is expected to extend beyond dyadic relations toward complex ecosystems of suppliers, partners, competitors, and customers [24], in ways that cannot be foreseen prior to the sharing of data (cf., [25]).

Data governance generally refers to decision rights, roles, and accountability [29], [30]. In the context of data sharing in ecosystems, data governance entails who owns data, how data can be processed, and who can access data under what conditions [27]. Within the context of IoT, data governance is assumed to be of great importance, as IoT data are typically highly detailed on each part of a production process, which makes it highly sensitive [31], [32].

This article examines the relative importance of ecosystem data governance for the decision of IoT data owners to share data through ecosystem data platforms, as compared to other well-known adoption factors from the IOS literature. The corresponding research question is

> *What is the relative importance of ecosystem data governance as an adoption factor for data sharing in ecosystem data platforms?*

Our scope is limited to machine-generated data originating from IoT devices, generated in operational business activities.

We conduct our research in the agricultural industry, in which sharing of IoT data is expected to yield great benefits for farmers.

Besides improving production processes, sharing of IoT data can help optimize distribution of products [1], [33]. Our empirical setting is the Netherlands, which has one of the most technologically advanced agriculture industries in the world. We specifically focus on the horticulture industry, which has the highest adoption rates of digital technologies and IoT of all Dutch agricultural industries [34], [35]. In this way, the decision to share IoT data with other businesses is highly realistic, and not contingent on the decision to adopt IoT at all. Yet, also in this industry, sharing of IoT data is still rare, despite several initiatives to promote it [36].

To answer the research question, we follow a multicriteria decision-analysis approach. From literature on adoption factors in IOS as well as ecosystem data governance literature, we construct a conceptual model with adoption factors. Next, we conduct a survey among Dutch horticulture firms, following the best-worst method (BWM) [37], [38] to assess the relative importance of all factors. For interpreting the results, semi-structured interviews were conducted with a subset of the survey respondents.

Compared to existing research on adoption of data sharing technologies between organizations, our main contribution is that we add ecosystem data governance, and examine its relative importance. Ecosystem data governance and platform governance have often been argued by researchers to be of great importance to the success and sustainability of data platform ecosystems [26]–[28]. This study is a first to examine whether ecosystem data governance also plays a relatively important role in platform adoption decisions of data owners. A secondary contribution is that, in this article, a more comprehensive set of factors is being compared as in most existing studies.

The rest of this article is organized as follows. Section II provides a background on data ecosystems, data platforms, and data governance. In Section III, we develop a conceptual model with adoption factors, drawing upon existing literature. Section IV details the method, followed by the results in Section V. Findings are discussed in Section VI. Finally, Section VII concludes this article.

II. Background

A. Data Ecosystems

The concept of business ecosystems was once coined by Moore [39] to reflect the competition and cooperation between businesses around a shared niche. Recent contributions provide more specific conceptualizations of the ecosystem concept, pointing out that complementarities are important to understand why companies organize themselves in ecosystems [40]. We follow Adner's [41, p.42] definition here, who considers an *ecosystem* as "the alignment structure of the multilateral set of partners that need to interact in order for a focal value proposition to materialize."

Here, we focus on platform ecosystems, which comprise economic actors that coordinate their business activities around a platform [9].

Data ecosystems can be considered a specific subset where the focal value proposition is enabled by data sharing. Data ecosystems comprise six main roles [42] given as follows:

1) data providers: provide access to data in return for (monetary or other) values;
2) data brokers: facilitate interactions between data providers and users, and maintain information on available data, qualities, pricing, and licenses;
3) service providers: deliver data services, such as data analysis, visualization, business development and data monitoring;
4) application developers: create functionality for using and analyzing data;
5) infrastructure and tool providers: deliver the technical aspects and tools, e.g., a digital platform or tools for application development;
6) application users: consume or utilize the data.

B. Data Platforms

In general, platforms are foundations upon which unrelated actors can offer complementary services and products [43, p. 54]. Platforms have a stable core and variable periphery [44]. The platform core provides reusable and generic functionality [45]. The platform periphery comprises additional functionality, typically applications that utilize the platform core. In between, boundary resources mediate access to the core [46].

Digital platforms can be defined as technical or sociotechnical artifacts [47]. From a technical view, a digital platform is an extensible codebase to which third-party modules can be added [45]. From a sociotechnical view, a digital platform also offers organizational processes and standards to interact with the technical elements [25]. The platform is often the core around which business ecosystems are formed [9], [48].

For IoT specifically, platforms provide a link between physical things and digital applications, the standards that enable these links, and the software and hardware platforms that are used [48], [49].

C. Ecosystem Data Governance

Data governance within organizations generally refers to who holds decision rights and is accountable for decision-making concerning data [29]. This definition of data governance builds on the framework for IT governance by Weill and Ross [50], who differentiate governance (i.e., how to make decisions) from management (i.e., the making and implementation of decisions).

In a context of data sharing between organizations in ecosystems, research on data governance is still in its infancy. We follow here the definition for *ecosystem data governance* by Van den Broek and Van Veenstra [51, p. 2]: "Arranged institutions and structures to ensure that individuals behave in line with the collective goals, conflicts between individuals are prevented or resolved, and the effective and fair use of collective resources within the inter-organisational collaboration."

A generic choice regarding governance of networks is the mode. Provan and Kenis [52] propose three different modes:

1) shared governance (i.e., organizations jointly exert governance);
2) lead organization governance (i.e., one of the network participants governs);

3) network administrative organization governance (i.e., an independent third party governs).

Van den Broek and Van Veenstra [51] suggest four modes of governance to data collaborations: market, bazaar, hierarchy, or network governance.

Data governance covers many aspects, as both the access and usage of data needs to be controlled. Within the decision domain of data ownership and access, the following data governance factors have been identified:

1) data ownership and access definition;
2) definition criteria to determine ownership of newly generated data;
3) estimation of contribution of users [53].

Within the decision domain of data usage, the following data governance factors have been identified:

1) defining the scope within which data can be used;
2) conformance to minimize unauthorized use of data;
3) monitoring of data usage;
4) data provenance (i.e., recording changes in the data) [53].

III. Conceptual Framework

To derive specific factors for adoption of IoT data platforms, we draw upon related work on IOS adoption. However, since data platforms are used for sharing data in ecosystems rather than dyads, we also draw upon additional literature on data-based ecosystems, digital platforms, and ecosystem data governance. Relevant and suitable literature was identified by consulting the online databases Web of Science, Scopus, and Google Scholar. The types of included literature are from scientific journals and conference proceedings. Primary starting point was literature reviews on IOS adoption by Bouchbout and Alimazighi [16], Rui [20], and Lippert and Govindrajulu [19]. Subsequently, other relevant literature was identified by consulting the reference lists, also known as the backward snowballing method as described by [54]. By first reading the abstracts, relevant articles were selected and those were thereafter studied in more detail. Although our focus is on the perspective of data owners, existing IOS adoption literature does not distinguish between data owners and users generally; hence, we derive concepts from a more generic set of literature.

A. Conceptual Basis: TOE Framework

As a conceptual basis for our model, we use the technology-organization-environment framework (TOE). The TOE framework is developed by Tornatzky and Fleischer in 1990 [55] and provides a starting point to study the adoption of technological innovations [23], [56]. TOE is suitable as it is specific for adoption decisions on the firm level of analysis [57], whereas frameworks such as technology acceptance model are more suitable for individual employee decisions [90]. The TOE framework captures not only the technology and organization context as discussed in the diffusion of innovation model, but also the external environment or interorganizational context. Furthermore, the TOE framework puts emphasis on the specific context in which the adoption process takes place.

The TOE framework is widely used to analyze IT adoption at the firm level [20], [23], [58]. Consistent empirical support has been found for the framework in studies on adoption of EDI [18], [59], [60], e-business [21], [22], IOS [61], big data [62], radio-frequency identification [63], web services [19], and open systems [58]. However, TOE does not provide a comprehensive set of adoption factors, as these differ between types of innovations [20], [64]. Consequently, researchers typically use the TOE framework to categorize contextual factors [23], [56].

B. Model Construction

1) Technology Context: The technology context entails factors related to the technology or innovation [56].

The *benefits* of adoption is considered one of the most critical factors for the adoption process [16], [19], [20], [59], including in the context of IOS [17]–[19], [58]–[60], [65], [66]. Perceived benefits refer to the benefits that the organization believes to achieve by adopting the technology [20]. In the specific case of data sharing, firms are only willing to share data if there is a clear benefit for them in return [67].

Costs of adopting a technology have been shown to be important in various studies, especially on IOS and EDI [16], [18], [20], [68]. Investments to adopt a technology result in fixed and variable costs for the organization. Costs may be incurred by acquiring or improving hardware and software, training and educating personnel, paying for access to technologies, or technology maintenance [16], [18], [69].

Both the literature reviews of Bouchbout and Alimazighi [16] and Rui [20] show that *compatibility* and *ease-of-use* are significant in most studies. *Compatibility* refers to the extent to which the innovation is aligned with values, norms, and existing practices [20]. *Ease-of-use* indicates how easy the adopter can use the technology [16]–[18], [20], [70].

Recent studies on IOS adoption also mention *security* to be very important for the decision of organizations to adopt a technology [16], [19], [66], [71]. Security compromises can have large impact due to loss of competitive advantage or damage to operations [19].

Scalability of the technology is found to be important for IOS adoption [16]. Scalability refers to how easy the IOS can be adjusted to changes in system size, scope, and function. *Reliability* of the technology is considered important as well, referring to trust of organizations in the technology to be available and functioning at all time [16], [19].

2) Organizational Context: The organizational context refers to the internal situation at the adopting firm [18], [56]. An organization is assumed to adopt a technology when it is perceived that organizational resources are sufficient to do so, achieve the benefits and cope with the costs [16], [18], [65]. When organizational readiness is perceived to be low, the organization is likely not to adopt the technology to prevent failure or loss of image [59], [62].

Prior research on IOS adoption distinguishes between available technological, financial, and human resources [20]. *Technological readiness* refers to available technological resources, such as hardware, high quality data, and suitable data management practices [18], [20], [22], [61], [68]. *Financial readiness* reflects the organization's available financial resources to allocate to the adoption of the IOS [16], [18], [20], [22], [61], [68]. *Human readiness* reflects the organization's ability concerning IT usage and IT management [20]. Knowledge and expertise of employees needs to be sufficient to adopt the technology without requiring training or recruitment [20], [22], [58].

3) External Task Environment Context: The external task environment context refers to the opportunities and constraints posed by the environment of the adopting firm [18], [20], [56].

IOS adoption studies exhibit several adoption factors related to trading partners [20]. Trust in the trading partner and the readiness of the trading partner are considered most important [16], [19], [20], [22], [62], [65], [66], [71]–[74]. *Trust* refers to the belief that the trading partner will refrain from actions that harm the adopting organization [16]. A trading partner's *readiness* reflects the willingness and ability of the trading partner to succeed in its role [16]. In the context of interorganizational collaboration, the *relative power* of trading partners is important as well [65], [72] as found in studies on EDI adoption [74]. When the trading partner has the power to influence the industry or other organizations, data providing organizations could choose not to adopt.

More powerful parties may put pressure on less powerful firms to adopt the IOS [20], which is referred to as *external pressure*. External pressure could come from competitors, partners, consumers, industry, government, or any other entity in the macro environment [59], [75]. The *regulations* set by government institutions can result in either barriers or incentives to technology adoption, including laws that incentivize adopting the innovation [19].

Ecosystem data governance is added as a new factor within the environmental context. Data governance is not discussed as an adoption factor in literature on IOS adoption, as these studies typically focus on sharing of data with one specific trading partner. Within an ecosystem, multiple parties will contribute, process, and utilize data, making proper ecosystem data governance of a crucial concern [53]. For that reason, we argue that ecosystem data governance is likely an important adoption factor within the external context.

As our aim is to examine the relative importance of ecosystem data governance, we include three subfactors in our conceptual model. Doing so allows deriving a deeper understanding into which aspects of ecosystem data governance are considered most important by data owners. In line with Section II-D, we add three subfactors: *governance mode*, *governance of data ownership and access*, and *governance of data usage*.

Model Overview: Table I provides an overview of the conceptual model.

TABLE I
ADOPTION FACTORS DERIVED FROM LITERATURE

Factor	Description	References
Main category: Technology		
Benefits	Benefits that the organization can achieve by adopting the platform	[16]–[20], [58]–[60], [65], [66]
Costs	Fixed and variable costs for the organisation resulting from adopting the platform	[16], [18], [20], [68]
Ease-of-use	Ease of use of the platform for the organisation	[16]–[18], [20], [70]
Compatibility	Conformity of platform with technology, values, norms and existing practices	
Reliability	Availability and continuity of the platform	[16], [19]
Scalability	Ease to adjust the platform (size, scope, function)	[16]
Security	Guarantee of confidentiality, integrity and availability of the platform	[16], [19], [66], [71]
Main category: Organization		
Technological readiness	Availability of internal technological resources for sharing data	[18], [20], [22], [59], [61], [68]
Financial readiness	Availability of internal financial resources to cover costs of sharing data	[16], [18], [22], [59], [61], [68]
Human readiness	Availability of internal human resources (knowledge, skills) to share data	[20], [22], [58], [59]
Main category: Environment		
Application user readiness	Application user's availability of organisational resources to fulfil role in ecosystem successfully	[16], [19], [62]
Enabling party readiness	Enabling party's availability of organisational resources to fulfil role in ecosystem successfully	
Trust in application user	Belief that application user will refrain from expected or unexpected actions that cause harm	[16], [19], [20], [22], [62], [65], [66], [71], [72], [74]
Trust in enabling party	Belief that the enabling party will refrain from expected or unexpected actions that cause harm	
Relative power application user	Application user's influence on the industry or ability to impose actions on other organisations	[16], [65], [72], [74]
Relative power enabling party	Enabling party's influence on the industry or ability to impose actions on other organisations	[16], [65], [72], [74]
External pressure	Coercion from competitors, partners, consumers, industry, or government to adopt the platform	[19], [20], [59], [62]
Regulation	Governmental regulations regarding the collection, distribution, and processing of data	[19]
Governance mode	Allocation of decision rights to actors	[51]
Governance of data ownership, access	Rules on data ownership and access	[53]
Governance of data usage	Rules on data usage and provenance	[53]

IV. METHOD

As discussed before, finding out the relative importance of ecosystem data governance is formulated as an MCDA (multicriteria decision analysis) problem, where we need to find the relative importance (weight) of the factors (criteria). There exist several methods to elicit the weights including Tradeoff [77], simple multiattribute rating technique [78], analytic hierarchy process [79], Swing [80], analytic network process [81], BWM [37]. In this study, we use BWM as one of the most recent major weighting methods, which has been used in many applications (e.g., in supply chain management [82]–[84]; in technology assessment [84] mainly due to its intuitiveness, reliability, and data efficiency. To see a comprehensive list of the applications and extensions of the method we refer to the review paper [85] and the BWM Bibliographical Dataset [86].

A. Best Worst Method

BWM [37], [38] is a method that makes use of pairwise comparison to establish the weights of the criteria (factors). In each comparison, the best and worst factors will be chosen from a list of factors and compared to the other factors on the list. The weights of the factors can subsequently be derived by formulating and solving a minmax problem.

The linear BWM, which is used in this study, is conducted in five steps discussed in the following [38]) (where the first four steps are done by the decision-makers).

Step 1: Determine a set of n relevant decision criteria or factors as $C = \{c_1, c_2, \ldots, c_n\}$.

Step 2: Identify the best (e.g., most important) and worst (e.g., least important) factors.

Step 3: Conduct a pairwise comparison to determine the preference of the best factor over all the other factors by using a number between 1 and 9 (1: equally important, 9: extremely more important). This results in the Best-to-Others vector

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}) \quad (1)$$

with a_{Bj} indicating the preference of the Best factor *B* over factor j.

Step 4: Likewise conduct a pairwise comparison to determine the preference of all other factors over the Worst factor by using a number between 1 and 9 (1: equally important, 9: extremely more important). This results in the Other-to-Worst vector

$$A_W = (a_{1W}, a_{2W}, \ldots, a_{nW}) \quad (2)$$

with a_{jW} indicating the preference of the factor j over the Worst factor *W*.

Step 5: Calculate the optimal weights of the relevant factors $(w_1^*,\ w_2^*,\ \ldots, w_n^*)$. This is done by minimizing the maximum absolute differences between the pairwise comparisons provided by the decision-maker and their corresponding weight ratios.

With the nonnegativity condition for the weights and the sum of all weights being equal to 1 the following minmax model is formulated:

$$\min \max_{\mathrm{j}} \{|w_B - a_{Bj} w_j|, |w_j - a_{jW} w_W|\}$$

$$\text{such that} : \sum\nolimits_{j=1}^{n} w_j = 1 \text{ and } w_j \geq 0, \text{ for all } j. \quad (3)$$

Model (1) can be transferred into

$\min \xi$

such that

$|w_B - a_{Bj} w_j| \leq \xi$, for all *j*

$|w_j - a_{jW} w_W| \leq \xi$, for all *j*

$$\sum\nolimits_{j=1}^{n} w_j = 1, \text{and } w_j \geq 0, \text{for all } j. \quad (4)$$

By solving this problem, the optimal weights $(w_1^*,\ w_2^*,\ \ldots, w_n^*)$ and ξ^{L*} are obtained, whereas ξ^{L*} indicates the reliability of the weights based on the consistency of the pairwise comparisons. The closer this value is to zero, the higher the consistency of the pairwise comparison system and thus the reliability of the result. The most important factors can then be identified by comparing the global weight of each factor.

It is possible to use BWM with multiple layers by first comparing the main criteria in the top layer to each other, and thereafter comparing the factors within the groups (lower layer) with each other. The global weights of the factors are derived by multiplying the local weight of the factor by the weight of the top layer main criterion that it belongs to.

B. Data Collection

We collect data from one specific industry in one geographical setting. Doing so avoids confounding factors, as, for instance, the relevance of sharing IoT data may differ widely between industries. We specifically choose an industry and geographical setting in which IoT adoption is high, such that the question of sharing IoT data is realistic for respondents.

We collect data on data owners in the horticulture industry in the Netherlands. Horticulture is a part of the broader agriculture industry, and entails agricultural activities within greenhouses, such as growing fruits, vegetables, and ornamental plants. In horticulture, IoT is particularly important to optimize cultivation methods, as IoT devices can measure air temperature, air and soil humidity, and sap streams of crops. Since cultivation methods are a key source of competitive advantage for horticulture firms, IoT-generated data are thus of high strategic importance. The horticulture industry in the Netherlands comprises over 3000 firms, of which roughly 50% produce flowers and plants [87]. Most horticulture firms in the Netherlands have adopted IoT devices [34], [35].

Respondents were mainly recruited via LTO Glaskracht, an interest group representing around 70% of the total horticulture area in the Netherlands. Through their channels, which reach out to 2000 member organizations, we recruited 25 participants. Five more participants were recruited through a horticulture cooperative. In total, 30 horticulturists completed the survey and provided a valid response. Only one participant stopped during the survey because the survey was found too difficult to complete. Respondents were only included when they satisfied three criteria: the firm currently uses IoT in its operations, the firm mainly works in horticulture, and the respondent is involved in the decision-making regarding data. To verify knowledgeability, respondents were also asked to provide their function title.

In the sample, the group of horticulturists that grow flowers and plants make up for 50% of the respondents, which corresponds with the generic statistics in the population [87]. About 46.7% of the respondents mainly grow vegetables. On average, respondents had 25 employees (full-time equivalents), which is higher than the population average of 12. Crop acreages differ widely, with most respondents having 4 to 6 ha. Out of 30 horticulturists, 19 indicated that they are currently sharing IoT data with others, while 8 others indicated they would be willing to do so in the future. This may indicate that respondents are early adopters of IoT data sharing platforms.

C. Survey

The survey was designed according to the guidelines of BWM, see Appendix for an overview. First, an instruction was provided on how to fill out the survey, including a framing of the issue of data sharing in horticulture. Next, the categories were presented, containing all factors from the conceptual model. In the main part of the survey, respondents were asked to a situation where they share their IoT data with other parties via a data platform. Respondents were asked to indicate which factor would be most and least important for the decision to share data with partners or suppliers. Respondents were then asked to compare the other factors to the selected most and least important factors. This was done by assigning a number on a scale of 1 to 9. Questions regarding personal information and demographics were placed at the end of the survey.

To pretest the survey, six horticulturists were visited and asked to fill out the survey, upon which they were asked whether factors had to be added. This pilot elicited no major issues. Next, an online survey was created and hosted on a private cloud server, accessible through a dedicated URL. Survey responses were collected in 2018. As incentives for participation, several "prizes" were allotted.

After collecting the data and getting the results, for interpreting the findings, six face-to-face interviews were conducted with horticulturists. Interviews lasted 30 to 60 min. Upon obtaining informed consent, interviews were recorded. During the interviews, respondents were asked to fill out the survey and explain the choices they made. Discussions focused on the most and least important factors.

D. Controls

To control for confounding effects, we compared global and local weights of respondents that already share IoT data ($N = 19$) to those that do not ($N = 11$). Mann–Whitney tests produced no significant differences. We also compared respondents producing vegetables ($N = 14$) with those growing flowers and plants ($N = 15$). We only found significant differences regarding local weights of environment category ($p < .05$) and financial readiness ($p < .05$).

TABLE II
LOCAL WEIGHTS OF CATEGORIES AND FACTORS

Category	Category weight	Factors	Mean weight
Technology	0.401	Benefits	0.259
		Costs	0.086
		Ease-of-use	0.166
		Compatibility	0.072
		Reliability	0.123
		Scalability	0.084
		Security	0.210
Organization	0.231	Technological readiness	0.404
		Financial readiness	0.283
		Human readiness	0.314
Environment	0.368	Application user's readiness	0.110
		Enabling party's readiness	0.125
		Trust in application user	0.173
		Trust in enabling party	0.150
		Relative power of application user	0.093
		Relative power of enabling party	0.081
		External pressure	0.038
		Regulation	0.064
		Ecosystem data governance	0.155

TABLE III
ECOSYSTEM DATA GOVERNANCE: LOCAL WEIGHTS

Factors	Mean weight
Governance data usage	0.369
Governance mode	0.185
Governance data ownership, access	0.446

V. RESULTS

Data are analyzed through a linear BWM Solver, as retrieved on January 6, 2018 from the website www.bestworstmethod.com. First, factor weights are computed for each individual respondent. Next, considering the whole sample, the mean of the weights of each factor is computed. Consistency of weighting is checked by looking at ξ^{L*} which is an output of the solver. All the consistency indicators are below the thresholds identified by Liang *et al.* [88], hence all are acceptable.

A. Local Weights

As the factors are categorized in three groups (technology, organization, and environment), first the local weights of the categories themselves were derived, see Table II.

For the organization context, respondents consider their own technological readiness the most important factor within the organization context based on the mean weights. Within the environment context, trust in the application user is considered the most important. Ecosystem data governance is assigned the second highest weight within this category, just slightly above trust in the enabling party.

Within the factor ecosystem data governance, the domain of data ownership and access is considered the most important, see Table III. The governance mode is considered to be the least important sub-factor of ecosystem data governance.

B. Global Weights

Global weights are derived by multiplying average local weights of the individual factors (as displayed in Tables II–III) with average local weights of the categories, see Table IV. Benefits are considered the most important (0.104) by a small margin over technological readiness (0.093). Ecosystem data

TABLE IV
GLOBAL WEIGHTS OF CATEGORIES AND FACTORS

Rank	Factor	Category	Mean global weight
1	Technology	Benefits	0.104
2	Organisation	Technological readiness	0.093
3	Technology	Security	0.084
4	Organisation	Human readiness	0.073
5	Technology	Ease-of-use	0.067
6	Organisation	Financial readiness	0.065
7	Environment	Trust in application user	0.064
8	Environment	Ecosystem data governance	0.056
9	Environment	Trust in enabling party	0.055
10	Technology	Reliability	0.049
11	Environment	Enabling party's readiness	0.046
12	Environment	Application user's readiness	0.040
13	Technology	Scalability	0.034
14	Technology	Costs	0.034
15	Environment	Relative power application user	0.034
16	Environment	Relative power enabling party	0.032
17	Technology	Compatibility	0.029
18	Environment	Regulation	0.022
19	Environment	External pressure	0.018

governance ranks 8th with a global weight of 0.056. The least important factors are compatibility (0.029), regulation (0.022), and external pressure (0.018). Another observation that can be made is the low spread of the global weights. This likely indicates that the horticulturists are considering various factors in their decision-making, rather than a few.

VI. DISCUSSION

A. Interpretation of Findings

We analyze the findings here, using the comments from interviewees to aid in interpretation.

Ecosystem data governance, it is considered the eighth most important factor (0.056). The factor had been chosen by eight respondents as the most important within the environment category. Interviewees confirm that this is an important factor. Within ecosystem data governance, governance of data ownership and access (0.446) is assigned a much higher weight than the governance mode (0.185), and slightly higher than governance of data usage (0.369). Hence, horticulturists are more focused on defining ownership of data and access to data rather than how to organize governance. Possibly, again the high strategic sensitivity of the IoT data explains these findings. Importance of ownership and access definition of data was confirmed by five of the interviewees, one of them expressing fear that unauthorized parties could access data and reap the benefits.

Benefits from sharing data are the most important factor based on the global mean weights (0.104). Five out of six interviewees stated that benefits are most important within the technology context, arguing it is a minimum condition before considering adoption. The type of benefits mentioned most were reducing costs of energy and labor, and increasing production efficiency.

Technological readiness (0.093) and human readiness (0.073) are weighted the second and fourth most important, respectively. As one interviewee stressed, the organization's ability to extract, store and handle data is very important. Hiring new personnel is considered undesirable. Human readiness is not considered to be a problem by three of the interviewees. Security of the data platform (0.084) is the third most important. Interviewees commented that, since their cultivation method is their competitive advantage, they want to control with whom data is being shared.

The ease-of-use (0.067) is the fifth most important factor. Interviewees explain that the easier it is using the platform, the more likely they consider participation, in part because costs and effort of participating are lower. Trust in the application user (0.064) is weighted the seventh highest. Interviewees explained that economic and strategic importance of IoT data makes trust more important, although contracts or governance can prevent misuse of data.The lowest weight was assigned to external pressure (0.018). One interviewee stated that horticulturists will always have the final say in whether they will share their IoT data. The participants clearly believe their decision to share data cannot be coerced. Regulation is likewise weighted very low (0.022), as there are, according to interviewees, no relevant regulations that affect their decisions to share data. Compatibility (0.029) is considered third least important in total, and least important within the technology context. Interviewees commented that compatibility is preferred but that solving compatibility issues would only be a one-time problem. Costs are weighted among the lowest factors (0.034) based on the mean global weights. The costs were also considered the absolute least important by four interviewees. As the benefits are considerably more important than the costs (0.104 versus 0.034), this reaffirms the importance of a positive benefit–cost ratio to the horticulturists. The high importance of benefits, combined with low importance of costs, indicates horticulturists are willing to invest if the benefits outweigh the investments.

B. Comparison to Literature

Our findings on generic adoption factors are largely in line with existing studies. Our finding that benefits are most important corresponds with most existing adoption research on IOS. Within the context of adoption of IoT in agriculture, value extraction and cost–benefit ratio have also been found to be the major driver [89]. Similarly, our finding that human and technological readiness are highly important factors is in line with TOE research [20]. Trust between platform users and other involved parties is also considered a crucial factor to the success of a platform ecosystem in general [10], [53] and to alleviate concerns over actions that can harm the data providing organization [16].

Our finding on the importance of ecosystem data governance is in line with existing research on control and platform governance [10], [45], [46], [51]. While ecosystem data governance is often mentioned as an important success factor for the ecosystem to sustain [8], [51], [53], we add to literature by providing preliminary evidence that it may affect adoption too, which should be looked into in future studies. Possibly, ecosystem data governance is considered important, since governance interacts with the other important adoption factors. For instance, trust in other ecosystem members becomes less important when governance is in place that ensures proper data ownership and data access, and vice versa [53]. Similarly, failing governance of data providers can hamper data quality, especially when partners lack readiness to properly handle data, which in turn negatively affects the perceived benefits of data sharing. Rules that are set within the governance domain of data ownership and access could require application users to pass certain checks before being allowed access to data. In these ways, ecosystem data governance likely plays a crucial role, both directly and indirectly affecting willingness to share data in ecosystems.

Concerns over governance of data ownership and control specifically were found to be most important, which is in line with extant research [51]. If IoT data becomes accessible for competitors, the interests of the data provider may be harmed, which can be countered by proper data governance mechanisms [51], [53]. We found governance for data usage to be important as well, which corresponds with claims in literature that unclear data ownership and usage are critical issues for data platforms [53]. The findings in this article confirm that data misuse is a serious concern for adoption as data providers want to protect their competitive advantage. Governance mechanisms can increase willingness to share data of data owners, when they effectively monitor data usage and prevent data misuse and unauthorized data modification. Our finding that governance mode is the least important is surprising since it is often argued to be important to platform ecosystem success [51], [52]. The findings show that horticulturists consider the object of governance more important than the mode.

C. Practical Implications

For data platform providers that intend to attract data owners, our study provides important implications. By showing which factors are considered from the perspective of data owners, platform providers can make decisions on how to design their platforms in attractive ways. The highest scoring factor of benefits largely results from exchanges of data that are, however, not under direct control of the platform provider. Similarly, human readiness and technological readiness can only be influenced indirectly, for instance, by offering training or consultancy to data owners. Security and ease-of-use are the highest ranked factors that are largely controllable by platform providers. Based on the mean global weights, ecosystem data governance is the third most important factor under control of a platform provider. Furthermore, as argued in Section V-B, proper ecosystem data governance can alleviate concerns over distrust and security and increase confidence that potential benefits can be accrued.

D. Limitations

A limitation is that the sample size is relatively small. Enlarging the sample may lead to higher generalizability of the findings. In terms of generalization, our study is specific regarding industry (i.e., horticulture) and geographical area (i.e., Netherlands). The Dutch horticulture industry is among the most innovative in the world, and advanced in terms of IoT adoption, which makes it a suitable setting. Still, macrolevel factors might partly explain the importance of adoption factors. For instance, the positive macroeconomic situation of the Dutch horticulture industry may explain why costs and financial readiness are less important. The technologically advanced state of the horticulture industry may explain why technological readiness is not the single main hurdle for data sharing. The lack of regulation and policies on data sharing in the Netherlands might explain the relatively low importance of environmental factors. Testing the model in other industries and geographical settings is therefore recommended.

VII. Conclusion

This article showed the relative importance of ecosystem data governance in adoption decisions for data platforms. Through data platforms, businesses increasingly share data within a complex ecosystem of partners, rather than in controllable buyer–supplier relationships. Literature on data platforms therefore posits that governing access and usage of data will be of crucial importance for data platforms to sustain. We confirmed this notion, and are the first to provide empirical evidence that ecosystem data governance is of relative importance for adoption of data platforms. At the same time, we also showed that ecosystem data governance is among a broad array of adoption factors, which also included perceived benefits, technological and organizational readiness, ease-of-use, and security. Future research on data platforms should consider governance of access and usage of data as a core issue, since it appears of relative importance for adoption decisions. Other future research directions are to zoom in on factors found to be important to understand their constituting elements, for instance, the different types of benefits that data sharing produces.

Appendix

Survey Introduction to Respondents

Because greenhouses become increasingly digital with sensors, large amounts of data are being generated. Data such as air or soil humidity are a few examples thereof. This type of data we will from here on called "sensor data."

By sharing sensor data, new opportunities emerge for horticulturists like you, to create added value with the data. For instance, dedicated advice can be provided to minimize energy usage or pesticides.

Sharing sensor data is enabled by data platforms, such as Letsgrow. Your opinion as a Dutch horticulturist is very valuable to develop data platforms successfully and to enable creating added value with data.

Explanation of factors to respondents

Factor	Description in survey
Benefits	Potential advantages of sharing data: what is in it for your company? (money, services, knowledge, relations both now and in the future)
Costs	Potential costs of sharing data: what does it cost your company? (both fixed and variable costs)
Ease-of-use	Ease of using data platform: for you as a user
Compatibility	Compatibility of data platform: with current technology and way of working in your company
Reliability	Stability of data platform: is the platform always available (no outages)
Scalability	Extensibility of data platform: can the platform be used for other types of data
Security	Security of data platform: protection of data on the platform
Technological readiness	Available technological means: appropriate infrastructure and technology within your company to share data
Financial readiness	Available financial means: sufficient money to cover potential costs of sharing data
Human readiness	Available personnel: personnel with the right knowledge and skills to share data
Application user readiness	Ability of the data receiving party: is the party data is shared with ready to use the data right (required technology, finance and personnel)
Enabling party readiness	Ability of intermediating party: is the intermediating party ready to facilitate right (required technology, finance and personnel)
Trust in application user	Trust in data receiving party: to honour agreements about data
Trust in enabling party	Trust in intermediating party: to honour agreements about data
Relative power application user	Power of the data receiving party: towards your company and the industry
Relative power enabling party	Power of the intermediating party: towards your company and the industry
External pressure	Pressure from outside (e.g. suppliers or government) to share data
Regulation	Rules and laws about sharing data
Ecosystem data governance	Rules about how to deal with data on the platform and who gets to decide about this
Governance mode	Responsible for governance: which party/parties can decide over the data platform
Governance of data ownership, access	Policy data ownership and access: rules about assigning data ownership, access to data and access to data platform
Governance of data usage	Policy data usage: rules about data may be used, and how the use and history of data can be checked

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