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Contextual variety, Internet-of-Things and the choice of tailoring over platform: Mass customisation strategy in supply chain management ☆

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ABSTRACT

This paper considers the implications for Supply Chain Management (SCM) from the development of the Internet of Things (IoT) or Internet Connected Objects (ICO). We focus on opportunities and challenges stemming from consumption data that comes from ICO, and on how this data can be mapped onto strategic choices of product variety. We develop a simple analytical framework that illustrates the underlying mechanisms of a product supplier/producer's choice between (i) producing multiple product varieties as a way of meeting consumer demand (a "tailoring strategy"), and (ii) offering a flexible and standardised platform which enables consumers' needs to be met by incorporating personal ICO data into various customisable applications (a "platform strategy"). Under a platform strategy, the ICO data is independently produced by other providers and can be called on in both use and context of use. We derive conditions under which each of the strategies may be profitable for the provider through maximising consumers' value. Our findings are that the higher the demand for contextual variety, the more profitable the platform strategy becomes, relative to the tailoring strategy. Our study concludes by considering the implications for SCM research and practice with an extension to postponement taxonomies, including those where the customer, and not the supplier, is the completer of the product, and we show that this yields higher profits than the tailoring strategy.

1. Introduction

In Supply Chain Management (SCM), the trade-off between efficiency and effectiveness at satisfying consumers' needs may take place at different points in the production cycle and even along the supply chain, providing opportunities for Mass Customisation (MC). The objective of Mass Customisation (MC) is to meet the needs of the customer for personalised products whilst allowing the provider of goods or services to derive the benefits of mass production (McCarthy, 2004). In a review of MC research, Da Silveira et al. (2001) state that MC can be defined using two different approaches: one is narrow and practical and the other is broad and visionary. The practical view emphasises the role of technology, process and structures in meeting specific customer needs; while the visionary approach focuses on the use of MC to reach mass markets when customers are treated individually. Building upon the work of Da Silveira et al. (2001) and Fogliatto et al. (2012) identify a number of research directions for future MC research. These directions include but are not limited to: the increasingly important role of Rapid Manufacturing (RM) in MC; the dynamics of value implications to individual customers; the design of quality systems that can deal with single items, and issues associated with warranty on customised items.

In this paper we identify a broad visionary approach to MC development that focuses on the role of customer value, and provide some insights into how organisations can approach the challenge of both scalability and customisation. We identify two possible MC approaches – a tailoring strategy and a platform strategy – and specify conditions under which each of them benefit providers of goods and/or services, placing a particular emphasis on the importance of contextual variety of use and its impact on customisation.

Since the customised manner in which customers' needs are fulfilled is uncertain at the point of consumption, not only for the providers but also for customers, one important aspect of a successful MC strategy is to defer the customisation of a product,

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in its form or place, until the last possible point (Fetzinger and Lee, 1997). For example, Dulux is able to offer a vast range of paint colours through in-store mixing of a relatively small number of basic paint colours; whilst Jigsaw uses its vehicles in different combinations to meet the different demands of consumer goods and general haulage (e.g., Mason and Lalwani, 2008).

The key to MC is to postpone, as late as possible, the point where the demand signal enters the supply chain, i.e., to postpone the point at which work in progress gets turned into specific end products (Forza et al., 2008). This leads to a resurgence of interest in *postponement* as a field of study. Postponement is therefore a supply chain management strategy where the manufacturer produces a standardised and generic (and often scalable) product, which can be modified at the later stages before it is finally delivered to the customer, thereby achieving some degree of customisation.

A number of typologies of postponement have been developed.[1] In Fig. 1 below, the framework proposed by Yang and Burns (2003), the focus is on the point of the process where the customer order enters the system and identifies a number of theoretically potential designs. At one extreme there is pure speculation (Shapiro, 1984) where all stages (design, purchasing, distribution, etc.) are forecast through intermediate stages such as 'make to order'. In other words, the design and purchasing are speculative but everything else is made according to customer order. On the other extreme is Engineering to Order (ETO), where the product's design, purchase, fabrication, etc. are all based on the customer order. In a later paper, Yang et al. (2004) characterise these extremes as pure standardisation through pure customisation, with mass customisation occupying various intermediate positions denoted by the dotted lines in Fig. 1.

Increased standardisation also helps the development and use of mechanisation, design optimisation, and simplified quality control, all of which result in high levels of capacity utilisation and declining average costs (e.g., Lee and Billington, 1992; Baker et al., 1986). Lee and Billington (1992) view the customer as an external input to the postponement system which requires careful redesign of products and processes to allow for simple postponement, such as labelling or bulk packing, or more complex postponement such as localisation or assembly tests. Baker et al. (1986) consider a stylised two-product, two-level inventory model, with the consumer as an outsider to the system, to calculate safety stock levels. Standardisation can also be cascaded through the supply chain to achieve the characteristics of Fisher's (1997) famous 'functional product' with, for example, a dampened Forrester effect and reduced transaction costs between parties.

The decoupling point in the postponement literature reflects the productivity-flexibility trade-off. In their discussion of the Customer Order Decoupling Point, Wikner and Rudberg (2001) characterise this as separating decisions made under certainty from those made under uncertainty. The positioning of the Customer Order Decoupling Point (CODP) balances the needs of the customer and the provider. The further the CODP is positioned downstream (closer to the factory), the greater emphasis is placed on productivity as more processes are subject to economies of scale. The provider may also gain from risk-pooling of inventory, reduced risk of inventory obsolescence, reductions in lot sizes for upstream (closer to the customer) activities, for example, through JIT (Just-in-Time) strategies (Forza et al., 2008). By placing the CODP further upstream a provider can achieve greater flexibility and give customers a greater input, but this greater variety impacts on efficiency as it may influence inventory management through stock outs and reduced operational productivity (Wan et al., 2012).

In much of the MC and postponement literature the product experience or consumption by the customer is explicitly outside the boundary of analysis. For example, Alford et al. (2000), in their consideration of MC in the automotive industry, see the customer as simply providing "needs" as a set of requirements (e.g., Alford et al., 2000, Fig. 2 in p. 102), rather than understanding the consumption activities that is antecedental to those needs. MacCarthy et al. (2003) identifies five fundamental modes for MC based on the consideration of the "*point at which customisation is undertaken*" (page 290), and emphasises the customer order as an input to the customisation decision. Salvador and Forza (2004), in their review of management issues of product configurators for MC, consider a configurable product as one where the "*company has rationalised ex-ante what it is going to offer the customer*" (page 275). In other words, the provider makes decisions about features that are available for the customer to configure, and customer chooses from the available set. Even those researchers who are expanding the systems boundary focus attention upstream by considering how postponement and different strategies around postponement affect providers. For example, Sun et al. (2008) consider the location of multiple decoupling points in the supplier network driven by the customer order, whilst Gosling and Naim (2009), in their analysis of issues of mass customisation in engineer-to-order companies, consider the production flow as being driven by actual customer orders.

Focusing only on orders as the starting point of the customer and not its antecedents implies that customer use/consumption activities are outside the boundary of the provider's activities. This has several drawbacks in considering an ideal MC strategy. It conforms strongly to what Vargo and Lusch (2004, 2008) would term 'Goods-Dominant Logic' (G-D logic), where the focus is on the exchange between two parties, provider and customer. From this perspective, customer consumption activities are outside the boundary since the provider's value proposition, and therefore what it is responsible for, is to ensure the product is satisfactorily transferred over to the customer in the form that the provider has promised, and the customer has accepted. For example, if the customer wanted blue paint and paid for it, the provider's duty is to ensure blue paint is given to the customer as efficiently as possible. If the customer opens the tin, begins to use it and subsequently realises that blue was not suitable, it would not be the provider's failure, but that of the customer to specify her need adequately. If the customer then returns the product as faulty then this is typically dealt with through returns processes, a topic that is usually considered under closed loop supply chain research.[2]

Yet, such customer failure is altogether very common. Indeed, one might not even call this a 'failure'. Since the product usage is in context of its own environment of use, the specific contexts of use may drive changes to the need and therefore the product specification that fulfills the need. In specifying the blue paint, the customer did not want to fail: there may have been insufficient information about the context beforehand and the customer took the risk to purchase and when the information became available later, the blue may just not be appropriate. This means that while both the customer and the provider are uncertain about the context of use at the point of purchase, the actual risk is borne by the customer, since it is she who agrees and pays for the product specified at that time.

An alternative conceptualisation of the customer within the system boundary is offered by Service-Dominant Logic or S-D logic

[1] See, for example, Lampel and Mintzberg (1996), Yang and Burns (2003), and Forza et al., 2008.

[2] For a detailed review of closed loop supply chain research see Guide and Van Wassenhove (2009).

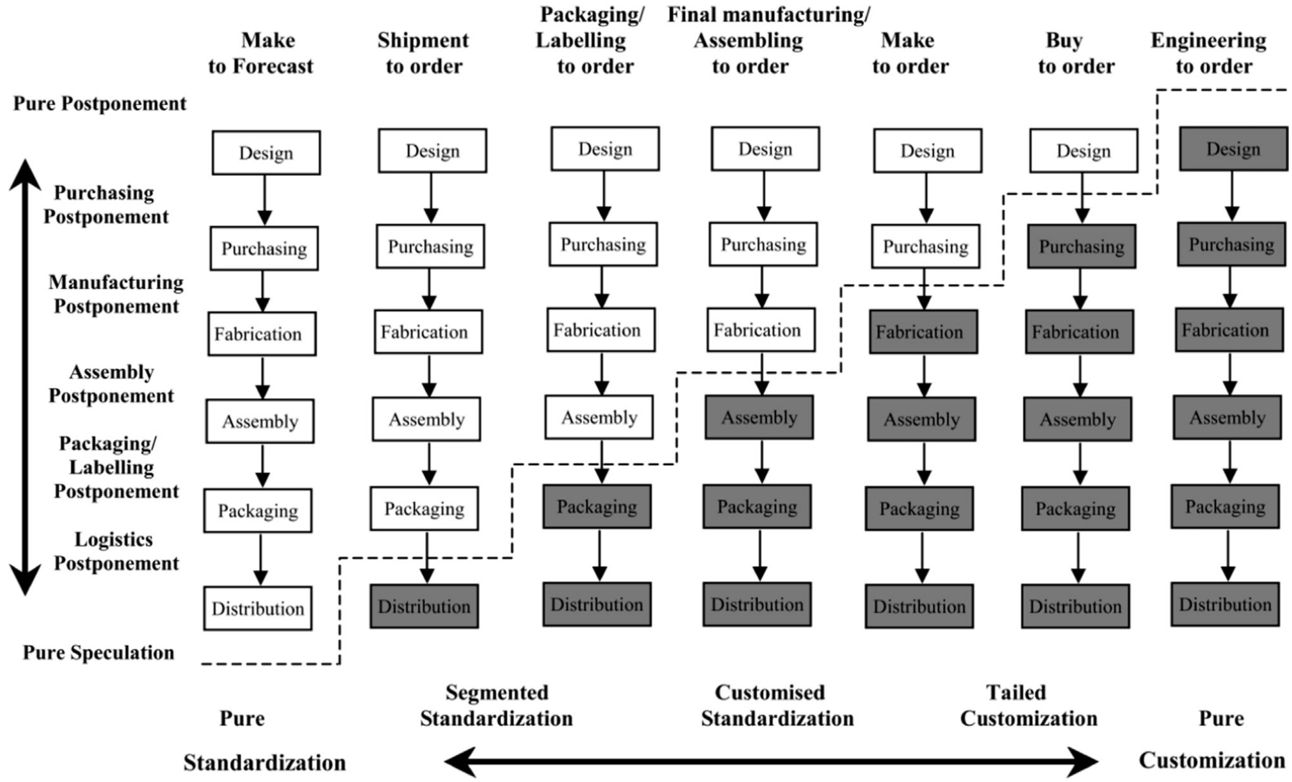

Fig. 1. Postponement and supply chain framework, as presented in Yang and Burns (2003), p. 2077.

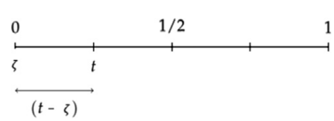

Fig. 2. Matching varieties with consumer characteristics.

(Vargo and Lusch, 2004, 2008). S-D logic places the customer inside the system, proposing that value is co-created 'in-use' and in the experience of the product by the customer rather than at exchange. S-D logic considers value co-creation in use as part of the provider's responsibility as well as that crucially, the customer brings resources (knowledge, time, usage information, etc.) to bear onto the system to realise that value. An S-D logic conceptualisation of a supply chain therefore includes the customer consumption and experience within the remit of supply chain management (Lusch et al., 2010). This would be a big challenge to providers, not least because first, the provider has no control or resources to engage in consumption activities to ensure outcomes are achieved satisfactorily (e.g., Prahalad and Ramaswamy, 2004). Second, the provider does not really benefit economically from such a conceptualisation under traditional business models of exchanging product ownership since customer contexts and their varieties occur after the exchange has transpired. The only two economic reasons for an S-D logic conceptualisation in a traditional business model of product exchange is therefore that of (1) achieving a more stable demand profile for the product, achieved from greater intelligence from when customer consumption would trigger specific customised needs or demand, and (2) to derive innovation that would achieve greater demand or higher prices from mass-customising the product. Even so, the heterogeneity present in customer consumption contexts may make an S-D logic conceptualisation of a supply chain unviable. In this paper, we argue that the era of the Internet-of-Things will change that dynamic.

Since the consumption space is not within the visibility of the provider, an S-D logic conceptualisation of the customer would mean that the provider suffers from uncertainty resulting from the asymmetry in information, whether it is between the customer and the provider, or between the purchase point and some future time of use. Some business models that have moved the transaction boundary from that of ownership transfer to outcomes, such as Rolls-Royce's Power-by-the-Hour©, have benefited from S-D logic conceptualisation because they focus the provider in terms of its capability development, i.e., achieving collaboration and reducing uncertainty is part of the provider's capability to achieve outcomes (Ng et al., 2012; Ng et al., 2013). Within the business-to-business (B2B) space, where customers and providers are more similar and symmetrically organised, an S-D logic conceptualisation to revisit the entire system of supply chain including value-creating use activities to achieve collaborative outcomes is certainly more feasible. However, as the previous discussion has made clear, the opacity of the *consumer* use and experiential spaces of products in the business-to-customer (B2C) domain poses a challenge to providers. We present this as three different kinds of informational-related challenges that must be considered and/or overcome. They are those caused by:

(1) Asymmetric information. Providers' supply chains may have very little visibility of the customer use spaces beyond product exchanges (i.e., providers have less information about usage than do consumers);
(2) Complexity in aggregating and ordering available information. Even under conditions of symmetric information about usage between providers and consumers, the provider may not be able to put the information in an order that makes it feasible to engage in mass customisation;
(3) Incomplete information on the part of both consumers and providers about future contextual usages. This kind of uncertainty is known in economics as ambiguity (Knight, 1921;

Ellsberg 1961) and if present, would imply that both providers and consumers may resort to non-optimal heuristic choices about future supply and demand for product variety.

Solutions to all three of these informational challenges would be necessary for the achievement of the full capturing of surplus. However, the literature offers very little insight into how this can be done. This paper seeks to fill this gap. Here, we argue that problems stemming from informational asymmetries and complexity (Points 1 and 2 above), can be solved through the Internet-of-Things (IoT); but the resolution of ambiguity (Point 3 above), would require a different supply chain strategy subsumed within the IoT space. We compare G-D logic and S-D logic by considering the supply chain strategy of tailoring (as one of the G-D logic representations) versus platform strategy (as one of the S-D logic representations). We also identify conditions under which G-D logic and S-D logic may be optimal supply chain strategies for providers. Our model shows that there are obvious advantages to adopting S-D logic, while G-D logic may be optimal only under very restrictive conditions. Our approach differs from the existing approaches in management literature in several ways. First, to date, the majority of mathematical models (e.g. Krishnan and Gupta, 2001; Jiao et al., 2007) were developed for product platforms (features and structural characteristics shared across a family of products) rather than platform products (process and feature developments over existing technology) as defined by Clark and Wheelwright (1993). In other words, existing research extensively considers the conditions and aspects of tailoring strategy for various types of industries and providers, yet it largely ignores the question of how tailoring strategy compares to platform strategy. Second, the model presented in this paper allows us to construct a meaningful framework of provider-consumer co-creation which can be tested empirically through an IoT market platform demonstrator such as the HAT.[3]

The remainder of this paper is organised as follows. Section 2 provides some background and intuition for our theoretical model. Section 3 first presents the static version of the model and then identifies ways in which this model can be adopted to allow for dynamics. Finally, Section 4 concludes with the general discussion of our main results and model implications.

2. Background: Internet-of-Things

The Internet of Things (IoT) is often considered to be part of the Internet of the future, consisting of billions of intelligent communicating “things” or Internet Connected Objects (ICO) which will have sensing, actuating, and often data-processing capabilities. Each ICO could have one or more embedded sensors that will capture potentially large amounts of data which can be analysed, clustered and queried in ways that could increase efficiencies or effectiveness (Perera et al., 2014).

The use of sensor data in the supply chain is not new. Many organisations such as Unilever, United Biscuits, Motorola and Ford, to name a few, already use Auto-ID data (such as RFID) within supply chains (Angeles, 2005). However, the use of Auto-ID data is often for location detection, and streaming of information through the supply chain to enable a more efficient flow of materials. The use of sensor data to understand consumption and hence customisation of the product, is under-researched (e.g., Zahay et al., 2009) and is the focus of this paper.

Sensor information from ICO could be used by providers to improve customisation since the value-in-use of different varieties of a product to a consumer depends on related customers' characteristics. For example, point-of-sale system providers have traditionally collected information about these characteristics and consumers' preferences from purchasing data (we will refer to this as the provider's ‘model’ of consumer's preferences, and for the purpose of this discussion, will assume that this is common knowledge). However, providers are typically unable to detect the characteristics of individual consumers when they engage in acts of consumption. Some online businesses have tried to improve on this by collecting information on individual preferences through repeat buys, and use that information to provide tailored suggestions of existing varieties of goods (Rowley, 2005). However, the tailoring that can be achieved through these schemes is limited because they use information that relates to a very partial picture of the consumer's activities (the buying) and only takes into account those consumption acts that flow through the same retailer.

Sensor-based information collected through ICO covers acts of consumption and use that can include many products and activities in the household, and can therefore be used to obtain a much more precise and complete picture of the consumer's characteristics and hence of their preferences. Therefore in principle, the detailed information available from the ICO data could make it possible to produce specific products and services tailored to an individual's characteristics and needs, as inferred by the ICO-based transaction information, rather than simply making tailored suggestions to the individual consumers about existing varieties. This may become viable because the increased value of mass customisation and tailoring to the provider might justify the fixed costs. It might also be facilitated by the reduction in fixed costs of tailoring afforded by technological advances such as 3D printing. By taking such an approach based on G-D logic approach to the extreme, providers could design and make a large number of product varieties and customise them to each individual consumer on the basis of the information collected through the IoT, i.e., there is a specific version of a product being manufactured just for that consumer. We consider this mass customisation strategy as a *tailoring strategy.*

The pervasiveness of the IoT has a second consequence that is of significance to supply chains. In the past when objects were not connected, our consumption and experiences of such objects were reasonably independent of other objects and were only connected through social practices. With the IoT, connecting up objects creates an intervention in the usage of the product, e.g., we see game consoles being used as communication devices, and set-top boxes being used as computers. And as more objects become connected, we may desire to see our heating system control our water and electricity supply or our appliances. What this implies is that single objects can exhibit ‘hyper-variety’ of use and greater usage demand from the user. Furthermore, the extra variety that is created at the point of usage could be observable through the ICO data. This leads to the possibility of applying the ICO data for mass customisation purposes.

To do that, a product or a product bundle must be able to take on customer data as a customisation strategy. We call this a *platform strategy,* where the product customisation by the provider is postponed indefinitely i.e. it is an *incomplete product* (Yoo et al., 2010). This is where ICO data of the person can be applied to complete the customisation of the product, e.g., using an individual's nutrition data to tailor food products for the coming week to meet increased fibre content needs. Using an individual's usage history may also help to determine when he needs specific products. With smartphones for example, the customer buys a standardised product and has to purchase digital applications that he can use to customise the phone so that it could be called on in context and on demand, allowing the phone to function as

[3] For more information, see http://hubofallthings.org.

multiple products from dictionary and calculator to e-book and torchlight.

One could even go further into personal data conversion into material space. For instance, the customer could apply ICO data to do 3D printing of a customised component, such as the 3D printing of bride and groom figurines for a wedding cake. This means that ICO data potentially empowers the customer with 'completing resources'. ICO-based information on digital interfaces may also be beneficial to providers with a platform strategy, as it would allow them to effectively select and recommend the satellite products which best answer consumer needs. For example, Apple has full control over the number and variety of applications it offers consumers. ICO information may suggest a more efficient way of selecting these applications as well as a more optimal way for improving customer satisfaction since context varieties are better served. We consider such a platform strategy to be a conceptualisation of S-D logic because applying personal consumption ICO data is a structured form of co-creating use value in context. Adopting a platform strategy means the provider creates a standardised product as an incomplete product platform, such that it can be completed by the customer. Unfortunately, while this is possible for some, over-tailoring by providers to improve customer service and increase market reputation may result in a conflict between individuals looking to complete a product through ICO data in context and on demand, and the provider who has pre-set requirements.

A tailoring strategy suggests that decoupling is at the point of exchange/purchase, which is the furthest point of a supply chain for postponement. Platform strategy, however, suggests that postponement is indefinite, i.e., customisation is performed by the consumer, in context and on demand, and we differentiate this by calling it *personalisation*. Our paper models a provider's optimal strategy (tailoring or offering a platform) based on a consumer's private observable and unobservable characteristics as well as the information exchange mechanism between the provider and the consumer.

3. The model

3.1. Preamble

In this section, we present our model which operationalises the provider-consumer experience based on product usage. As explained in Section 1, this experience is associated with three kinds of information-related challenges, all of which are captured by the model presented below. First, we show how ICO systems can solve (1) the issue of asymmetric information with regard to product usage between provider and consumer, and (2) the provider's problem of aggregating and ordering information accumulated about consumer usage. Second, we provide both an analytical as well as a dynamic mathematical model that not only offers a solution to the issue of incomplete information about future contextual product usage[4], but also finds an optimal customisation strategy for the provider.

In Section 3.2 we describe how providers may infer useful (and not always easily observable) information about product usage by obtaining and analysing observations of multi-level consumer behaviour. In Section 3.3, we turn to the issue of how these obtained observations (even under conditions of no information asymmetries) can be structured and aggregated by the provider to customise products in a meaningful way. Finally, Section 3.4 explains that even if problems of asymmetric information and information aggregation and ordering are resolved, the provider-consumer experience still suffers from incomplete information because providers need to generate a reliable mechanism to enable them to anticipate future product usage and thereby, predict consumer demand for variety. Our model suggests such a mechanism and makes specific recommendations for provider strategy. We concentrate on the two types of strategies with regard to enhancing customer value from product usage:

- *Tailoring strategy* (based on G-D logic) refers to a situation when a provider opts to produce multiple varieties of tailored products and offers them to consumers.
- *Platform strategy* (based on S-D logic) refers to a situation when a provider creates a flexible but standardised platform that allows customers to purchase additional custom-made products which are developed by other providers but are compatible with the platform.

Consider, for example, the current market for smartphones. In this market, Nokia adopts a tailoring strategy by offering different varieties of tailored smartphones, whereas Apple opts for the platform strategy by offering a standard iPhone platform, which customers can adapt to their individual needs by uploading and using applications developed by other providers. In Section 3.4, we analyse the benefits of ICO information for providers which adopt the tailoring and platform strategies under conditions of two-sided (provider and consumer) incomplete information, and specify conditions when it is more efficient for a provider to resort to the tailoring strategy and when they should opt for the platform strategy.

3.2. Dealing with issues of asymmetric information between provider and consumers

In this subsection we concentrate on the factors at play when providers use ICO to obtain consumer product usage information, which may help them formulate a customisation strategy. We first consider an example to illustrate the idea of customisation that takes into account the consumer's usage considerations with regard to product variety. We begin by noting that individuals or consumers who make decisions about products in terms of both demand and usage, do so to try to enhance their own value. In turn, this value depends on the varieties of products that they consume, $t \in T = \{t_1, \dots, t_n\}$, and on their own (consumer) characteristics, $\zeta \in \alpha = \{\alpha_1, \dots, \alpha_m\}$. The vector of characteristics is not something that can be easily 'seen' by standard business models – while it is true that some consumer characteristics are observable and can be readily incorporated into standard business models (such characteristics may include an individual's gender, age, etc.), there are other characteristics that are not observable but are rather personal and private. It is these characteristics that are associated with informational problems since they cannot be incorporated into business models unless there are the correct incentives in place for the revelation and categorisation of 'true' characteristics (and this incentive problem could be quite severe for some private characteristics such as sexual habits, mental health status, and details of 'not easy to observe' product usage inside and outside of the home).

To further illustrate the idea of characteristics, consider a household that can have either one or two rooms, $r \in \{1, 2\}$, and either one or two children, $k \in \{1, 2\}$. A provider might very well have information about k but unless they also know r and take into account all of the different possible combinations of rooms and kids, $(k, r) = \{(1,1), (1,2), (2,1), (2,2)\}$, then they will be making decisions based on asymmetric information (i.e, they will not have access to all characteristics which may be known to consumers

[4] This solution cannot be offered by ICO.

Table 1
Example of consumer characteristics and their combinations.

(k)	**(r)**	**(k, r)**
1	1	(1, 1)
1	2	(1, 2)
2	1	(2, 1)
2	2	(2, 2)

and which could, potentially, affect their product usage). We can represent the primary characteristics (in our example, rooms and children) and their combinations in a table (see Table 1):

Therefore, there exists information asymmetry between providers and consumers as providers have access only to a minor subset of consumer characteristics which (may) affect product usage.

Now consider a different example. Several varieties of the same product (a smartphone, for example, can be ergonomic or basic, with keyboard or touchscreen, black or pink, etc.) can each be produced at some fixed production cost (the 3D printer needs to be adjusted for every variety). The varieties of smartphones can be represented by the T set of possible varieties. Now assume that there is some 'model' that maps consumer characteristics onto a value for consumers and let it be denoted by $V(T, \alpha; \omega)$, where ω is some positive real valued parameter. To begin with, assume that this 'model' is something that providers know about[5], but other than this, providers would also like to know exactly what the model looks like for each and every consumer, i.e., they would like to know each consumer's value functions. This would allow them to match the product variety to characteristics in a way that delivers the maximum value to consumers (which would then allow the provider to charge a higher price and maximise profit). But this can only happen if the provider can observe α and the mapping between T and α.

Using a simple example, suppose that a consumer's value function is given by the following mapping:

$$V(T,\ \alpha; \omega) = \omega - (t - \zeta)^2 \tag{1}$$

where $t \in T$ and $\zeta \in \alpha$. This consumer places a value on the product consumed that depends on how well the offered product variety matches her ideal product variety (which in the example above depends on a single characteristic, ζ). The 'distance' between the offered product variety and the ideal product variety is given by the term $(t - \zeta)$. To generalise this notion, we can suppose that each consumer has characteristics $\zeta \in [0,\ 1]$, that there is one product that is consumed and there are $t \in [0,\ 1]$ possible varieties of it. The line depicted in Fig. 2 captures the ordering of varieties and the preferences over varieties: an individual with $\zeta = 0$ is best matched with the variety $t = 0$. As t diverges from 0, that consumer becomes less satisfied and places less value on t (which has implications for the price that can be charged for t).[6]

Now the provider that makes smartphones needs to decide about the variety that they want to produce. They can get a higher price with an exact match to preferences but consumers will more generally have a lot of unobservable characteristics. In our example, the best thing the provider can do in the absence of information about unobservable characteristics is to choose a variety of smartphone that maximises the expected total value of product usage to consumers. If there are two consumers (subscripted by 1 and 2) identical in every way in their characteristics, then the expected total value to consumers is $E[V_1(T, \alpha; \omega),\ V_2(T, \alpha; \omega) = 2\omega - (t - EV_1[\zeta_1])^2 - (t - EV_2[\zeta_2])^2]$, where $\zeta_1, \zeta_2 \in [0, 1]$, and where $EV_1[\zeta_1]$ and $EV_2[\zeta_2]$ represent the expected preferred variety of the product for consumer 1 and consumer 2 respectively. In this case, the best variety that the provider can offer is the one that maximises total expected value net of the fixed cost of production, that is, $E[TV] = E[V_1(T, \alpha; \omega), V_2(T, \alpha; \omega)] - F$. This results in a best guess of variety which is equal to $t = (1/2)$, the average variety. For this choice, if consumer 1 actually has $\zeta = 0$ and consumer 2 actually has $\zeta = 1$, then the total value to the provider of producing $t = (1/2)$ is equal to $2\omega - ((1/2) - 0)^2 - ((1/2) - 1)^2 - F = 2\omega - (1/2) - F$.

How can product tailoring add value for the provider? Continuing on with our example, now suppose that the provider has information on α and not just its expected value. Then if products can be customised to "match" the ideal variety of each consumer, the business will make two varieties, one for each consumer. The total value to the provider then is $TV = 2(\omega - F)$. If $\omega = 1$ and $F = (1/2)$ then $E[TV] = (5/4)$ and $= (3/4)$, customisation can create value for the provider (and for the consumer) through a better match.[7]

Since ICO allow providers to represent consumer behaviour as a complex system of multi-level observations, from which information about individual usage given consumers' private characteristics can be inferred, the model presented above lays out the foundation of how providers can use information obtained via ICO to optimise customisation.

3.3. Solving aggregation and ordering problem of contextual variety: how ICO observations can be translated into meaningful information for the provider

In the previous subsection we have looked at a simple model of customisation where variety was endogenously determined and information asymmetry exists between provider and consumer. Yet, even in the absence of information asymmetry, providers need an algorithm to be able to efficiently accumulate, analyse and aggregate information about usage in order to translate it into meaningful input for product customisation. To show how ICO can solve this problem, we first need to consider the notion of contextual variety and modify our model (presented in Section 3.2) to endogenise T and ω. Contextual variety is defined as "the degree of variability in the set of contexts within which the individual faces in co-creating value" (Ng et al., 2012, p. 4). In other words, using our example, the same feature of a smartphone can be applied to multiple contexts. For example, the camera device built into a smartphone can be applied to taking pictures or videos but also to scanning "smart" mobile tags (two-dimensional bar codes which allow the quick finding of URLs).

Although consumer characteristics, α, cannot be directly measured by ICO, ICO can measure actual patterns of product usage. Suppose an individual may have a camera in her smartphone and may use it (for simplicity's sake, we assume that the camera could be used in only one context but it is easy to imagine multiple contexts: taking pictures, making videos or scanning bar codes).[8] Let $k \in \{0,\ 1\}$ now stand for the number of cameras in the smartphone and let $r \in \{0,\ 1\}$ stand for the number of contexts in which the camera is used by a particular consumer. As in the

[5] For the moment we assume this to be deterministic, but in Section 3.3 we discuss the implications of this for consumer value when it is stochastic.

[6] We can think of the line as all the varieties of smartphones that can be manufactured. For example, the least ergonomic is positioned at and the most ergonomic positioned at $t = 1$. A consumer with $\zeta = 0$ likes the least ergonomic smartphone and if the only thing on offer is a more ergonomic one, her value will diminish relative to the value she would get with the least ergonomic phone, i.e., by the square of the distance that she is from her ideal point. Therefore, consumers place higher value on product types that exactly match their preferences.

[7] Obviously, if fixed costs are really high then ω must be pretty large relative to F to make it worthwhile, but for providers with positive but small fixed costs, it should always be worthwhile to produce more than one variety.

[8] For example, in a two-person household, both members of the household can have the same type of smartphone or different types of smartphones.

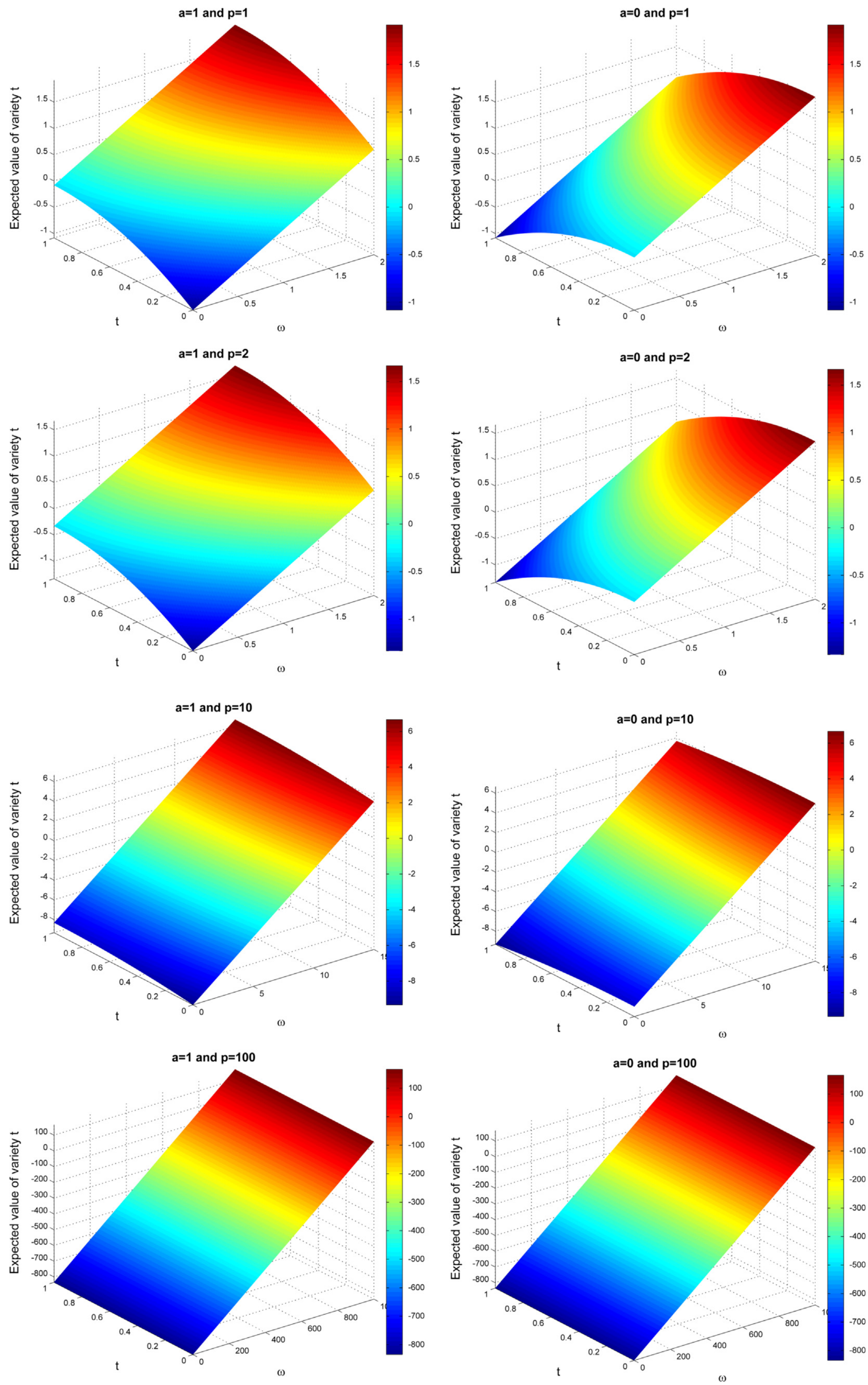

Fig. 3. Simulated expected values $E[V(T,\ \alpha,\rho:\omega)]$ of the consumer.

previous example of characteristics, the different possible ways of combining smartphone varieties are given by $x \equiv (k,r) = \{(0,1),\ (1,1),(1,0),(0,0)\}$.

To be able to use the information collected in ICO for product customisation, one has to have an idea about how ICO measurements would be associated with personal characteristics of consumers and their contextual variety preferences. For that purpose, volunteer ICO participants would supplement ICO information with additional information on consumers' private characteristics as well as individual preferences for a product's contextual variety. Then the expected value of variety t to a consumer of type ζ in a household where sensor measurements x is captured by Eq. (2) below:

$$E\left[V(T,\ \alpha,\rho:\omega)\right]=\omega-\frac{1}{\rho}\int_{\alpha-\rho/2}^{\alpha+\rho/2}(x-t)^2dx, \tag{2}$$

where ρ measures variety or "variation in the consumption context". Consider the following examples of graphical representations of Eq. (2):

Fig. 3 shows that the higher the consumers' contextual variety (captured by ρ), the more varieties of a product a provider needs to produce and the higher its costs are going to be. Therefore, for very high ρ, each provider should set ω' to be very high to compensate for the ω generated from Eq. (2).

Notice that apart from providing a mechanism of aggregating consumer information from ICO and translating it into meaningful input for customisation, Eq. (2) also allows us to make three intermediate conclusions. First, Eq. (2) gives us an opportunity to derive the provider's optimal strategy in a static setting and prescribe either the tailoring strategy or platform strategy for this case. For a given support of consumer characteristics with mean zero, and comparing two products (e.g., iPhone and Nokia smartphones, where providers adopt the platform strategy and tailoring strategy respectively) such that $\rho_1<\rho_2$ and that have common value $EV\left[(1/2),\alpha,\rho\right]$ which presupposes different values $\omega_1<\omega_2$ - the value of tailoring varieties of product 1 to individual consumer types will be greater than the corresponding value of product 2. Thus, all things being equal, commodities that feature a broader consumption context (commodities that are 'platforms') need less customisation. Furthermore, when ω' is very high, it would make more sense for the provider to customise its product by adopting the platform strategy and outsource customisation to other providers. In other words, the higher the demand for contextual variety, the more profitable the platform strategy becomes relative to the tailoring strategy.

The optimal choice of variety offered to the consumers is then the variety t' (which can be reached via tailoring or via providing a platform) that yields the maximum value of $E[V(T,\alpha,\rho)]$ for the observed x. As shown earlier, if the value of the customisation is enough to justify the additional costs of producing an extra variety, then tailoring the product will produce additional value to consumers and/or the business (i.e., the Nokia strategy will be more profitable than the iPhone strategy). Alternatively, if the value of customisation is not enough to justify the additional costs of producing an extra variety, it is more profitable for the provider to offer a platform rather than to tailor a product.

Second, since the richness of sensor measurements x would be more complete and useful to the provider if these measurements contain information about consumer contextual variety preferences, it would be highly complex and impractical if any part of this information does not belong to the consumer. For example, if providers had to deal with a third party to obtain any part of consumer measurements (related to product usage or other characteristics), the information would become very costly to obtain, as providers are unlikely to collect a complete multi-level set of all available information for the same individual. Therefore, the conditions of our model imply that a mechanism of informational exchange where consumers own their usage data and make decisions about sharing their data with multiple providers (on a proprietary basis or otherwise) seems more optimal than the outsourcing of information-sharing decisions by consumers to a third party.

Finally, an additional important component of the ICO software, as implied by our model, is a feedback mechanism that allows consumers to provide ex-post measurements of the value experienced from customised products. This would allow for the updating of the initial mapping V, which would in turn provide for even more precise tailoring in subsequent consumption rounds. In Subsection 3.4 we look at the provider's optimal strategy choice in a dynamic setting.

3.4. Tailoring versus platform strategy under incomplete information: a dynamic model

The previous subsection shows how ICO sensor information x is related to consumers' private characteristics/contextual variety preferences ζ for a set of varieties of different products as well as how a contextual variety can be captured in the model. In this subsection we show how our general framework can be extended to model the process of product customisation (via tailoring and/or via offering a platform) using ICO.

Even though ICO mechanisms solve the problems of asymmetric information between providers and consumers (as shown in Section 3.2) as well as allow for the efficient aggregation and employment of consumer usage information to customise products (as shown in Section 3.3), ICO cannot solve the problem of incomplete information between providers and consumers. This problem arises from the fact that providers need to anticipate future contextual usage of products in order to provide the customisation desired by consumers. We provide an analytical and dynamic mathematical model of customisation under situations of incomplete information, and derive conditions in which tailoring should be a preferred strategy over the platform strategy and vice versa. Consider the following extension of our initial model presented in Sections 3.2 and 3.3. Assume that there is one provider in the market producing one type of product. This provider has a choice of adopting the tailoring strategy or the platform strategy (e.g., in the smartphones market, a provider may be in favour of the tailoring strategy, like Nokia, or opt for the platform strategy, like Apple).

Stage 1 Consider that in time period $d\in\{1,\dots,d-1,d,\dots,D\}$, the ICO detects observable sensor information x about product usage as well as other consumer characteristics which can be translated into the consumer's desired consumption criteria $c\in C=\{c_1,\dots,c_N\}$, specified in N dimensions for the product developed by the provider.[9] These criteria set targets for the provider's potential development of new product variety based on the new characteristics in period $d+1$ for N different dimensions of the product $c_1^d,\ \dots,\ c_N^d$.[10] The current product variety of the provider in period d (product variety before customisation, that is, before any change according to the consumption criteria) has a set of characteristics which correspond with the dimensions of consumers' usage interest $s_1^d,\ \dots,\ s_N^d$. We assume that there exists at least one dimension $i\in N$ where the current product variety's characteristic lies below the consumption criteria: $s_i^d<c_i^d$ (otherwise the consumer would automatically buy the initial variety of the product and no further customisation of this product would be necessary). Such criteria arise due to a latent need created by the variety of consumption contexts.

Stage 2 After receiving the information from the ICO and translating it into a set of consumption criteria for a new

[9] The criteria c is set to maximise the expected value of variety t as specified in Eq. (2).

[10] For our smartphone example, these dimensions can be the interface, speed of information loading, personalisable features, etc.

variety, the provider adopts changes/customisation q_i^d in each dimension $i=\{1,\ldots,N\}$. These changes can be made via tailoring or via making new satellite products (e.g., smartphone applications) available on a platform. Subject to a combination of internal and external conditions and circumstances, the provider may opt to do nothing to meet the consumer variety criteria $q_i^d=0$; to commit a maximum effort to fulfil the consumer variety criteria $q_i^d=1$; or to meet the criteria only partially $0<q_i^d<1$ (this may manifest itself in the development of a new product which meets only a subset of consumer variety criteria).[11]

These consumer variety criteria could be incorporated by the provider using low consumer resource (with little input from the consumer in product value co-creation) or high consumer resource (with large consumer involvement in value co-creation). From conditions set out in Stages 1 and 2 we can expect that when choosing between the tailoring and the platform strategies, the provider faces a trade-off between consumer product variety criteria (which we call product variety) and consumer resource (the amount of consumer input in the product co-creation which is available or desired by the provider).

The trade-off matrix summarised in Fig. 4 represents our analytical model for provider strategy choice.

For a particular product, a provider considers the relative certainty about the contextual product variety versus the consumer resource to which this provider has access. When consumer resource is relatively low and contextual variety relatively certain, this means that the provider can anticipate contexts in which the product will be used quite well, and has low access to consumer input or does not want to rely on it. In this case, the provider will offer homogeneous products as there is no need for customisation. When consumer input is low but contextual variety is relatively uncertain, the provider will try to customise the product by using the tailoring strategy. When the provider is certain about contextual variety with regard to its own product but has access to high consumer resource or expects consumers to engage in product value co-creation, such a provider will customise the product using the platform strategy. When variety is uncertain and consumer resource is high, it is obvious that customisation is required. However, both the tailoring and platform strategies may be optimal. In order to specify the conditions necessary for each of the two strategies to be adopted by providers for this particular part of our analytical model (see upper right corner on Fig. 4), we need to introduce an additional criterion which allows customers to distinguish between providers – provider's reputation.

In addition to developing a new product variety after analysing consumer's variety criteria, the provider also formulates a signalling response λ_i^d, which could be positive $\lambda_i^d>0$, negative $\lambda_i^d<0$ or neutral $\lambda_i^d=0$. For example, a provider may pre-announce the release of a new feature of the product (positive signalling response), announce no intention to release a particular new feature of the product (negative signalling response), or send an irrelevant or no signal (neutral response). These signals form the provider's reputation $\hat{\lambda}_i^d$. Each signal highlights the provider's effort to incorporate consumer product varieties into its production line which may have an impact on the provider's profit.[12]

In this case, if the provider adopts the tailoring strategy, similarly to the platform strategy, consumer variety criteria c_{iT} will be based on the ICO sensor information x (by maximising expected value specified in Eq. (2)). However, while in the tailoring strategy, the provider takes sensor information and makes decisions about which new characteristics of the product it wants to develop for consumers in a new product variety, in the platform strategy, the provider gives consumers a possibility to decide for themselves which satellite products they want to obtain/buy. Therefore, the consumer product variety criteria c_{iT} for the tailoring strategy will be a lot noisier than the consumer product variety criteria for the platform strategy c_{iP}. Since changes q_i^d depend on the consumer product variety criteria, if the provider adopts the platform strategy, the changes it will make to the product q_{iP}^d will fulfil the consumer product variety criteria better compared to the changes it would make if it adopts the tailoring strategy q_{iT}^d.

On the other hand, if the provider adopts the tailoring strategy, it will send more positive signals to the consumers than if it opts for the platform strategy. This will happen because the provider which tailors a product is more likely to pre-announce new product modifications to the consumers by sending positive signals $\lambda_i^d>0$ on a regular basis. Whereas the provider with the platform strategy will mostly send out neutral signals $\lambda_i^d=0$ due to the fact that other providers develop satellite products for the platform.[13]

Stage 3 In this stage, both the product change and the signalling strategy are realised. The outcome is depicted in *Lemmas* (1) and (2) below.

Lemma 1. *In time period $d+1$, the product's level of customisation (change) according to the consumer product variety criteria on the dimension (area) i (s_i^{d+1}) satisfies Eq. (3):*

$$s_i^{d+1}=s_i^d+\sum_{i=1}^{N}\sum_{j\neq i}q_i^d\cdot\beta_{ij}+\varepsilon_i \tag{3}$$

The intuition for this is as follows. The product customisation (change) depends on the initial characteristic of this variety of the product according to that dimension (s_i^d) the adopted customisation (changes) on all dimensions $\sum_{i=1}^{N}q_i^d$ at time d weighted by the 'cross-dimensional impact coefficients' β_{ij} with $i\neq j$ and on a random shock ε_i. The cross-dimensional impact coefficients β_{ij} capture the effect of an adopted customisation (change) on one dimension on the state of development on the other dimension.[14]

The intuition for this is that a provider's decision about the way the new customised variety of product should look may have an impact on its packaging. For example, any changes in the smartphone size and dimensions lead to the development of new covers which are capable of fitting the new phone dimensions.

The customisation outcome product variety with new characteristics (s_i^d) is complemented by the signal, sent by the provider to

[11] Note that our model allows for the changes to be negative $q_i^d<0$ in which case for one reason or the other the provider's product variety characteristic deteriorates relative to consumers' variety criteria. This may happen, for example, if the provider opts for cutting production costs by making their product less environment-friendly. While such changes are possible in practice, in this paper we restrict our attention to non-negative changes which are most relevant for the customisation problem.

[12] Note that our model can be extended to cases when providers may misuse the signalling and pre-announce customised product varieties which are then not actually produced (such as, e.g., vaporware). In this paper, we leave such cases aside and restrict our attention to the product varieties which are developed.

[13] Additionally, providers which opt for the platform strategy are likely to take less responsibility with customisation compared to providers adopting the tailoring strategy, since they rely on other providers to deliver features desired by consumers. Therefore, providers using the platform strategy bear a higher reputational risk compared to providers with the tailoring strategy: if other (supporting) providers offer low-quality additions to the main product/service, this may hurt the reputation of the whole platform.

[14] Note that when $\beta_{ij}=1$ the cross-dimensional impact is non-existent and can be ignored.

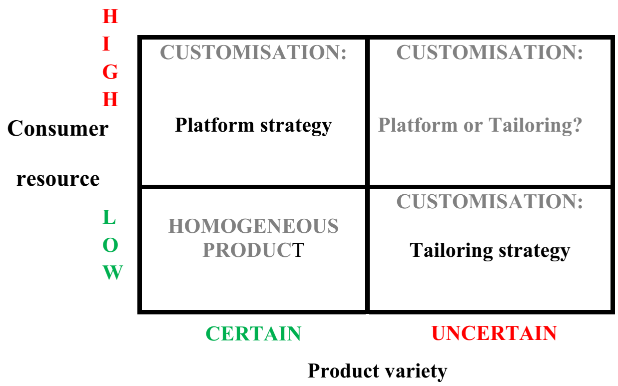

Fig. 4. Analytical Model of variety versus consumer resource.

the consumers (via advertisements, marketing campaigns, promotions, etc.)

Lemma 2. *The provider's reputation in the eyes of the consumers in the period $d+1$ ($\hat{\lambda}_i^{d+1}$) is given by Eq. (4):*

$$\hat{\lambda}_i^{d+1} = \hat{\lambda}_i^{d} \cdot \sum_{i=1}^{N} \sum_{j \neq i} q_i^d \cdot \delta_{ij} + \sum_{j=1}^{N} \sum_{j \neq i} \lambda_j^t \cdot \gamma_{ij} + \varepsilon_i \tag{4}$$

The intuition for this is as follows. The provider's reputation in period $d+1$ is simply the reputation of the provider in the previous period $\hat{\lambda}_i^d$ adjusted for the recent customisation changes $\sum_{i=1}^{N} q_i^d$ and signalling efforts $\sum_{i=1}^{N} \lambda_i^d$ through their impact coefficients δ_{ij} and γ_{ij}, and corrected for the random shock ε_i. The impact coefficients δ_{ij} refer to the effect of an adopted customisation (change) on one dimension of the provider's reputation according to a different dimension. For example, consumers may believe that the iPhone is of better quality because it offers more personalisable features compared with its competition. The impact coefficients γ_{ij} describe the effect of the signalling effort according to one dimension of the product on the provider's reputation according to the other dimension.[15]

Stage 4 Finally, the consumer evaluates the provider's customisation efforts based on the decision rule formulated in Proposition 1 below.

Proposition 1. *The consumer evaluates the product's customisation according to each dimension as a weighted sum of the actual characteristic of this product after customisation (change) s_i^{d+1} and the formation of the new provider's reputation $\hat{\lambda}_l^{d+1}$. If the product change outruns the corresponding benchmark c_i^d derived from the ICO measures of x, consumption criteria for the future product remain unchanged $c_i^{d+1} = c_i^d$ and in period $d+1$ we are likely to observe no change in consumption patterns.*

However, if the provider fails to meet the consumption criteria, this does not necessarily mean that consumers would stop buying the product or would not buy a product which has an incomplete set of desired characteristics. In this case, consumers will consider lowering their desired consumer product variety criteria exactly to the level of the current product variety's characteristics. The revised consumer product variety criteria c_i^{d+1} (and weighted by their relative importance θi) are compared to a predetermined minimum consumption standard (current consumption level x). If these new criteria c_i^{d+1} (derived through observing new x in period $d+1$ via the ICO mechanisms) are above the current consumption standard, i.e. if $\sum_{i=1}^{N} c_i^{d+1} \cdot \theta_i \geq x$, the consumer will buy the new customised product (obtained through either tailoring or through the offering of new satellite product options via a platform). This can happen when only a subset of the desired consumer product variety criteria is fulfilled. Otherwise, when $\sum_{i=1}^{N} c_i^{d+1} \theta_i < x$ the variety criteria remain unchanged and the provider's product is not accepted by the consumer.

Let $\mu \in [0,1]$ refer to the relative weight of the customisation (changes) made to the product and the provider's image. We assume that consumers weigh changes and reputation concurrently: in the extreme, they may place all the weight on changes or on the reputation. The intuition behind this assumption is as follows: When customers are faced with a product/service offered as a platform, they have to rely on supporting providers to personalise this product/service. Some customers might dislike this as the quality of the personalisable features may be low, which in turn may hurt the reputation of the platform provider, hence making providers using a tailoring strategy more attractive to consumers. Other consumers, however, would be willing to take the risk of dealing with multiple providers and tolerate quality heterogeneity to gain more functionality. These consumers will, therefore, opt for providers with a platform strategy. Therefore consumer product variety criteria for the future products $x^{d+1} \Rightarrow c_i^{d+1}$ minimises $\mu \cdot s_i^{d+1} + (1-\mu) \cdot \hat{\lambda}_i^{d+1}$ c_i^t subject to the constraint that $\sum_{i=1}^{N} c_i^{d+1} \cdot \theta_i \geq x$

Note that our model has several interesting features which allow for the construction of a meaningful comparison between the tailoring strategy and the platform strategy under conditions where consumer product variety is uncertain and consumer resource is high. First, it describes the dynamic process between observing behaviour via ICO, translating it into consumption criteria (desired product characteristics), making changes to the product and then observing new purchasing patterns. Second, as long as the level of product variety characteristics in period $d+1$ is not lower than the current consumption level inferred from ICO-measured x, consumers may be willing to purchase products which only partially fulfil their variety criteria.

Which strategy is more efficient: should the provider resort to tailoring or should it adopt the platform strategy? Given Proposition 1, we can formulate the following 3 corollaries for the case when consumer product variety is uncertain and consumer resource is high.

Corollary 1. *If the weight $\mu > 0.5$, then consumers weigh the changes made to the product (new product characteristics s_i^{d+1}) higher than they weigh the provider's reputation $\hat{\lambda}_i^{d+1}$. In this case (according to Stage 2 and Proposition 1), the provider with the platform strategy will observe (through ICO mechanisms) new consumption variety standard x^{d+1} and infer new consumer characteristics ζ which will exceed consumption variety standard of the previous period x^d: $x^{d+1} \sim \zeta^{d+1} \vdash \sum_{i=1}^{N} c_i^{d+1} \theta_i > x^d$ (consumers will increase[16] their variety criteria); whereas the provider with the tailoring strategy will fail to exceed the previous period's consumption standard: $x^{d+1} \sim \zeta^{d+1} \vdash \sum_{i=1}^{N} c_i^{d+1} \cdot \theta_i < x^d$ (consumers will not change their variety criteria). This implies that when $\mu > 0.5$, a provider with the platform strategy would be able to achieve a better correspondence between consumer product variety criteria and the new product variety characteristics compared tothe provider with a tailoring strategy. Therefore, if $\mu > 0.5$, the platform strategy is more optimal than the tailoring strategy.*

Corollary 2. *If the weight $\mu < 0.5$, then consumers weigh the changes made to the product (new product variety characteristics*

[15] Note that coefficients δ_{ij} and γ_{ij} can be ignored if they are equal to 1.

[16] This increase can manifest itself as an increase in usage of the product, increase of the number of contexts in which the product is used, addition of another product user in the same household, etc.

s_i^{d+1}) lower than they weigh the provider's reputation $\hat{\lambda}_i^{d+1}$. According to Stage 2 and Proposition 1 of the model, the provider with the tailoring strategy would be able to achieve a better reputation than the provider with the platform strategy. The provider with the tailoring strategy will, therefore, observe (through ICO mechanisms) new consumption variety standard x^{d+1} and infer new consumer characteristics ζ which will exceed consumption standard of the previous period x^d: $x^{d+1} \sim \zeta^{d+1} \vdash \sum_{i=1}^{N} c_i^{d+1} \cdot \theta_i > x^d$ (consumers will increase their variety criteria); whereas the provider with the platform strategy will fail to exceed the previous period's consumption variety standard: $x^{d+1} \sim \zeta^{d+1} \vdash \sum_{i=1}^{N} c_i^{d+1} \cdot \theta_i < x^d$ (consumers will not change their variety criteria). This implies that when $\mu < 0.5$, the provider with the platform strategy would be able to achieve a better consumer value. Therefore, if $\mu < 0.5$, the tailoring strategy is more optimal than the platform strategy.

Corollary 3. *If the weight $\mu = 0.5$, then consumers weigh the changes made to the product (new product characteristics s_i^{d+1}) in exactly the same way as they weigh the provider's reputation $\hat{\lambda}_i^{d+1}$. In this case, the provider will be exactly indifferent between choosing any of the two available strategies.*

4. Discussion

This paper offers a model that allows both customers and providers to infer consumer preferences for future product variety from the day-to-day observation of consumption patterns in the household through the IoT. Our approach shows how Internet Connected Objects (ICO) can help providers use observed consumer behaviour to infer unobservable consumer characteristics as well as product usage patterns. We also show how providers can employ data collected via ICO to translate it into meaningful input to inform the development of new customised products. Finally, we model a dynamic mechanism which allows providers to anticipate future consumer product variety desires and efficiently fulfil these desires by choosing an appropriate customisation strategy (tailoring strategy or platform strategy). Our model specifies conditions under which the benefits of tailoring strategy and platform strategy become apparent, given different levels of consumer product variety and consumer resource.

Our study does not make a judgement on who should own or have access to such consumer resource, in terms of the ICO data collected. Privacy champions would of course insist that since the ICO data is collected within the private consumption space of individuals, it should certainly be owned by them. Yet, this may be simplistic as the data can only be collected through the technology embedded within the products, and there must be a case for manufacturers to incur the cost of embedding that technology in the first place. From our paper, we would propose a solution that is market-based. Since value is created in context and context exhibits variety that could be unknown and uncertain at the point of purchase, it is optimal that the resource to match the variety is best employed by the entity that has access to these uncertain and unknown contexts, when they become known, so as to create better value. Furthermore, personal data will not normally be generated if consumers do not buy and place ICO in their homes and attempts by providers to do so may encounter resistance. If consumers have the main decision power about the use of their data, they may be incentivised to collect more of it, and use it well. The increase in demand for the technology may then render it viable for the technology to be incorporated. It is left to future research to explore this question in more detail both theoretically and empirically.

The implications for Supply Chain Management (SCM) are considerable. If the weight $\mu > 0.5$, then consumers choose a platform strategy. In this case, the provider is simply offering the platform which consumers may personalise. Obviously, the development and establishment of such a platform is deeply problematic and subject to extensive network effects (Gawer, 2009). However, once established, such product platforms have many advantages including for example, component commonality (Pasche et al., 2011). This in turn leads to considerable standardisation in all the stages of the supply chain with improved demand forecasting, lower inventory holdings and attendant reductions in the Forrester effect and lower search and transaction costs. Conversely, where $\mu < 0.5$, $t = 0$ a tailoring strategy is more optimal compared to a platform strategy. For the provider, such an option is fraught with difficulties and challenges. For example, from the firm's perspective there is strong evidence that higher product variety results in failure to meet customer orders (Wan et al., 2012), higher managerial complexity (Xia and Rajagopalan, 2009), cost increases and reduced productivity (Stalk, 1988, Yeh and Chu, 1991), etc. From the customer's perspective, there is also evidence that too much choice confuses the customer, leading for example to post-purchase regret and resulting in the ‘product variety paradox’ (Salvador and Forza, 2007). Solutions based on mass customisation, postponement and product configurators (Trentin et al., 2011) might mitigate these effects. However, the impact of extensive increases in variety will be felt throughout the supply chain in the Forrester effect and higher transaction costs. Finally, as has recently been highlighted by Hazen et al. (2014), all of this is predicated firmly on the quality of data associated with ICO and is linked strongly to the emerging methods of data science, predictive analysis and “big data”.

The advent of IoTs has provided the opportunity to transform the landscape. Postponement can now occur with the customer, in effect adding a new stage to the supply chain framework of Yang and Burns as shown in Fig. 1: the final stage is not logistics postponement but customer postponement. The movement to a platform-based business model may also represent an opportunity to change the provider's perspective from a relatively linear supply chain to one of an eco-system where the platform provider acts as the system architect and standard setter. Such platforms have many downside risks, with increasing evidence of a single provider becoming dominant and creating winner-takes-all markets (Schilling, 2009). The associated transition of business model to platform provider also suggests development of new organisation capabilities, which evidence from other sectors suggest firms struggle to achieve (Benedettini and Neely, 2010).

5. Conclusions

This paper considers two alternative provider strategies in a world of ICO where far more consumption data and contextual data become available for providers to complete products. The first is a *tailoring strategy*, based on G-D logic where a provider opts for producing multiple varieties of tailored products and offers them to consumers. The second is a *platform strategy*, based on S-D logic where a provider creates a flexible platform that allows customers to purchase additional custom-made products developed by other providers but compatible with the platform. Our model postulates that the higher the demand for contextual variety, the more profitable the platform strategy becomes, relative to the tailoring strategy.

The implications for SCM research and practice are profound. We contend that the transition from product to platform requires a movement in supply chain logic from linear to network, web or eco-system. Providers need to put mechanisms in place to enable customised solutions to emerge, and place their strategic focus on the platform and the design of standardised interfaces. In the platform world, those suppliers upstream of the provider may find themselves in an increasingly commoditised environment as they compete to provide standardised features to the customisable platform. Other businesses will emerge in the eco-system to meet customer demands that the new contextual data highlights.

In terms of ICO and the data it will produce, there are a number of empirical studies currently being developed. One major research project is the development of the HAT (Hub-of-All-Things)[17], the first project of its kind to create a live multi-sided market platform in the home, connecting consumers, Internet companies and manufacturers to trade personal data for future personalised products and services. Data from the HAT will help this research team develop our theoretical model further by endogenising the image-variety trade-off in consumer preferences as well as introducing multiplicity of contexts in which a product could be used. We will also test our model using the HAT technology. While only empirical studies will be able to reach conclusions about the relative optimality of the tailoring strategy versus platform strategy, we anticipate, given consumers' desire for hyper variety and multiplicity of contexts, that the real-world consumers will behave according to our *Corollary* 1: they will weigh changes made to the product characteristics higher than they weigh the provider's image/reputation. Therefore, the platform strategy would be a more optimal way for providers to enhance value.

Research into platforms is at an early stage with many questions and issues. For example, empirical research is required to address such issues as: how to create platforms where none have previously existed; when is it better to have an open market, what are the different platform strategies, what are the tipping points and how do they emerge? The IoT has opened up a completely new set of opportunities for research and practice in SCM.

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