VALUE FLOWS IN IOT ECOSYSTEMS: TOWARDS AN IOT DATA BUSINESS MODEL

Research in Progress

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Abstract

The promise of IoT technology to provide a 'neural network for the physical world' that opens new vistas for value creation has long been touted in information systems research. However, in many domains, this promise in large parts is still untapped due to clash between linear business models bound to singular organisations and distributed IoT infrastructures. In this paper, we propose a framework for conceptualising and quantifying value flows in IoT ecosystems and illustrate its potential usefulness for modelling the dynamics of IoT business models. We do so by presenting an illustrative system dynamics model of value flows in case of the Smart Office IoT ecosystem. Our research proposes venues of further research to model IoT value flows and thereby move closer to identifying specific IoT ecosystem value flows and their related business models.

Keywords: IoT, ecosystems, business model, system dynamics.

1 Introduction

A driving force in digitalisation of businesses and society at large is the value derived from smart and connected physical objects implemented in Internet of Things (IoT) ecosystems as they involve the collection and aggregation of vast amounts of data from numerous, often embedded, sources and their application across multiple domains (Gubbi et al. 2013). The academic discourse on IoT has panned in focus from technological infrastructures for data capture and smart objects (Kortuem et al. 2010), over applications in specific domains, to increasing interest in value creation from IoT from a business perspective (Whitmore et al. 2015). The development is prompted by the immense promise of new sources of value creation based on new and innovative business models emerging from sensor networks that are distributed across multiple members. Despite the promise of IoT as a value driver, there are still significant barriers to be overcome in order for IoT ecosystems to actualise this potential (Leminen et al. 2012). These barriers include both technical issues relating to the flow of data in the infrastructure and issues related to the ecosystem business models (Iivari et al. 2016). The technological difficulties persist in aggregating data that has been generated from a plethora of heterogeneous sensors across a range of different physical environments. Both in terms of collecting data from various sources into a single repository, and in terms of transforming generated data from diverse sources into a format that allows relevant data sources to be compared and analysed. These technical issues are increasingly being addressed in fields of engineering and computer science (e.g. Gubbi et al. 2013). The second category of barriers relates to the flows of business value in IoT ecosystems as they transcend organisational and institutional boundaries (Iansiti and Levien 2004; Iivari et al. 2016; Leminen et al. 2012; Moore 1996).

This research seeks to inform the literature on business models (Hedman and Kalling 2003; Kuk and Janssen 2013; Leminen et al. 2012) by conceptualising ways of ensuring reciprocal and multi-faceted value flows in IoT ecosystems. The aim is to pave the way for business models in which a single member does not exclusively account for all of the costs and revenue, but where each member in the ecosystem contributes and profits proportionally to the value they derive and deliver to the ecosystem. In order to address the challenges and calls for research to empirically test the issues in relation to the dimensionality, scope and scale of value capture and creation in IoT ecosystems (Iivari et al. 2016), this paper outlines the first steps in modelling value flows in IoT ecosystems using the system dynamics framework. This paper therefore addresses the research question: *How can value flows in IoT ecosystems be conceptualised and modelled to create new business models?*

The paper is organised as follows: First, the notions of IoT ecosystems and value flows are defined, followed by a definition of the main parameters. Then, we present a first take on how value flows in IoT ecosystems can be modelled with system dynamics as well as some initial findings. We conclude with a discussion of the direction of further research for the project.

2 Value Flows in IoT Ecosystems

The concept of the ecosystem in general and ecosystem modelling in particular has been imported to management and information systems research from biology, where natural ecosystem is defined as a biological community of interacting organisms plus the physical environment with which they interact (Iansiti and Levien 2004; Moore 1996). Drawing on this analogy, a firm's business ecosystem has been defined as the network of suppliers, customers, producers of related products and services plus the regulatory bodies and related institutions in its socio-economic environment (Moore 1996). Business ecosystems are seen as evolving around paths of innovation analogous to the branches of an evolutionary tree in biology. Consequently, rather than flows of genetic material, business ecosystems are organised around flows of a core set of assets (Iansiti and Lakhani 2014; Iansiti and Levien 2004; Leminen et al. 2012).

This core organising flow can be in the form of technologies, platforms, standards or other assets that are commonly shared by the members of the business ecosystem as an integral part of their business. Specifically, the core flows in business ecosystems enable each of its members to leverage some advantage for their business resulting in cost savings, higher levels of productivity and innovation, higher revenue generation rates, decreased market volatility and regulatory pressure etc. In other words, the flow of core assets in business ecosystems generate value for each of its members. A common characteristic of value flows in business ecosystems is that they are governed by network effects, meaning that they increase in value with the number of ecosystem members sharing and contributing to the flow (Uzzi 1996). In the case of IoT ecosystems, the core value flows are comprised of sensor data. In order to translate the notion of business ecosystem as a network of interconnected members exchanging value-generating assets within a socio-economic environment, we need to shift the focus of our definition from individual firms or organisations to the technological-economic assemblage of sensors, data aggregation infrastructures, and application beneficiaries (Leminen et al. 2012).

Based on this notion of IoT and extant literature on business ecosystems (Moore 1996; Talvitie 2011) and IoT business models (Iivari et al. 2016; Leminen et al. 2012; Turber et al. 2014), IoT ecosystems can be defined as a network of members interconnected by value-generating flows of data facilitated by an assemblage of connected sensors and data aggregation infrastructure interacting within a socio-economic environment. Members cooperate through exchange of core data assets derived from the interconnection of a physical setting with the virtual setting represented in data and analytics infrastructures (Mazhelis and Luoma 2012). These assets are derived from events in the physical world that are recorded by sensors, aggregated in a data infrastructure, and distributed to ecosystem members in the form of new services. Next, we operationalise the notion of value flows in IoT ecosystems that we substantiated in this section to propose a conceptual framework that will guide our efforts to model value flows in specific IoT ecosystems.

3 IoT Ecosystem Value Flow Parameters

As a corollary to the definition above, IoT ecosystems consist of assemblages of connected physical objects with varying data capture capabilities and applications across a range of organisational domains.

Previous research focusing on business models in IoT ecosystems suggests that such models should account for three parameters representing technological IoT capability, ecosystem scope, and IoT value (Iansiti and Levien 2004; e.g. Turber et al. 2014). The first parameter, IoT capability, accounts for the sensing and data processing capability of IoT infrastructures. The second parameter relating to the scope of the IoT ecosystem relates to who is affected by and involved in the exercise of specific IoT capabilities, and the third parameter refers to the level of value created at each scope of the ecosystem through the exercise of IoT Capabilities, denoting why members are inclined to engage in the ecosystem (Turber et al. 2014). Before moving on to proposing a modelling approach for value flows in a specific IoT ecosystem, we first in turn discuss the three dimensions of IoT ecosystems that determine the parameter space of our system dynamics model.

3.1 IoT Infrastructure Capability

IoT infrastructures include a broad range of physical objects such as various sensors, meters, cameras, motors, signals, RFID chips, etc., that are interconnected and automatically share data over the internet. The core notion of an IoT infrastructure therefore refers to physical objects equipped with sensing, processing, and networking capabilities (Whitmore et al. 2015). These capabilities allow configurations of connected devices to communicate with other services or with each other to achieve some valuable objective. IoT infrastructures can therefore be said to include a combination of devices with some sensory and representational capability, connectivity to a digital infrastructure to share data via a network, and practical applications to specific value creating processes (Gubbi et al. 2013). The sensory and representational capability of an IoT component to react to changes in its physical environment is particularly significant in relation to the value it creates in the application domain. Specifically, these different capabilities of IoT devices in terms of sensing and processing their environment can be classified by degree of awareness into activity aware, policy aware, and process aware devices (Kortuem et al. 2010).

Activity aware devices understand the world in terms of event and activity streams, where each event or activity is directly related to changes in the device's environment, its handling or use (e.g. move in front of, heat up, shake, pickup, turn on, operate, and so on). Its application model consists of aggregation functions for accumulating activities over time. Activity-aware objects primarily log data and rarely provide interactive capabilities. *Policy aware* IoT devices can determine activities according to predefined rules and policies (e.g. if x then y). A policy-aware object understands to what extent real-world activities and events comply with organisational policies. Its application model consists of a set of rules that operate on event and activity streams to create actions. A policy-aware object provides context-sensitive information about object handling and work activity performance. In particular, it can issue warnings and alerts if workers violate policies. *Process-aware* objects are programmed to understand the sequence of a specific work process and can alert human or nonhuman workers to take a specific action at a given step. A process-aware object understands the organisational processes that it is part of and can relate the occurrence of real-world activities and events to these processes. Its representational model consists of a context-aware workflow model that defines timing and ordering of work activities. A process-aware object provides users with context-aware guidance about tasks, deadlines, and decisions. Finally, some IoT objects are, mostly in connection with a central storage and processing infrastructure, programmed in such a way that they can either provide *decision support* for human decision makers (Hosack et al. 2012), or exercise some degree of autonomous decision-making within the application context based on advanced algorithms capable of adapting to changes in data input from the environment (Andersen et al. 2016).

3.2 IoT Ecosystem Scope

One of the main barriers to deriving value from IoT platforms originates from the fact that IoT platforms span across organisational and industry boundaries that encompass multiple contexts for data capture, aggregation and application involving a plethora of diverse members (Kortuem et al. 2010). The interconnectivity of IoT ecosystems across different application domains that each impact on each other, means that, similar to flows of biomass through natural ecosystems, data flows drive value creation across tiers of organisational and institutional borders in IoT ecosystems (Mazhelis and Luoma 2012). Hence, an important element in determining the value flows of IoT data relates to identifying the scope of the application domain including its members and their respective value propositions and interconnections (Iansiti and Levien 2004). IoT ecosystem scope can be divided into three tiers; core business, extended enterprise, and business environment.

First, defining the *core business* in an IoT ecosystem can be a tricky endeavour. IoT applications have been divided into 'home' and 'enterprise' categories (Gubbi et al. 2013). However, if we observe actual applications of IoT ecosystems, these boundaries are often blurred; personal GPS enabled activity trackers and mobile units are used to track traffic flows for e.g. Google navigate and city planning. Health data from e.g. Apple Watch is used to develop new pharmaceutical and medical products as well as develop public and private healthcare services etc. Consequently, the IoT ecosystem's core business consists of the members that generate the core services of the application domain, i.e. the providers of the IoT platform, and their direct suppliers and customers.

In addition to this, other members including, market intermediaries, and more peripheral suppliers make out the *extended enterprise* tier of the IoT ecosystem. This tier consists of extended supply chain and other third-parties that might benefit from or contribute to the IoT ecosystem. Even though the network effect dictates that extended enterprise members could potentially generate substantial value, they often fall outside the scope and industry of core business models and are not considered by members in the core business (Enders et al. 2008). Also, core business and extended enterprise members operate within a socio-economic *business environment* that includes, in addition to regulatory bodies and competing organisations, a host of related institutions and organisations that affect and perturbate the IoT ecosystem in various ways (Talvitie 2011). Together, interacting ecosystem members across the core business, extended enterprise, and business environment represent the 'organisms' of the IoT ecosystem and together they form the foundation of the economic community delivering services to direct users and generating value for other members of the business ecosystem (Moore 1996, p. 15).

3.3 IoT Data Value

All members of an IoT ecosystem are interdependent on one another, each creating value for one or more of the remaining members. In this respect, value generation and flow in IoT ecosystems is equivalent in many respects to business ecosystems in other contexts, such as e.g. payment ecosystems (Hedman et al. 2013). As IoT ecosystems span across multiple organisational boundaries and supply networks, value must be derived in relation to the specific business needs and performance criteria of each ecosystem member. Consequently, value can be defined as the relevance of IoT data in terms of its effect on the performance criteria of individual IoT ecosystem members. In order to identify the specific effects of IoT data in terms of effects on the performance criteria of each member, we can follow existing research (Enders et al. 2008; McAfee and Brynjolfsson 2012) that identifies at least four different types of IoT value; cost savings, direct revenue, asset generation, and indirect value.

First, many of the most obvious value flows are generated by employing IoT to increase operational effectiveness and transparency and thereby lower operational and transaction costs. *Cost savings* are typically realised through automation or improved decision support. *Revenue generation* refers to the sale of IoT based services directly to its core users. As value is directly exchanged between a service provider and its direct customers, this type of value generation takes place within the core business scope of the IoT ecosystem. *Asset generation* refers to the generation of value in the form of IoT data assets used to deliver a service to a third party or extended enterprise member e.g. in other industries, geographies etc. Even though network effects would dictate that IoT data assets could potentially generate substantial value to the extended enterprise, they often fall outside the scope or industry of core business models and are rarely considered by members in the core business (Enders et al. 2008). *Indirect value* is non-monetary and represent often unforeseen long-term consequences of other value streams. Indirect value creation could relate to environmental benefits, increased public health, or even entertainment value to specific members.

In summary, this research – albeit in progress – conceptualises the emergence of IoT value flows as conditioned by IoT infrastructure capability and ecosystem scope. In the following, we apply this framework to model value flows in a specific IoT ecosystem. The model stems from three month of direct participant observation as a part of initial efforts to collect and aggregate data in the specific case in question. This has allowed us access to the preliminary IoT infrastructure as well as to the members of the IoT ecosystem. Though the ultimate purpose of this research is to develop a conceptual framework and modelling approach for value flows in IoT ecosystems, the preliminary model and empirical case presented here is limited in that subsequent data collection will provide sensor data that can serve to refine and validate the model and simulation results.

4 Preliminary Findings: Modelling IoT Value at Smart Office

Smart Office is a shared office concept that is developed and built by a major Scandinavian construction company, which profits from selling the Smart Office to large companies, which then provide SMEs with office space and shared facility services such as reception, canteen, meeting facilities etc. on a subscription basis. Within the current smart office buildings, many technological systems are data-driven at the component-level, but there is a lack of connectivity between different subsystems and no existing way of aggregating the data across subsystems such as HVAC (Heating, Ventilation and Air Conditioning), electrical, security, alarming and usage specific component systems has previously existed. As a direct response, a novel IoT-infrastructure is being developed to address the lack of connectivity between different technological subsystems with different degrees of IoT capabilities. The Smart Office IoT infrastructure connects members across all tiers of the IoT ecosystem scope. Members of the core business include subsystem providers, building owner, building operators and building occupants. For this particular use case, the members of the extended enterprise include building designers. The business environment of Smart Office IoT ecosystem comprises of regulatory bodies.

4.1 The System Dynamics of Value Flows for Smart Office

In order to quantify value flows related to the generation and exchange of data in IoT ecosystems, we need a framework that is capable of modelling complex and dynamical systems. Such a framework can be found in System Dynamics (SD). SD captures a crucial feature of IoT ecosystems that is often neglected in other frameworks: feedback between multiple interconnected system components that lead to adjustments of system state over time (Sterman 2000). Changes in one part of the system will affect other components and reinforcing or dampening other system components in time generate changes to the overall state of the system. Complex dynamic systems are self-regulating systems that accumulate quantities, or stocks, of variables that are central to system function. SD is a well-established approach for simulating management of complex ecosystems including management of forest fires (Collins et al. 2013) water resource management (Simonovic 2002; Stave 2003), agricultural development (Saysel et al. 2002) and global climate change (Sterman 2011). We therefore hold that it presents a suitable framework for modelling value flows in IoT ecosystems. Figure 1 shows a preliminary SD stock and flow diagram of IoT value flows in the Smart Office IoT ecosystem.

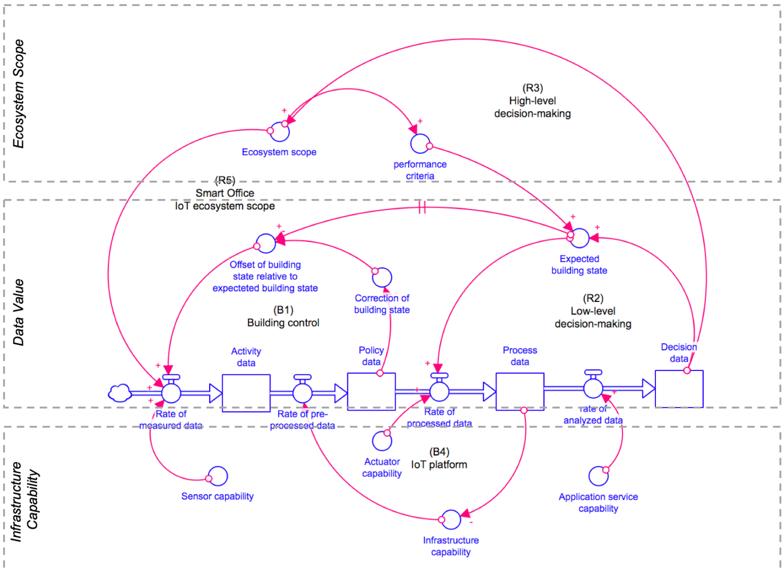

Figure 1. Stock and flow diagram of IoT value flows in Smart Office.

This initial model has been developed based on preliminary findings from participant observations and initial informal interviews. For this iteration, we formulated the model based on analysis of data from 3 full-day observations and 12 semi-structured interviews of 40-67 minutes. We first transcribed the interviews verbatim and open coded the resulting text (Glaser and Strauss 1967). We then performed theoretical coding for value flows, levels, and rates of change specifically related to data value in relation to IoT capability and ecosystem scope. Based on the qualitative analysis we finally derived our illustrative stock and flow model. Future iterations of the SD model will be validated using sensor data that is currently being collected.

The source of the Smart Office value flow begins with the environment that is to be measured; the Smart Office building. Data volume increases as more sensor capability is added to the infrastructure. This increases the assets of activity data. The outflow from activity data will form the inflow to policy data, which can be described as activity-data transformed to an action based on a policy. The resulting pre-processed data rate increases when the actuator capability increases. This is elaborated best by an example: The temperature in a south-facing office room is measured and thereby analogue data is pre-processed to digital data and formatted as °C. This information is used by the room thermostat, which has the policy that if there is an offset between measured temperature and expected temperature, the thermostat will perform an action accordingly. This example describes the first of the five feedback loops in the model, the 'Building control' loop (B1). This feedback loop describes the behaviour of the building control or regulation system, which is a balancing loop, that is initiated by the offset of building state relative to expected building state.

The resulting output flows to policy data is mediated by the rate of pre-processed data, which can be described as the rate of aggregation of pre-processed data enhanced by IoT infrastructure capability. Decision data is then enhanced by actuator capability and flows to the stock of decision data depending on the level of data analytics that is performed. As the application service capability increases the rate of analysed data increases as well. Continuing with the previous example, the action performed by the thermostat will be collected and compiled with other relevant information such as time and outdoor temperature with the purpose of analysing the data to identify the behaviour and performance of the temperature control policy in the south-facing office room. This analysis generates decisions, which can be used to change current policies in building control or affect the ecosystem scope. This describes the second and third feedback loops, the 'Low-level decision-making' (R2) and 'High-level decision-making' (R3) respectively, which are both reinforcing loops. The low-level decisions refer to decisions made to the expected building state. This expectation is a concrete translation of the performance criteria, which can directly be used in the building control, illustrated by the link from expected building state in the low-level decision-making loop to offset in building control loop. The high-level decision-making targets the decisions that affect ecosystem scope, which in turn affect the performance criteria. This can e.g. be new knowledge and insight on how the occupants of the building perform under certain indoor climate conditions, which can change a certain member's view on building performance, thereby changing their criteria and expectation to how the indoor climate of the building should perform.

The infrastructure capability is the central element in the fourth feedback loop labelled 'IoT-platform' (B4). As described earlier, the IoT-infrastructure connects all devices by collecting their data in a single database. This is illustrated by the relation between the infrastructure capability to the rate of pre-processed data. The centralisation of data in a single repository gives the possibility of accessing data to perform data processing and analysis. This relation is depicted by the link between process data and infrastructure capability. This link is denoted with (-), because as more process data is collected, there is less need for infrastructure capability and less need for pre-processed data. The loop is thereby balancing. The fifth feedback loop 'Smart Office IoT ecosystem scope' (R5) is a reinforcing loop, which represents the relation between the dimensions of ecosystem scope and IoT value.

4.2 Main Effects of IoT Capability and Ecosystem Scope

Running a simulation run of the preliminary SD model reveals how manipulation of IoT capability and ecosystem scope parameters influence the value of different types of IoT data over time. We simulated the SD model using generic values with levels defined in the range from one to ten and rates of change between 0 and 1 so that the formulas specifying each parameter mapped the relation derived from the preliminary analyses based on respondents' estimations of parameter values. We simulated the model setting the baseline value 5, low settings to 1 and high settings to 9 (0.1 and 0.9 respectively for rates of change) in order to illustrate the main effects of each parameter. Figure 2 shows how focusing on low IoT capability devices can leverage activity-based data assets, thus generating significantly high value. However, the high generation of activity specific value comes at the expense of value creation related to policies, processes and decision making that all converge on 0 by tick 12. On the other hand, while high IoT capability constrains the generation of activity-based value flows, it promotes a higher degree of decision-making thus increasing the performance of the IoT ecosystem as a whole.

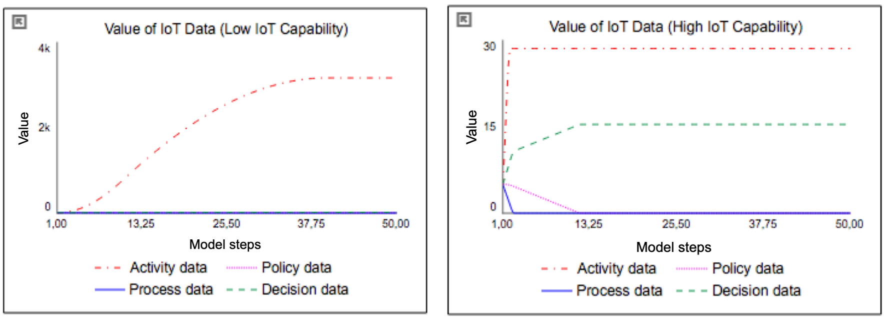

Figure 2. IoT capability simulation results.

Similarly, low settings on the IoT ecosystem scope parameter seem to promote value flows related to decision-making while a high setting retains decision-making value and promoting activity-based value flows as shown in figure 3.

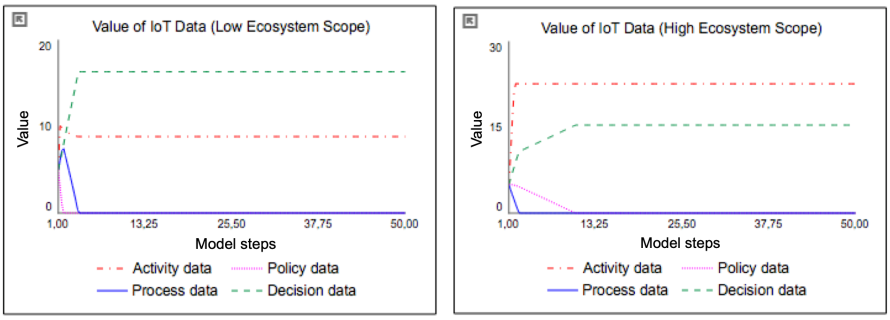

Figure 3. Ecosystem scope simulation results.

While the preliminary SD simulation shown here use generic equations and parameter settings and therefore does not provide validated predictions of specific IoT ecosystems, they do illustrate how SD modelling can be a useful instrument to explore the behaviour of value flows in IoT ecosystems over time. Next, we conclude the paper by discussing the limitations of this research in progress and propose next steps for our research.

5 Limitations and Further Research

In this paper we have proposed a conceptual framework for value flows in IoT ecosystems and proposed an approach for quantifying them over time. However, while pointing out a way forward, there are several steps that should be taken in subsequent research to mitigate the obvious shortcomings of this preliminary research.

First, we are in the process of collecting additional sensor data from the Smart Office IoT infrastructure. This will enable refinement and empirical validation of the model and further development of its component parts as necessary. As it stands, the results are based on generic parameter values with a baseline set to 5, high values to 10, and low values to 1. Validation and calibration of the model would enable several Monte Carlo runs of the simulation to more firmly and in greater detail establish the causal and generative effects of each of the model parameters. Also, interaction effects between model parameters should be simulated to account for the contingencies and specific scenarios of various IoT business models.

The key elements of the model proposed in this paper would be relevant across a number of contexts involving IoT ecosystems other than building design and operations. For instance, the model would be suitable for contexts containing several institutional ecosystem members, such as financial services or government contexts, whereas its applicability in IoT ecosystems made up primarily of individual members might be limited. The generalisability of the model is a pressing concern for our further research.

We hope that further exploration of value flows in IoT ecosystems would inform and encourage business model generation for IoT ecosystems. Specifically, such novel IoT ecosystem business models can increase the scope of value generation beyond a single firm or organisation by leveraging the capabilities of emerging IoT infrastructures.

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