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Monetizing the IoT Revolution

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Abstract: Academics and businesses alike tend to fail at understanding how the IoT revolution is monetized. We outline three main categories of how IoT will impact business models: (a) improved customer matching and tracking of marketing returns, (b) individualized offers and pricing when consumer demand and price elasticities can be identified, and (c) smart device and usage monitoring that allows for outcome-based contracts and servitization. Data convergence creates context-based-intelligence, which enables a shift from using consumer profiles for targeted advertising to individualized offers and pricing. The required depth of both consumer data and understanding of context will require collaborative efforts between companies and blur the lines between industrial- and consumer-IoT applications. Outlining concerns for privacy and cybersecurity, we find that consumer demand for decision-simplicity and relevant content aligns with the business model of "free" services in return for data, despite consumer concerns relating to data collection.

Keywords: Internet of Things; business models; smart cities; big data; consumer data

1. Introduction

The Internet of Things (IoT) revolution makes it possible to collect real-time data on the preferences and activities of consumers and set these in a geographical and temporal context [1]. The rapid development of IoT is illustrated by the fact that 90% of the world's data was generated during the last two years, and that the pace is still exponentially increasing towards an amount of data that is 40 times the size of 2017 by 2020 [2]. This is fueled by appliances, vehicles and smartphones that are rapidly becoming data-gathering devices.

However, just as consumers tend to lack understanding of the data that is collected about them [3], companies typically fail at understanding how big data translates into monetization [4,5].

This study provides a review of the business impact of IoT by categorizing three main drivers of business model impact, covering both consumer- and industrial-IoT applications. The former refers to goods and services targeted to end-users such as smartphones, and the latter are services that create industry transformation such as data aimed at supply chain efficiency [6].

From an academic perspective, most smart-city research emphasizes public sector applications of IoT and government-driven initiatives to achieve goals relating to issues such as knowledge-transfer, mobility, and sustainability [7–10]. Research analyzing the business impact of IoT tend to be application specific, covering topics such as smart contracts [11], healthcare [12], or smart-city technologies for mobility [13,14]. From a business model perspective, a more holistic perspective on the impact of IoT is necessary [6,15–19].

The impact of data is rapid and is closely related to the development of low-cost sensors and network technologies such as LTE, Wi-Fi, Bluetooth, and the fifth-generation of mobile networks (5G) that make it possible to both collect and transfer ever larger amounts of information [20]. Improved cloud storage and computing solutions allow for cost-efficient and fast computing, in addition to insights through AI algorithms.

Despite enormous amounts of data collection, there is still a lack of understanding about how to capture value from data, among both academics and practitioners [5,6]. Most corporate big data projects fail [21], and social scientists sometimes stress the difficulty in creating insight from big data [22], as large datasets could tell us large scale patterns but not create contextual depth [23]. Recent research stresses a need for additional research on the impact of IoT on society and business [6].

Closely related to how IoT will impact business models is the issue of cybersecurity and privacy. When consumers use services such as social-media, mapping tools that provide directions, platforms to find goods, services and housing, users trade personal information in return for a "free" service [24–26]. This allows companies to gain insight into consumer preferences and learn about what content they should be exposed to. Consumer insights enable data-driven business models, such as retailers that target their advertising efforts, automakers collecting data on driving patterns to predict breakdowns, and ridesharing services setting prices through monitoring of congestion and demand patterns [27–29].

The outline of this study is as follows. Section 2 provides a background on consumer profiling from a marketing perspective, as advertising is at the forefront of data driven industry disruption. Section 3 outlines three main ways of business model impact from IoT across industries: (a) improved customer matching and tracking of marketing returns; (b) individualized offers and pricing, and (c) device and usage monitoring. Section 4 summarizes concerns raised in relation to privacy and fairness. Section 5 concludes.

2. Background: Internet of Things and the Consumer Profile

Researchers have noted a shift in the overall analysis of IoT, going from a pure technology perspective to viewing IoT as a business ecosystem, and going from analysis of a singular firm towards an eco-system of organizations [19]. This aligns with researchers that have focused on analysis of networks, by separating the network value of partners ("who"), sources of value creation ("where"), and the benefits of collaboration ("why") [16,17]. The ever-increasing amounts of personal data that is collected, transferred, and analyzed illustrates that the eco-system approach is necessary to understand the impact of IoT on business models.

This shift in focus towards eco-system business models is known as "value designs" [15]. Four pillars are used to evaluate business models in such a framework; *value drivers*, the motivations to create value, and the *value nodes,* which refers to the parties, networks and processes for value creation. For a retailer, a *value driver* is the ability to increase sales, while the ability to find the right partners for data-sharing, or algorithm development is a *value node*. *Value exchanges* are the tangible and intangible flows of value between nodes in the ecosystem, such as money or insights. *Value extracts* are components that extract value, i.e., monetization, such as a specific service offering [15,19].

At the center of the above-conceptualized data eco-system are companies such as Google and Facebook that have their entire business models based on the collection of data, and an industry of data brokers, such as the company Acxiom, that collect consumer data and sell it to third parties. In 2012, their database was estimated to have information of about half a billion consumers, with about 1500 data points per person [28].

As consumer data is collected, transferred, and analyzed to guide decisions across industries, it is becoming an increasingly valuable asset that is bought and sold like any other commodity. Across industries, customer databases are a substantial part of corporate value [30]. Illustrations of this value are sales of customer databases, securities issued with consumer data as the underlying asset, that companies are developing new insurance solutions based on data transfers [26], and massive interest in IoT and data driven businesses from venture capital.

2.1. The Consumer Profile: Reaching the Right Person for Goods and Services

The technology sector is becoming an increasingly dominant part of the economy, and it is in large due to the concept of the consumer profile. The value of personal data can be described in terms of advertising. A newspaper ad is worth very little per view if it we cannot identify those who are exposed to it; traditionally, a common truth among marketers was that; "*I know that half of my advertising dollars are wasted . . . I just don't know which half*" [31]. Not only have marketing efforts by companies traditionally been limited in terms of making sure that they are exposed to the right target audience, but the actual effectiveness of campaigns has been difficult, if not impossible, to measure. Looking at these issues, companies like Google have had a transformative impact—shifting marketing spending from traditional sources towards online search advertising, as it becomes possible to; (a) spend more selectively on those with a higher likelihood of responding through profiling based on location and search history, and (b) track the impact of advertising.

The more detailed the consumer profile becomes, the more targeted campaigns become—consequently increasing the price of each individual add. An example is so-called AdWords campaigns, where ads are shown based on search keywords, so that the company offer is shown when people search for their product or service type. This type of campaign typically includes several ads with different texts targeted at different groups of consumers based on their geography, device segmentation, and product type [32]. This is where the convergence of data sources and location-based information comes into play. In fact, many applications now run in the background of devices with the purpose of tracking location for advertising purposes [26].

Facebook now show ads based on geolocation and display ads based on the user's history of viewing pages, groups, and events. The ability to collect, store, and analyze big data will make it possible for say, a diaper manufacturer, to identify families with small children, who buy a competing brand, and use targeted offers to identify their price sensitivity and the cost of getting a specific customer to switch brand. It is likely that this will lead to marketing wars when companies identify and target their—and their competitors—target customers [33–35].

Marketing, customer acquisition, and retention is now fundamentally changing as it becomes possible to monitor the effectiveness of campaigns. The ability to measure ROI on advertising helps companies to direct effort where it has the most effect i.e., how many views of an ad resulted in a purchase, signup, web page visit or lead—all of which are tracked by Google for those who purchase ads [36]. As this type of data improves the consumer profile, customer lifetime value can be estimated and related to the cost of acquisition, and customer intent and position in the buying cycle can be identified (i.e., what products a customer wants or needs) [37]. When this type of estimation is done on data from social media interactions, comments, reviews, search queries, the concept of the *constantly connected consumer* becomes a reality [38], and a resulting shift towards a two-way dialog between companies and consumers.

2.2. Context-Based Intelligencroce: Reaching the Right Person, at the Right Time, at the Right Location

Data is now transforming industries beyond the initial application of consumer profiling for advertising purposes. Insights on demand, preferences, usage of goods and services create value through marketing and product offerings. The commercial value that is created by converging data is exponential, and this is resulting in both new service offerings and new ways for marketing when information on consumption, location, preferences and even health are merged to form an increasingly granular consumer profile. Drugstores CVS and Walgreens gain access to the number of steps taken from wearable devices, records of blood glucose values, and prescription history, in exchange for discounts to customers that participate [39]. Similarly, some life insurance premiums are now set based on data from fitness trackers [40], and insurance companies just received regulatory approval to use social media information to assess risk [41].

Offline and online activity is now converging in consumer profiles, so when Google and Mastercard collaborate, online searchers can be used to understand offline purchases—such as what browsing a certain product tells us on subsequent purchases at physical stores [42]. Similarly, Facebook buys third-party data on your characteristics and offline activity, to create an even more granular understanding [43]. Biometric and health data such as heart-rate and movement is creating new opportunities and has already been found to be merged with social-media information to target consumers [44]. Facial recognition technologies are connected to payment in stores and public transit, and monitoring of public and private spaces is becoming increasingly prevalent [26]. This will allow companies to identify individuals entering a store, and the context of consumption.

When companies create insight from data, and use it to drive business decisions, this implies context-based intelligence, i.e., "*The ability to understand the limits of our knowledge and to adapt that knowledge to an environment different from the one in which it was developed*" [45]. Context-based intelligence and the convergence of personal data are closely related, as the latter enables the former and that every time an app or service is used, it creates additional data that feeds into services in what can be likened to a feedback loop.

An illustrative example of what context-based intelligence implies is that search engines personalize search results based on search history and social activity—so when Google knows more about an individual's habits, preferences, location, and network, it becomes possible to tailor search results even better—and notably increase advertising revenue when the match between product and likely buyer becomes increasingly accurate. Consumers actively participate in creating insight on their demand and preferences. A key part of this trend is what is referred to as the "*quantified self*" and "*lifelogging*"—people gaining self-knowledge through collected data about themselves. Typical examples are fitness trackers, "smart" scales, applications aimed at tracking locations of interest, identification of DNA and heritage, and identification of human microbiomes related to behavior [46].

App-based services are often based on the continuous tracking of movement, as location-based services (LBS): "*integrate a mobile device's location or position with other information so as to provide added value to a user*" [47]. This enables an ad for a coffee shop near you, or a free coupon to the gym close to your work. As we carry our smartphones everywhere, LBS is at the heart of monetizing consumer data. Looking forward, LBS will be increasingly integrated into a key variety of solutions—and be essential for autonomous applications and virtual reality—as knowing the location of various things at the same time and relating it to mapping data is essential for such systems.

3. Categories of IoT Impact on Monetization

As customers carry their wearable devices, they create data trails from activity such as searches, purchases, and movement. Companies will be able to continuously follow their changing needs and preferences over time. It is also possible to monitor usage and performance of devices, which in turn enables new business models.

We outline three main categories of impact from IoT on Monetization, that we define below.

3.1. Customer Matching and Tracking of Marketing Returns

Application integration, collaborations, and third-party data transactions enable better insights and linkage of offline and online activity. Social media companies are increasingly either buying or collaborating with companies that provide additional data points [48]. Examples of characteristics that are used by Facebook to filter advertising are "*1. Location 2. Age 3 . . . Gender 5. Language 6. Education level 7... School 9. Ethnic affinity 10. Income and net worth 11. Home ownership and type 12...14. Square footage of home 15 . . . 16. Household composition . . . . . . 21. Users in new relationships . . . 29. Mothers, divided by "type" (soccer, trendy, etc.) . . . 33. Employer . . . 39. Users who plan to buy a car (and what kind/brand of car, and how soon) . . . 50. Users who have donated to charity (divided by type) . . . 61. Early/late adopters*

of technology . . . 65. Number of credit lines . . . 66. Users who are active credit card users . . . 69. Users who carry a balance on their credit card . . . 71. Preference in TV shows. 80. Users who buy groceries (and what kinds) . . . 85. Users whose household makes more purchases than is average . . . 87. Types of restaurants user eats at." [49].

With this information, companies can have their content or campaigns displayed for the most relevant audience. Another industry example is what Google describes as their "Customer Match". A tool for companies to "*use your online and offline data to reach and re-engage with your customers across Search, Shopping, Gmail, and YouTube. Using information that your customers have shared with you, Customer Match will target ads to those customers and other customers like them.*" [36].

Consumer profiling is not only about the initial matching of campaigns with potential customer. It is now possible to track the effectiveness of a particular campaign when marketers can link exposure to an add and a subsequent action or purchase. Identifying if a campaign was effective and on whom a dollar spent on coupons, promotions or any other marketing effort made a difference, and on whom it was wasted.

Despite spending upwards of 20% of revenue on campaigns, large companies have historically had little insight into their effectiveness [50]. Marketing efforts are typically analyzed in isolation, and without knowledge about any counterfactual outcome. Consequently, most marketers often misattribute outcomes to marketing efforts, and finance departments tend to doubt if marketing spending is worthwhile as the returns are double counted—so when added together, the marketing ROI sometime adds up to twice the actual sales [51].

The need for looking at the whole picture when analyzing return on marketing investment (ROMI) is amplified by companies marketing their products through several touch points and sales channels—so when a consumer is exposed to car reviews, paid adds, YouTube content, billboards, and mail campaigns, the question of how to attribute a final sale arises. This is where companies take advantage of increasingly data-driven strategies as it becomes possible to track who got exposed to what and use algorithms to determine optimal marketing strategies [51]. IoT and data convergence is central for the ability to identify target audiences and measure ad effectiveness. An illustration is that the effectiveness of Facebook ads can now be tested by seeing how exposure in a persons feed translates into in-store purchases, phone orders, and bookings through their "*Offline Events*" service that also measures offline return on ad spend and allows companies to reach people based on thief actions they take offline, in addition to audiences believed to be similar to those they have offline data for [52].

The ability to communicate with consumers through smart devices is an essential enabler of the constantly connected consumer, as the data that is created when the application is used becomes additional data-points in the overall consumer profile. The device is also a medium of communication and a channel that enables additional sales and marketing.

As companies become able to identify their most likely consumers, the next step is to design the best fitting offering for those consumers, based on insights about the individual and context. We cover this in in the following section.

3.2. Individualized Offers and Pricing

From a marketing perspective, context-based-intelligence is about giving people the information they want, when they want it [53]. As smartphones create "hyper-context" into customer preferences, they enable strategies for timely and targeted campaigns [33]. Analyzing the future of marketing, Rust [54] notes that technology, notably AI and IoT, drives deeper customer relationships and expansion of the service economy. It is also noted that these trends make the 1960s-style 4 Ps increasingly obsolete.

3.2.1. The Impact of Decision Simplicity

Smartphone users value simplicity and seldom actively search information on the internet—on average, making only 1.25 online searches [53], while spending 3.35 h on

their mobile devices every day [55]—it becomes increasingly important that applications basically spoon-feed the user with information perceived as valuable [53]. Examples of this type of context-based intelligence is that an iPhone automatically keeps track of where a car was parked and shows suggested routes in the morning (knowing that it is likely that the user will drive to work). Similarly, Facebook and LinkedIn show users increasingly relevant content by understanding how user interest and context interplays [49].

As brand loyalty is declining and consumers increasingly value simplicity, the ability for a company to have enough data points and contextual understanding will be essential for customer acquisition and retention. In fact, the single most important factor for making a customer "*sticky*" in the sense that they follow through on intended purchases, make continuous purchases, and recommend the products to others is "*decision simplicity*", meaning how easy it is to get information about the product or service that is deemed trustworthy and allows for an efficient comparison of options [56]. We find that a consequence of these consumer preferences is that what the customer wants aligns with the business model of search advertising based on consumer profiling.

3.2.2. Identification of Consumer Price Elasticities

Consumer profiling can provide insight into the preferences and purchasing power of consumers, so that a company can individualize offerings and prices. Individualized pricing is already seen in the insurance industry, with health and life insurance premiums set by fitness tracking data [40], or car insurance set by where and when someone drives [57]. Employers such as BP incentivize employees to allow for tracking of fitness and movement through wearables [58]. Similarly, it is now possible to identify financial risk using spending habits and bank account flow data, which is improving risk management in finance [59], and machine learning is now "*taking credit-risk scoring to the next level*" according to the company SAS [60]. Not only is risk management improved, but companies also have the ability to individualize interest rates and insurance premiums—i.e., prices—to a much higher degree.

Consumer profiling is also about how an individual is likely to spend and the ability to set prices through "*behavior-based pricing*" [61]. Researchers have given some attention to the overall market implications of targeted advertising, having found that it has the potential to increase business sector profits under certain conditions [62]. Other studies indicate that targeted advertising leads to increased market fragmentation and results in local monopolies [63]. Consumers could however benefit more than companies in some scenarios, with studies of individualized smartphone-based offers finding that profits increase from unilateral price differentiation, but that these returns are likely to be mitigated by competitors engaging in similar practices [35]. Similarly, the ability to set higher prices for consumers with a strong preference of the product is offset by increased price competition for value conscious shoppers that compare price [64].

A loyalty program at a grocery chain can serve as an example of how behavioral based pricing can be applied. Consumers receive offers based on past purchasing habits and other information on likely preferences. If a consumer has small children, they might get targeted offers for diapers. The customer relationship management program (CRM) keeps track if whether or not a consumer took up on specific offers. Thus, if a discount of $1.5 on a new brand of pasta sauce does not work this time around, perhaps a $2 offer will be offered next week. Over-time, it will be possible to identify price-sensitivities and break it down by product, so that offers can be tweaked to maximize the likelihood of a purchase. It will be possible to identify what promotions someone responds to and drives loyalty behavior, so that an exact customer value can be assigned based on expected contribution to profit over time.

As the limits of big data analysis decrease, it makes it possible to gain unprecedent insight into human behaviors and prediction of actions when the data is both deep in insight and large in numbers. Research aimed at linking personality with spending habits [65] enables identification of personality traits and likely spending from credit card data.

3.2.3. The Components of Individualized Offerings

We propose to conceptualize the impact of individualized goods, services, and pricing into three main categories of enabling data and analytics, as companies need to: (a) know their consumer, (b) the context in which the consumer is currently in, and (c) understand how consumer needs and preferences interacts with context so that it can be translated into an offering of a good or service. (a) requires large amounts of data of previous activities, while (b) adds the complexity of dynamically updated data i.e., for context to be relevant, a company needs to be able to take advantage of an opportunity. (c) requires analytics, that finds the needle in the haystack in relation to understanding how past behavior translates to future behavior, and the impact of context.

3.3. Device and Usage Monitoring

The ability to gather, store, and process big data can have a profound impact on all aspects of the corporate *Value Chains*, i.e., the set of activities conducted to deliver a service or product [66], and create competitive advantage through more efficient logistics, operations, marketing, and service.

For supply chains, knowing the location of all products, supplies, and deliveries enables precise estimates of estimated time of arrival.

Smart devices create the ability to monitor the performance of a product, such as a car, which enables better life cycle management by predicting when the car needs servicing and what parts that will break—based on observations from hundreds of thousands of other cars—which in turn can be used to optimize capacity and inventory at local service centers. It also enables new and more efficient ways of contracting across the supply-chain, such as outcome-based contracts when the manufacturer can identify if a particular part performed in accordance with specification [22]. Smart devices allow companies to predict issues such as how breakdowns correlate with usage and weather, and lower risk by more precise predictions of how a piece of equipment will perform. However, to reap the benefits of IoT, all parties along the supply chain need to collaborate on what data to collect, and the standards it should take [67].

For capital goods, this ability to create insight from data enables a shift towards product-service system (PSS) business models that are focused on as a system of products and services that are continuously updated to meet customer needs [23]. PSS has been driving profits for goods manufacturers as services increase margins [68]. This entails a completely new value proposition and business model [69]. Similar to how software as a service (SaaS) changed how enterprise applications are sold, companies across all industries transition of from a product-centric business model towards a continuous service-centric business model, through what is known as *Servitization* [70].

For advanced—business-to-business—products, companies have used performance and usage data to optimize complex maintenance contracts and extended warranties, thus shifting towards a greater focus on service as IoT enables better risk management. Traditionally, risks have been too high for servitization of the core product [71]. However, better management of assets and the ability to monitor performance is changing this. Prominent examples of companies that have managed to do this shift are Rolls-Royce Aerospace, offering power-by-the-hour, so that the buyer buys say 20,000 h of operation rather than an airplane engine; Xerox having shifted from selling printers and copying machines to selling complete solutions for document management; and Alstom selling train-life services spanning installation and servicing of a train over several years. Typically, this implies a 10-year contract, where the manufacturer shares some of the risk that the equipment works, and the buyer has a payment scheme that is linked to actual usage [72]. The long-term nature of this type of business model, and the necessity to understand the customer business model, naturally leads to much closer business relationships—leading to both business model and organizational impact [73]. Often, new offerings emerge, with an example being that the network manufacturer Ericsson has shifted from selling

network equipment towards solutions for telecoms providers spanning maintenance and data insights through AI [74].

When customer needs are understood, typically services adapt, such as a logistics company using trucks on a pay-per-mile model, with costs and maintenance as part of the contract [72]—in contrast to just buying trucks. This shift across industries is often driven by outside forces. Notably, technologies that fundamentally change an industry—such as AVs that are predicted to change the automotive industry. Automakers are responding, as Ford is now stating that they have shifted from selling cars to selling mobility and investing in ridesharing applications and AV technology [75]. Similarly, Volvo has increased focus on monthly car plans rather than just selling cars [76]. And data is central in the ability to tailor the product to customer needs, optimize risk management, supply chain contracts, and manage the inbound and outbound logistics.

IoT makes it possible to better manage both revenue and costs, and risk will be shared across a greater number of parties that will be bound for longer-periods of time. This provides incentives to increase trust and fundamentally change how sales are done—illustrating how both operations and business models change.

Impact of Data on Pricing

As devices and applications collect ever more data, a key aspect that will change business models is the monetization of this data, shifting the model from making money from selling a product or a service towards gathering data, with the initial product and service being an enabler that is optimized for creating insight. This is a fundamental part of the data-for-service model of smartphone apps, but is also impacting sales of devices such as TVs that collect data on what users watch, and when [77,78], vacuum cleaners that collect home layout data [26], fridges that monitor how often someone opens the door [79], and cars that monitor travel patterns and in-car activity [80].

Even as smart devices might not be completely free, the value of the data will change the model for how companies gain competitive advantage. Companies that are skilled at monetizing their data will succeed in the marketplace through an impact on pricing. Across industries, data from smart devices can generate revenue, and enable lower priced products. This creates a business model where a traditional approach is blended with the data-for-service business model.

4. Concerns for Cybersecurity, Privacy, and Fairness

Several regulatory issues emerge relating to consumer profiling, such as that of fairness and transparency when consumers trade personal data in return for services, that of heightened risk associated with security breaches and the consequences of algorithmic bias as algorithms become pervasive in determining increasingly important commercial and social aspects of life.

4.1. Regulations, Privacy Policies, and the Return on Data

The current model where consumers trade their personal data in return for using a service has been criticized. However, there has been almost no analysis of the relationship between the utility gained by consumers and the value of the data they provide—the "*Return on Data*" [81]. As such, it is impossible for consumers to compare data-for-service deals. Thus, some researchers suggest that this return needs to be analyzed in conjunction with privacy laws [81]. Others suggest entirely new models for transacting data. Notably, the personal-data-economy (PDE) model implies that companies would buy data from individuals, giving every persona a piece of the action when data is monetized. Another alternative is the pay-for-privacy (PFP) model where users of a service would pay extra in return for not giving up data and receiving personalized adds [25]. Although promoted by some, actual implementation of these models would be highly complex. There are also concerns that these models might exacerbate existing inequality issues as lower income and less educated consumers would be unfairly targeted [25], and studies show that lower

income individuals have a lower confidence in their ability to protect their digital data, in addition to also experiencing higher degrees of monitoring [82].

Algorithms are "*Unseen and almost wholly unregulated*" [83], so that when the consumer sees the service—but not the underlying consumer profiling data that enables it—it can be likened to the tip of an ice-berg. Questions relating the impact of targeted offers and individualized pricing in relation to fairness arise when offerings are based on a consumer's perceived willingness to pay and psychological traits [84]. Potentially, companies would be able to identify psychological traits associated with bad financial decision-making and make offers that take advantage of those traits.

Almost every time an app is installed or even a device is used, some information is traded in return for this service—so the company gets access to location, photos, search activity, music listened to, and so forth [85]. As data is becoming more valuable and the amount of it that is collected increases, regulation is increasing, with the European Union through the General Data Protection Rights law (GDPR), leading in increasing individual rights coupled with an enforcement regime. The United States is characterized by a decentralized regime with little ability to enforce those regulations that exist, in addition to a greater focus on commercial needs [86].

On an individual basis, consumers are increasingly concerned about advertisers and companies getting access to their social media information. Sixty-one percent of respondents in a study of U.S. adults stated that they wanted to do more to protect their privacy [87]. Similar results can be seen in the recent studies in the U.K. [3]. We find that there is an inherent contradiction as individuals are increasingly concerned about their social media data being shared, while also demanding services that offer simplicity and ease of use.

At the moment, it is the privacy agreement or user agreement that regulates what data a company is allowed to collect, and what to do with it (such as transferring it to third-parties) [25]. However, only about 26% of free mobile apps and 40% of paid apps have such policies [88], and most privacy agreements allow for transfer of data to third parties in anonymized form [25,85], or a transfer of data in the case of a company acquisition, merger, or bankruptcy [26]. Academics have made the case that such policies are insufficient [89]. It is also increasingly difficult for consumers to keep track of what is collected, as many third-party applications are built as part of applications and collect data without active consent or privacy agreements [24]. If a policy does not exist, a company is often free to monetize consumer data without risk relating to privacy violations [26].

Consumers are also unlikely to read privacy policies [90], or, if they do, understand this type of documentation [91–94]. In 2014, half of internet users did not know what a privacy policy was [95]—and if they do, researchers question if they understand what they sign up for when installing an app or making a payment through their phone, when they buy a device such as smart TV that tracks usage [77,78], or a toothbrush that tracks brushing habits [85]. Even when providing active consent, consumers are unlikely to understand the full scope of profiling and its implications [25,26,96]. About half of U.S. adults state that they do not fully understand what happens with their data when they share information with companies [87,88,97].

4.2. Probabilistic Inference

Even if a consumer declines a service, or if new regulation makes it more difficult to collect data—technology is now able to fill in the data gaps. Non-consenting consumers are assigned characteristics from similar consumers for which there is a representative sample through probabilistic inference. Machine learning can now accurately identify romantic partners in 55% of cases with only anonymized relationship data and Facebook can identify social relationships even the users are unaware of [98]. Another study was able to identify 90% of consumers from anonymized credit card transactions, stating that even data with very little information provide limited anonymity [26].

4.3. Cybersecurity

As companies are collecting increasing amounts of data—some of it highly sensitive biometric data—the risks associated with cybercrime increases. As noted by Peppet [99], the high likelihood of security breaches and the challenges associated with meaningful consumer consent results in serious concerns relating to discrimination, privacy, security, and consent. Large corporations have seen data breaches of millions of customer records with sensitive information such as social security numbers, address, and credit card information—with one example being the credit scoring company Equifax [100]. The risks associated with biometric data are even higher, as unlike a credit card, the characteristics of your iris or fingerprint cannot be changed [26]. Transfers of health and biometric data are increasing. In 2014, the Federal Trade Commission found that 12 mobile health applications transferred information to 76 third-parties, with some 18 parties receiving device-specific identifiers, 14 receiving user-specific identifiers, and 22 receiving other types of health information [101].

Cyber-threats will become potentially more harmful as algorithms become pervasive in determining key aspects of everyday life such as if a mortgage will be approved and even if a suspected criminal is going to get bail and the length of sentencing. Researchers have begun to address potential solutions for mitigating these risks, emphasizing the need to build trust in how data is managed among consumers [6,102].

With advances in machine learning, risks rise in relation to how such insights can be used when it is possible to identify if a young child has autism through how they use an app [103], depression and mood from how we move [104], and spend [105], linking personality to eye movement [106], the risk of insuring your car through how we drive [107], the likelihood to default on your debt based on spending habits [108], if you are likely to get fired on your new job based on assessment of cultural fit based on the language you use [109]. Online crime is now evolving into protection against increasingly advanced devious manipulation, rather than just brute force data theft. States and criminal organizations could potentially use deep fakes (i.e., fake audio and video that looks convincingly real) and adversarial machine learning for malign purposes and make small changes in datasets to infuse bias in algorithms [110].

5. Summary and Concluding Comments

We have outlined how data is impacting business models and how the convergence of various data layers from devices and applications creates increasingly granular consumer profiles. Specifically, this enables a shift from targeted marketing towards increasingly individualized offers and pricing. A key aspect of this development is that location-based-services set demand and preferences in a geographical context, creating context-based-intelligence.

The outlined development builds on earlier research, as it illustrates the need to view IoT from an eco-system perspective, rather than viewing firms in isolation [16,17]. As data convergence creates context-based-intelligence, companies increasingly need to collaborate to reap the benefits of IoT [67]. Demarcations between industrial- and consumer-IoT applications are increasingly blurred, when data is transferred and used for other applications than initially intended.

We find three primary channels through which data is transforming business models: (1) improved customer matching and tracking of marketing returns; (2) individualized offers and pricing, and (3) device and usage monitoring.

The first category has an impact on value proposition and marketing, through identification of the right target audience and the ability to track the efficiency of marketing campaigns.

The second phase of monetization of IoT data comes from identification of the right consumer, to identifying the best product, price, and timing for an individualized offer for that consumer. This type of individualized services and pricing is enabled by context-based-intelligence and is likely to lead to behavioral based pricing.

The required data components of individualized offers and pricing illustrates the implementation challenge, and the need for a deeper understanding of the data eco-system, as context-based-intelligence will require; (a) the ability for companies to know their consumer, through rich data on previous activities (b) the context in which the consumer is currently in, through near real-time data on geography and social-context, and (c) understanding how consumer needs and preferences interact with context so that it can be translated into an offering of a good or service. As few organizations can achieve the scope of necessary data on consumers and context, collaborations will be necessary, and in-turn drive the commoditization of data.

The third category of IoT impact on business models comes from the ability to monitor devices usage and performance. This enables new ways of contracting across the supply-chain, such as outcome-based contracts with suppliers and more refined risk-sharing when relationships between companies shift from far-in-between transactions of goods to ongoing partnerships, as IoT enables what is known as *servitization* [73].

As devices gather data that can be monetized, competitive advantage will be gained by lower priced products supported by data revenue, resulting in blended business models that are part traditional and part data-for-service.

From a privacy and cybersecurity perspective, collection of biometric data and generation of psychological insights increase the risks associated with data breaches. We find a contradiction in that individuals are increasingly concerned about privacy, while consumer preferences towards ease-of-use applications perfectly align with consumer profiling.

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