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# Digital Social Signal Processing - Theoretical Underpinning and Research Agenda

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# DIGITAL SOCIAL SIGNAL PROCESSING – THEORETICAL UNDERPINNING AND RESEARCH AGENDA

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## Abstract

*Organizations make increasingly use of social media in order to compete for customer awareness and improve the quality of their goods and services. Multiple techniques of social media analysis are already in use. Nevertheless, theoretical underpinnings and a sound research agenda are still unavailable in this field at the present time. In order to contribute to setting up such an agenda, we introduce digital social signal processing (DSSP) as a new research stream in IS that requires multi-facetted investigations. Our DSSP concept is founded upon a set of four sequential activities: sensing digital social signals that are emitted by individuals on social media; decoding online data of social media in order to reconstruct digital social signals; matching the signals with consumers' life events; and configuring individualized goods and service offerings tailored to the individual needs of customers. We further contribute to tying loose ends of different research areas together, in order to frame DSSP as a field for further investigation. We conclude with developing a research agenda.*

*Keywords: Social Media, Social Media Analysis and Engagement, Social Signal.*

# 1 INTRODUCTION

The proliferation of social media such as facebook and twitter enables organizations to design new business models and introduces new phenomena into the IS research agenda. Facebook started as a Harvard-restricted online community in 2004, and experienced substantial growth by integrating other organizations into the community later on. Since 2006, some 22,000 organizations have already registered themselves in the facebook directory (Ellison, Steinfield, & Lampe, 2007). In late 2011, more than 700 million active users joined the facebook community by setting up their online profiles and access this online social network site daily.

In academia, the proliferation of social media has brought various traditional research areas to flourish, including social network analysis, impression management, or privacy issues. From a managerial perspective, social media is a crucial asset that companies can tap into to generate and sustain competitive advantage. Some prospects include generating and exploiting rich information about their customers (Boyd & Ellison, 2007), and building up more intimate interaction channels in the spirit of co-creation (Constantinides, Romero, & Boria, 2008). Moreover, the publicity of social media leverages word of mouth communication (Boyd & Ellison, 2007) as positive impressions spread through an online social network and reach other customers. However, even if early adopters begin to capitalize on these business opportunities, many companies lack the skills and tools to fully analyze user generated content in social media, which would enable them to configure new services matching the individual context experienced by users of social media. Although early movers started as solution providers to capitalize on social media analysis based on innovative analyses techniques (i.e. sentiment analysis, business intelligence solutions), social listening or even social media engagement (e.g. radian6.com), the huge business potential of analysing consumers' online data seems to have remained underexploited still.

The purpose of this paper is to conceptualize digital social signal processing (DSSP) as an innovative research stream to sense, analyze, and build on the data that individuals emit, either intentionally or unintentionally, on social media. We conceptualize a digital social signal to be a piece of information that reflects current individual attitudes or the overall social situation, as long as this information is emitted in an electronic way (such as adding people as friends on facebook, or posting pictures on flickr). We assume that information systems that contain these data (such as facebook, twitter, flickr etc.) represent a digital public asset (DPA) that can be accessed and utilized by users and businesses at low or even no charge, and that the users give companies permission to analyze their data.

We offer a four step process to conceptualize DSSP. First, analyzing any data that were added to social media might enable companies to *sense* that a digital social signal has been issued. Second, by *decoding* user generated content from various social media, companies might be able to identify the underlying social signals conveyed by these data. Third, the social signals are then *matched* with life events, expressing a consumer's current needs, wants, or demands. Fourth, by building on this information, companies might be able to *configure* more elaborated value propositions by combining goods and services that fit the attitudes and current situation experienced by the consumer. The proposed approach would, therefore, enable companies to generate superior business returns, as well as decrease search costs of customers that they would have to spend on compiling appropriate solutions themselves. Based on these assumptions, we offer a set of propositions and a research agenda to further investigate this phenomenon.

The paper proceeds as follows. In Section 2, selected previous research in adjacent research streams is reflected. In Section 3, we argue that the proliferation of social media as a DPA augments traditional supplier-consumer interactions, since social media providers enter business as additional actors that moderate some of the interactions of providers and consumers. Based on this observation, we introduce a four stage process of DSSP. In Section 4, the phenomenon of DSSP is structured with a five layer framework, organizing some of the intellectual challenges related to DSSP. The paper is concluded in Section 5.

## **2 THEORETICAL UNDERPINNING**

### **2.1 Social Media as Digital Public Assets**

Users increasingly utilize social media, especially online social network sites, in order to keep connected with their friends, to communicate their activities and share experiences happening in their daily lives (Boyd & Ellison, 2007; Ellison et al., 2007). Aiming at understanding the phenomenon of success of social media, considerable research has been conducted on exploring the structures of social networks (e.g. Ellison et al., 2007; Hsu, Lancaster, Paradesi, & Weniger, 2007) and their behavioral aspects (e.g. Benevenuto, Rodrigues, Cha, & Almeida, 2009; Golder, Wilkinson, & Huberman, 2007).

Building on the proliferation of online social networks such as facebook, organizations have joined these networks, too. On the one hand, they start analyzing the behavior of their customers, search for similarities between them and, hence, try to understand their consumers more comprehensively (Ansari & Koenigsberg, 2011). Thereby, information offered by the customer, without making use of the privacy protection features granted in social media, can be analyzed to understand the consumer's demand and offer tailored solutions of goods and services. This approach can be enabled by advanced data analysis techniques. For instance, customers' profiles can be analyzed in order to identify clusters with similar preferences. Another method is to analyze orders placed by similar customers to identify the preferences they share (Adomavicius & Tuzhilin, 2005; Montaner, 2003). Websites like amazon.com use transaction data and reviews in order to offer additional products based on collaborative filtering approaches. Recent trends in establishing online social networks as businesses indicate that this trend starts to be taken up and extended with data from social networks, too. On the other hand, organizations utilize social media as a communication channel to extend their marketing strategies. In order to actively involve the customer in promotion activities, they take part as an organization within the network (such as with starting their own company profile on facebook) and try to get their customers involved into their activities, like commenting on a product or a marketing activity, and, to share their opinions with others in the network (Taylor, Lewin, & Strutton, 2011).

Up to now, providers have taken some first steps to get involved in online social networks. However, the prospects offered by Social Media as Digital Public Assets provide additional opportunities to connect with customers. According to Teece, the successful commercialization of innovation depends on complementary assets (Teece, 1986). Rosemann et al. (Michael Rosemann, Andersson, & Lind, 2011) introduce digital complimentary assets as resources that feature particular properties. First, they are non-excludable which means that everybody can use these assets without technical, price, or contractual barriers. Hence, every customer can consume these services or engage with them in a simple way (i.e. by free consumption). Second, they are non-rival, as consumers can use the services without competing with each other. Third, their versatility is high as the services can reach a significantly large group of users. Fourth, the value proposition of the service is fostered by positive network effects. Digital complementary assets can reach a very high number of users and hence reveal a considerable exploration potential for providers. We refer to those as Digital Public Assets (DPA). Examples for DPAs include online social network sites (e.g. facebook, orkut), social photo services (e.g. picasa, flickr), social music services (e.g. lastfm, spotify), or professional online social network sites (e.g. Xing, LinkedIn). Teece (1986) argues that if a firm does not possess complementary assets, it may capitalize on assets of firms in the market. This capitalization requires either an integration strategy (e.g. a firm merger) or a contract strategy.

### **2.2 Social Signals**

“The ability to understand and manage social signals of a person we are communicating with is the core of social intelligence” (Vinciarelli, Salamin, & Pantic, 2009). Traditionally, social signals are described by cognitive sciences as the non-verbal visualization of a person's attitude towards a

specific situation. Behavioral cues (e.g. gestures and postures, face and eye behavior) are directly associated with a person's social signals (Vinciarelli, Pantic, & Bourlard, 2009). Research in this field is focused on identifying the correlation between a person's social signal (dependent on the behavioral cues) and perceptions based on observations of perceivers (Ambady & Rosenthal, 1992). Aiming at the automated analysis of social signals, the computer science discipline of social signal processing was established. This area of research is focused on finding out how humans act, how these actions can be interpreted automatically, and which social signals can be clustered together (Brunet, Donnan, McKeown, Douglas-Cowie, & Cowie, 2009). The underlying assumption is that non-verbal behavior (such as gestures and facial expressions) is to some degree machine-detectable (Vinciarelli, Salamin, et al., 2009).

In our understanding, social signals are not restricted to signals which can be identified as behavioral cues that are communicated by individuals, but can be expressed by communication on all media, constrained by the richness a medium offers (Daft & Lengel, 1986). For instance, the change of a person's relationship status or a job specialization that an individual publishes on social media can be viewed as a social signal. Of particular interest is to identify the underlying meaning of these signals, i.e. the expression of attitudes towards an organization, situation, product, service, etc.

We suggest that the meaning of these signals can be interpreted in terms of needs, wants, and demands of a consumer (Baida, Akkermans, & Gordijn, 2006; Baida, 2006). A need is "a state of felt deprivation of some basic satisfaction" (Kotler, 1988). Typically, needs are abstract and difficult to capture (Baida, 2006). Therefore, they have to be identified in a systematic process. A want is a desire for specific satisfiers of deeper needs (Kotler, 1988). This means that a need (although possibly subliminal) turns into wants for something. An example might be the need for "relaxation and time to think about the sense of life" that manifests as a want for "holiday". A demand is a want for specific products (i.e., physical goods or services) that are backed up by an ability and willingness to buy them (Kotler, 1988). In our example, the demand is the concrete intention of the consumer to book a holiday offered by a travelling agency.

### **3 DIGITAL SOCIAL SIGNAL PROCESSING**

#### **3.1 Interaction patterns moderated by DPAs**

Currently, the interaction between a customer and a supplier is a dyad that involves both parties (Ferstl & Sinz, 1995) regardless of the intention underlying the interaction (e.g. contracting or payment) (Ford, 2001). Therefore, it can be described by a send/receive interaction pattern (Barros, Dumas, & Hofstede, 2005). Service interaction patterns capture the interactions amongst actors in scenarios of service provision. In the send/receive interaction pattern, the consumer engages in two causally related interactions. For example, a consumer wants to book holidays with a travelling agency. The first interaction is triggered by the consumer, who sends a message to the provider (request, i.e. booking a flight). Depending on the request the provider configures a solution that is offered to the consumer. Subsequently, the consumer receives a message from the provider (response, i.e. confirmation and invoice) (Barros et al., 2005). In this scenario, the first contact can be either mediated by an online sales platform (e.g. amazon.com, ebay.com, webshop of the provider) or be conducted in a face-to-face interaction.

In order to react to a consumer's particular needs, wants, and demands, providers need to set up individually configured bundles of services and/or physical goods. In order to do this, organizations need to change the way in which they communicate with their customers, by shifting from a send/receive interaction pattern to a more complex and even consumer-centric interaction pattern. This shift is based on the proliferation of DPAs and is fundamentally changing the existent actors, processes, and interactions (see Figure 1). Consumers increasingly use DPAs as platforms for performing social interaction with their peers, by posting status messages, tweeting current locations, or publishing what they "like". Therefore, it can be assumed that solution providers can capitalize on

DPA by identifying some of the consumers' wants, needs and demands that they would be unable to identify without social media. With this information, more individualized solutions may be configured and offered to consumers. In terms of the interaction pattern of providers and customers, DPAs have joined into the game as additional actors that augment or even mediate the other actors' traditional patterns of communication

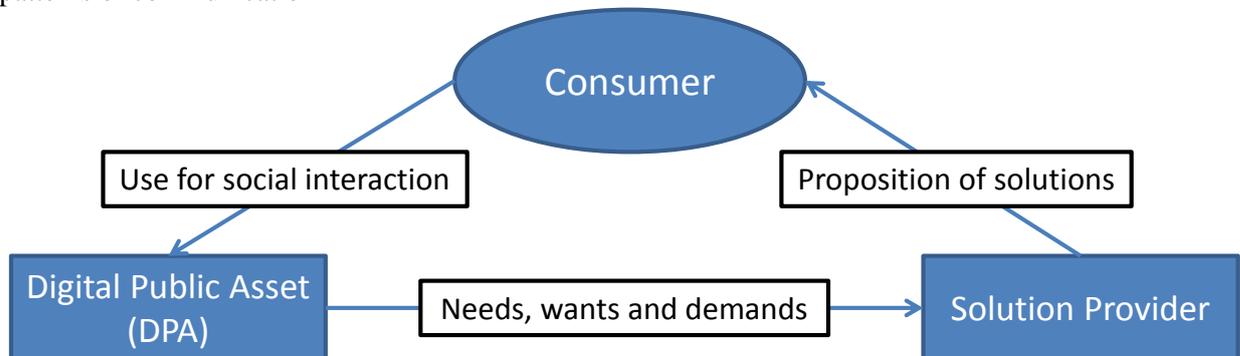


Figure 1: Interaction pattern moderated by Social Media as DPAs

The extended interaction pattern can be expected to have positive (but might have negative) impacts on all involved actors. First, the consumer may profit from physical goods and service offerings that are individualized to fit his/her real needs, without having to conduct complex search processes. Second, the solution provider has closer access to its consumers without being forced to launch large scale marketing campaigns. This would free up considerable resources that are currently spend on advertising. Third, the DPAs would benefit from their role as an interaction platform, on which additional acts of communication and business transactions are performed. This could enable the platform owners to generate business value from their data, which in the past has been proved hard to do. However, it is clear that utilizing social media sites as digital public assets for selling goods and services is restricted to the data that is publicly available. For instance, facebook provides data protection features that user should apply to disclose their personal data or to hide them from organizations. In this paper we assume that some subsets of personal information are available for analyses by the organizations (which users might “like” or are connected with in an online social network) or are disclosed by customers in exchange for some benefit.

### 3.2 Basic concepts in Digital Social Signal Processing (DSSP)

DPAs may be used as a means to engage with consumers for initiating sales activities. However, in the light of the abundance of data on personal interactions that are available on DPAs, establishing meaningful individual interactions with consumers seems cumbersome. In consequence, a systematic approach is needed to (semi-)automatically transform consumer interaction data into tailored offerings. For this reason, we introduce the approach of digital social signal processing (DSSP).

“Life status change per se, independent of the type of change, appears to be a key predictor of change, and possibly of propensity to change. [...] Measures of status change can be found in many existing secondary data sources. [...] And they appear to be potentially useful in understanding a wide range of purchase situations.” (Andreasen, 1984) In consequence, events that happen in the consumer's life are likely to be of interest for solution providers. The term life status change or life event is defined as situations in which a consumer's lifestyle changes – often in relation with experiencing stressful events (Andreasen, 1984; Mathur, Moschis, & Lee, 2003). In our understanding, we define a *consumer life event* as a change in the life of a consumer, impacting on his/her needs, wants, and demands. Since life events might change the needs, wants, and demands hierarchy of an individual (including the proliferation of entirely new needs, wants, and demands), they create new market opportunities for providers of physical goods (Lee, Moschis, & Mathur, 2001; Mathur et al., 2003). As a result, a provider might react on the identified life event by offering an individualized, bundled solution of goods and services tailored to the identified consumer need. For instance, if a couple gets married (the

life event is marriage), providers such as government authorities or wedding planners could offer tailored services that couples who get married would be likely to consume. Other life events could comprise the desire to move into another flat or house, the 50th birthday of a loved one, or the desire to spend holidays abroad (for an exemplary overview of stressful life events see Lee et al., 2001).

*Digital social signals* can indicate the occurrence of a life event. In line with the notion of social signals in the field of psychology, we define digital social signals as any bit of digital communication on DPAs that reflects a particular life event that is experienced by a consumer. Examples of digital social signals may be the acceptance of another actor as a new friend or a posting of one’s current location on an online social network site. Traditionally, providers could only perceive social signals that were actively communicated to them by the consumer. With the recent rise of DPA, those signals may be observable ubiquitously at no charge. This offers a huge opportunity to goods and service providers to approach potential consumer at the right moment, in the right place, with the right solution. Tying together the introduced concepts, we define *digital social signal processing* as a systemic, automated transformation process of single digital social signals or a set of digital social signals emitted by individuals on DPA with the intention to offer individualized solutions that fit to their (expected) life events. We now turn to the description of DSSP as a systematic process.

### 3.3 The Four-Stage Process of Digital Social Signal Processing

We conceptualize digital social signal processing as a four step process (see Figure 2).

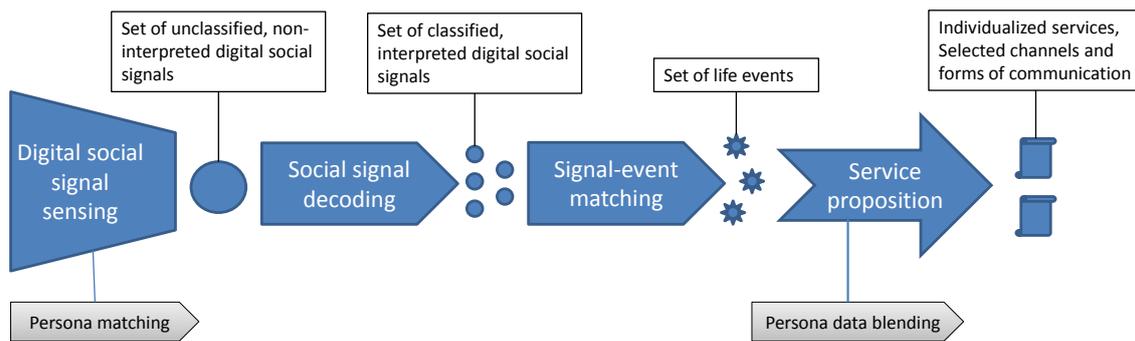


Figure 2: Digital Social Signaling Processing, Conceptualized as a Four-Step Process

In general, the proposed process resembles the process of complex event processing: event producing, event processing, and event consuming (Janiesch & Matzner, 2011). However, we offer a refined version of this process, adapted to the context of DPAs.

**Step 1: Sensing of digital social signals.** Social signal sensing is the gathering of signals communicated by the consumer on DPAs. The output of this phase is a set of unclassified and non-interpreted data that contain social signals. To allow for the recognition of social signals in the overall data repositories of DPAs, they have to be predefined in a formalized way. Only then, appropriate techniques of pattern matching can be applied (Luckham & Frasca, 1998). Prior classifications of social signals foster their formalization. We propose three alternatives: First, signals may be categorized according to the DPA they stem from (social network sites, music services or shopping communities). Second, digital signals can be distinguished based on whether they correspond to individual data or group data. For online social network sites, individual data comprise status messages, profile information, or the current location of the user. Group data may reflect the ego-network of an individual, i.e. the network that includes themselves and all digital personas they are directly connected with. Here, social signals include a new friend in the ego network or membership in a new group. Another classification of digital social signals can be derived utilizing signal origin and engagement as two orthogonal classification dimensions. Signal origin refers to the IS from which the social signal is emitted, whereas engagement denotes how digital social signals are emitted. A signal may be actively emitted by the user. It can either be sent on a public social network by posting a message on a social network site like Facebook or twitter. In addition, a signal can be sent by

proprietary systems that are owned by a provider. For instance, a consumer might book a flight on a DPA (i.e. with Delta Airlines on facebook) with his/her frequent flyer account, signaling to the airline that she/he plans to travel and also might need a rental car or a hotel booking. The signals may also be passively generated by the user. Telematics systems, such as GPS tracker in a mobile app, may provide information about the geographic position of a consumer allowing for the proposition of location based services, provided that tracking and analyzing these data has been approved by the consumer.

**Step 2: Digital social signal decoding.** The social signals obtained have to be processed to extract the information that is relevant for the discovery of life events. An analogy of that process step is processing complex events (Wu, Diao, & Rizvi, 2006). The output of this phase is classified and semantically interpreted digital social signals. Different techniques may be used for that purpose, which also depend on the type of social signals. These may include text mining, picture recognition in photos and videos, or audio decoding. Since many social signals are represented as text messages, the challenge is to identify those messages that provide clues of social signals. Text mining techniques may be applied for that purpose (Berry & Castellanos, 2007). In general, a better understanding on how consumers “encode” and communicate their social signals and life events in social network sites is needed. For offering goods and services, the information on the individual properties and the social context of the individual can be useful. Social signals are embedded in a greater social context of the individual (i.e., in the consumer’s ego-network). To address this issue data of the digital persona help to enrich the social signals in the phase of sensing. According to Clarke (1994), a digital persona “is a model of an individual's public personality based on data and maintained by transactions, and intended for use as a proxy for the individual.”

**Step 3: Signal Event Matching.** Qualified digital social signals have then to be matched with a formerly defined set of life events. Since the signals may be of high variety, efficient ways of signal-event-matching have to be provided. A related approach has been developed under the term of the event cloud, which is “a system that allows searching for business events in a variety of contexts that also take the relationships between events into consideration.” (Vecera, Rozsnyai, & Roth, 2007) The outputs of this phase are life events that implicitly express a customer’s needs. As a preparatory step to this, life events and the social signals that might indicate that these life events have occurred, have to be identified. Specifications may include social signals associated to the event and actions that have to be triggered in response to the specific life event. Further, the life events of interest will be different to each service provider, depending on the services they offer. Life events will be classified in different *generic* classes, such as a birthday, a grocery purchase desire or an upcoming travelling (Lee et al., 2001). However, the life events have then to be individualized according to the individual social signal. This will e.g. include the age reached, preferences for a specific food, or specific travelling destination information.

**Step 4: Configuration of a value proposition.** The final step in DSSP is to offer consumers individualized *value propositions*. Life events identified from consumer data on DPAs can be expected to draw a much more sophisticated picture of the needs, wants, and demands of a customer than traditional approaches can. In order to configure and offer a service or good, a supplier has to carry out a sequence of steps: To uniquely identify the customer, the life events from DPAs have to be blended with personal data existent on the providers’ proprietary (CRM) systems. Moreover, the data may be blended with profiles from other DPAs and information systems. Second, techniques for configuring value propositions have to be applied based on this information (e.g. service configuration, service bundling; see section 2). These techniques may require modifications in order to adequately respond to the identified life event data. Third, after a specific need has been identified, appropriate channels have to be selected to contact the consumer (Rangan, Menezes, & Maier, 1992). These channels may include the DPAs themselves or other channels such as emails, letters, or telephone calls.

## 4 A 5-LAYERED FRAMEWORK FOR RESEARCHING DIGITAL SOCIAL SIGNAL PROCESSING

Arguably, DSSP is a field of investigation that involves diverse research areas. In order to systematize some first ideas on how loose ends could be connected with each other to make DSSP work, we propose a framework of five layers in order to motivate future research. Each of the layers is focused on a different unit of analysis (Figure 3). Notably, the layers are closely interconnected with each other. On the upper two layers, an individual publishes a digital social signal by leaving publicly available data in social media. We refer to this process as digital social signal encoding, since the social signal emitted by an individual is hidden in whatever text message, picture, or like is published. Once the process of social signal encoding is completed, these publicly available data might be analyzed by others. This is performed in line with the four phases of DSSP, as conceptualized in the preceding section. First, an organization needs to detect that new data has been made publicly available on the platform (digital social signal sensing). Second, the data needs to be analyzed and triangulated in order to identify any social signals (social signal decoding). Third, these social signals need to be made sense of by interpreting them in order to extract a need, want, or demand that the person that emitted the data might have (digital social signal decoding and signal-event matching). These two steps in DSSP are a specific implementation of digital social signal decoding. The resulting information is an interpretation of the life event that might have been encoded by the person in the original data. Fourth, value propositions, including physical goods and services, can be configured and offered to the client, provided that the client has approved to be contacted by the company. This assumption seems quite realistic for companies that have a strong fan base, such as (at the time of writing) Apple Inc. The configured value proposition might be much better suited to fulfill the needs, wants, and demands of the consumer than a standard value proposition offered to a general audience might be.

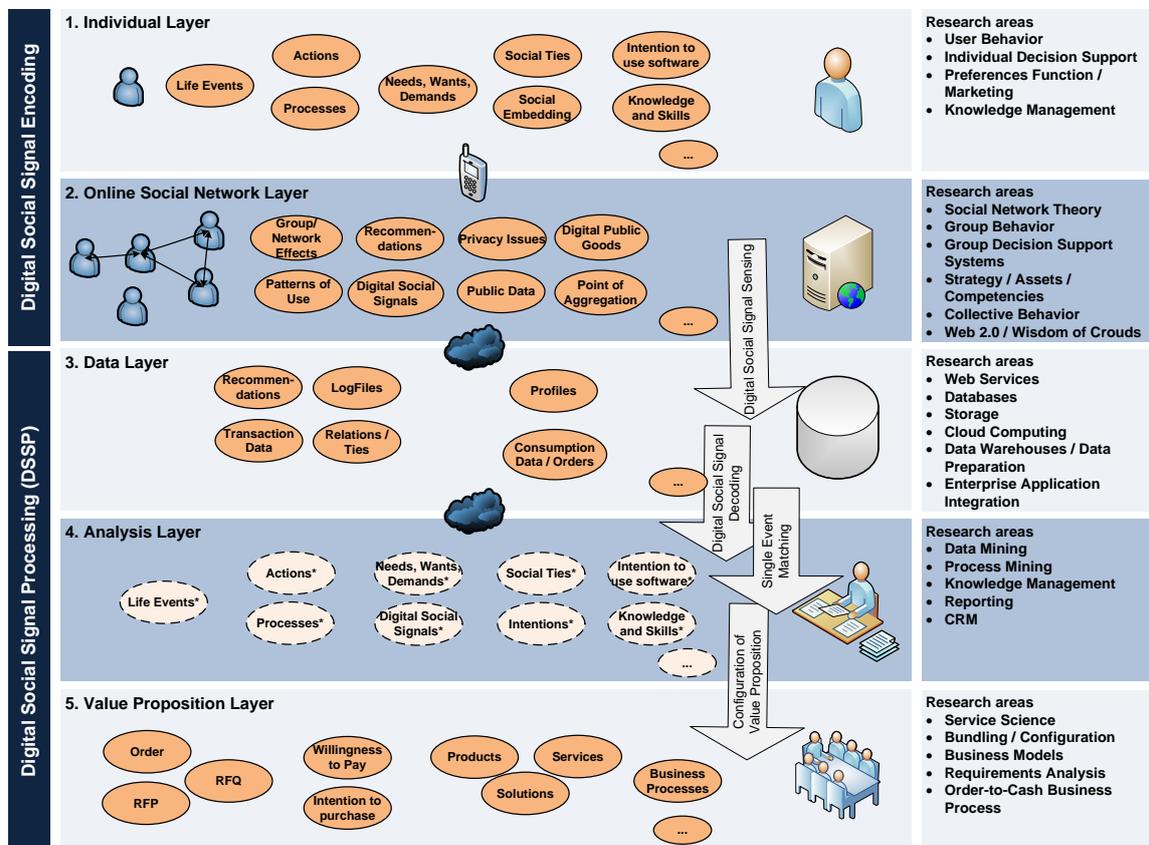


Figure 3: Five layer framework of Digital Social Signal Processing (DSSP)

In the following, we propose some research prospects inspired by the proposed layers. These prospects are not intended to be testable theoretical propositions. Instead, we want to compile and systematize some early ideas on research areas that might benefit from the advent of large Internet-based social media platforms that feature characteristics of DPAs. These ideas need to be taken up and refined in future research, in order to make substantial additions to the body of knowledge.

**Layer 1: Individual Layer.** Taking the individual as the primary unit of analysis, it is safe to assume that people experience life events that change their overall perspective on the world (Mathur et al., 2003). They strive to satisfy their needs, wants, and demands, in line with their preferences (Baida, 2006). These preferences can be expected to be shaped by the life events experienced. Furthermore, individuals build and uphold social ties with other people and are embedded into social networks (Granovetter, 2005), a subset of which manifests in interactions on online social network sites such as facebook. On these platforms, individuals perform actions, some of which become manifest in content that is stored digitally. As has been discussed in this article, we propose that by interacting with others individuals on social media, people intentionally and unintentionally emit digital social signals. To some extent, these signals are shaped by the life events experienced earlier. We, therefore, suggest further research on the following topics:

- (P1) To identify to what extent digital social signals that an individual emits depend on the characteristics of the individual, as well as on the situation in which the individual finds himself/herself acting.
- (P2) To ascertain, if social signals encoded by customers reflect their ‘true’ life events, at all.
- (P3) To analyze if combinations of digital social signals reflect a life event as experienced by an individual more precisely than can any of the involved digital social signals alone.

**Layer 2: Online Social Network Layer.** On a group level of analysis, many individuals nowadays use social media, such as online social network sites, to interact with their peers. An example is the increasing use of facebook as an online social network site to perform social interactions online. On these sites, individuals engage in and uphold relations, parts of which they could not have established or upheld without such systems. Shaped by their interactions in the online social network, users influence each other (online word of mouth being a case in point), which can create unforeseen network effects (Katz & Shapiro, 2011). From an economic standpoint, social media constitute Digital Public Assets (Rosemann et al., 2011) that may be capitalized on by organizations, too. The DPAs represent points of aggregation for users and user-generated content, respectively. We, therefore, suggest further research on the following topics:

- (P4) To find out if and to what extent digital social signals that are emitted by individuals on DPAs are influenced by the embedding of individuals into their social environment (ego network).
- (P5) To analyze if digital social signals on DPAs evolve in ways that cannot be fully foreseen a priori, due to the dynamic of group interactions. If that is so, digital social signals might represent the ‘true’ life events of individuals incompletely or even incorrectly.

**Layer 3: Data Layer.** On a data level of analysis, digital social signals published by individuals in social media become manifest in data that is stored electronically and is administrated by the provider of the platform, such as facebook. Such data might comprise user profiles, relationships with other users, referrals, blog entries, purchase histories, and other content. Even if these data would be scattered on various social media, we assume that they can be integrated from a technical point of view, with tools of Data Management, Application Integration, and Data Warehousing (Rosemann, Eggert, Voigt & Beverungen, 2012). Although this integration is likely possible from a technical point of view, the organizational and legal surroundings of the integration are equally important to consider. As a major issue when aggregating and analyzing data that individuals publish on social media requires legal and/or ethical clearance. By law, the user has to be guaranteed the full control over his/her digital persona on the internet (Pessino, 2004). We, therefore, suggest further research on the following topics:

- (P6) To find out if data that resides in different data repositories (representing different social media) can be integrated with each other from a technical point of view.

- (P7) To design and establish contracts and business models based on which the involved companies are willing to integrate digital persona data, provided no law is violated and the users of the involved DPAs themselves give the providers permission to do so.

**Layer 4: Analysis Layer.** From an analysis point of view, it is possible to interpret data published in social media for the purpose of reasoning on the underlying preferences, characteristics, and actions of individuals. Such analyses can be carried out by utilizing established techniques as discussed in the Business Intelligence, Data Mining, Knowledge Management, or Consumer Relationship Management literature (e.g., by applying sentiment analysis techniques (Asur & Huberman, 2010)). However, since the interaction of individuals and suppliers is mediated by the social media platform itself and is subject to dynamic interactions of users with other people, the results identified in the analyses would likely differ from the ‘real’ preferences experienced by individuals. In other words, it is likely that suppliers can only partially reason about the true life events experienced by individuals, based on their interpretation of the data. To outline this likely incorrect matching, the involved constructs are marked with an asterisk (\*) in Figure 5. We, therefore, suggest further research on the following topics:

- (P8) To identify if an analysis of the publicly available data in social media can reveal information (such as life events) that is indeed experienced by the consumer, at all.
- (P9) To analyze whether life events require to be detected by triangulating social signals encoded in different social media.
- (P10) To find out to what extent misleading information can be attributed to unforeseeable group interactions in the online social network.

**Layer 5: Value Proposition Layer.** On the level of analysis of a value proposition, the needs, want, and demands elicited for particular individuals can be used to configure bundles of physical goods and/or services that the individual might be willing to buy. This work has to build on previous research in Marketing, including analyzing a customer’s willingness-to-pay, and Requirements Engineering, including new methods to elicit the requirements of users and to configure value propositions accordingly. We, therefore, suggest further research on the following topics:

- (P11) To investigate if bundles configured based on consumer information identified with DSSP satisfy the needs, wants, and demands of consumers better than standard off-the-shelf offerings.
- (P12) To measure, what effect this improved fit has on the customers’ willingness-to-pay for the solution, compared to standard off-the-shelf value propositions offered via traditional channels.
- (P13) To design and implement adequate business models, based on which innovative interactions between providers and customers can be carried out, mediated by social media platforms as a third actor. As a result, social media join into the interaction as platforms on which the co-creation of value by suppliers and customers is initiated, conducted, and concluded.

## 5 CONCLUSION

We argued that the emergence of powerful Digital Public Assets (DPA), such as Facebook or twitter, greatly alters the way in which providers of physical goods or services and customers interact. In particular, detecting and making sense of social signals that are intentionally or unintentionally communicated by individuals on a DPA can be expected to enable companies to far better tailor their offerings to the individual needs, wants, and demands of customers. We conceptualized this process of Digital Social Signal Processing (DSSP) as a four step process, involving the sensing and decoding of social signals, matching them to predefined life events, and configuring individual offerings.

In doing so, organizations are able to intensify their current marketing activities by providing direct offerings to the customer within his daily life social activities. Thereby, current marketing activities of organizations are enhanced to configure individualized offerings.

In order to make this emerging research area accessible for the IS community, we designed a 5-Layer framework that embeds DSSP into a broader research environment. For each of the proposed layers, we derived propositions, supplementing the research agenda for consecutive research.

A general concern is that individuals should be aware that they might intentionally or unintentionally emit social signals that might be processed and made sense of by companies who strive to offer tailored goods and services. Therefore, besides the business potential to be realized based on these data, an important area for future research is to help individuals to balance their privacy needs with their desire to utilize social media as platforms for consuming goods and services.

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