Can Social Media be Sustainable: Economic and Industrial Modelling Instruments to Mitigate the Unneeded use of Resources in Social Media and Artificial Intelligence

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Discussion topic: Market-driven developments: Economic forces driving the industry towards sustainability

Abstract: Social media can help businesses and society implement sustainable practices (Bodin & Prell (Eds.), 2011). They also contribute to excessive resource use in data collection and sharing, digital resource use, and energy consumption (Kamin & Paireekreng, 2018). Thus, TikTok's feeds consume 15.81 mAh per minute and emit 2.63 gEqCO2/min in 2021. (Derudder, 2021). The generation that uses this tool most (Burns-Stanning, 2020) is also the most demanding and aware of climate change issues (Knight, 2016), even though its practices contribute to the current degradation. This hiatus illustrates how difficult it is to reconcile individual and collective goals. We propose shifting the question from the end-user to the service provider by detecting sobriety pits in data use and access to perpetuate or avoid disrupting end-user practices. Sobriety (frugality) is a critical variable in energy transition scenarios (Balzani, 2019) and one of the ecological transition's pillars. Social media and AI are particularly tense on these issues (Stein, 2020). Current solutions often pit energy efficiency against performance (Ikhlasse, Benjamin, Vincent & Hicham, 2021). Given the industry's promises of information access, automation, intelligent decision-making, human error avoidance, and more, this is unacceptable. Thus, we propose an operational framework to pose a model of sobriety for data access, consumption, and use (such as in social media or AI agents training) that does not impair performance or accuracy.

Keywords*:* Sustainable consumption, Green AI & ICT, Eco-design & changing business models, accuracy and sustainability, ecological sobriety

1. Introduction

Social media can support sustainable business and societal practices (Bodin & Prell (Editors), 2011). However, they also lead to excessive resource use, such as data collecting and exchange, digital resource utilisation, and energy consumption (Kamin & Paireekreng, 2018). In 2021, TikTok feeds will utilise 15.81 mAh per minute and produce 2.63 gEqCO2/min. (Derudder, 2021). Nonetheless, its practices contribute to the current crisis. This demonstrates how challenging it is to reconcile individual and community objectives.

Service providers can continue or avoid interrupting end-user practices by identifying sobriety pools (s-pools) in data use and access.

Sobriety (frugality) is a critical characteristic in energy transition scenarios (Balzani, 2019) and one of the cornerstones of the ecological transition. Existing systems frequently pit energy economy versus performance (Ikhlasse, Benjamin, Vincent & Hicham, 2021). This is unacceptable, given the industry's promises to improve information access, automation, intelligent decision-making, and avoiding human mistakes. The situation is very tense regarding social media and AI (Stein, 2020).

Hence, we propose an operational framework to present a model of sobriety about data access, intake, and utilisation (whether for direct use, such as in social media or agents training in AI) that does not compromise performance or precision.

Accuracy—satisfaction as a response to an expectation or need—is the key to data consumption processes and AI systems (Giese & Cote, 2000). Satisfaction is achieved when the process produces enough output to answer the question without a statistically significant error. A "satisfaction function" meets this imperative. This makes modelling sobriety difficult. As a result, satisfaction is directly related to system production, a function of resource allocation, which we have mapped using activity best costing (ABC) tools (Ray & Gupta,1992). This mapping helped us identify the drivers of artificial intelligence activity and test how their variation affected accuracy, the expected deliverable. The ABC approach shows that task and resource allocation both affect satisfaction, but interdependencies and constraints require further analysis. We tested drivers' dependencies, showing that energy consumption was a function of the algorithm and the volume of data used to train the learning system. By stressing interlinkages and tensions, we found that optimal accuracy was achieved when data consumption reached 68% and that further data processing did not increase precision.

Thus, the satisfaction approach allows us to identify sobriety pools and reduce data consumption by 32% by analysing drivers and resource interdependencies without changing the process. Thus, such systems have 32% sobriety potential. This analytical approach, which analyses homogeneous activity drivers, should be portable beyond the proof of concept (Thomas & Gervais, 2010).

Sobriety pits are wasted parts of a production process. Consuming a complementary resource has no marginal utility because it contributes little to the process. After conceptualising these pits, stakeholders must redesign and streamline their industrial processes to eliminate resource waste. This vision aims to identify (1) whether social networks have sobriety pits and (2) how to identify them (and potentially put them into practice).

Figure 1: The sustainable social media challenge

2. Framework

2.1 The Social Media Sobriety Challenge.

This work describes our theoretical framework. Finding sobriety pits requires a deep understanding of the production process (Figure 1).

Why do we produce this way? Why this method? If there is no clear operational and, most importantly, quantified answer to this question—we produce this way because it improves the productivity of x; for example—sobriety pits may be detected at this point in the production cycle. Thus, business routinisation may be hindering cycle productivity, so it may be wise to reassess it (Gibson, 2003).

2.2 Linking production processes, costs, and end-user satisfaction.

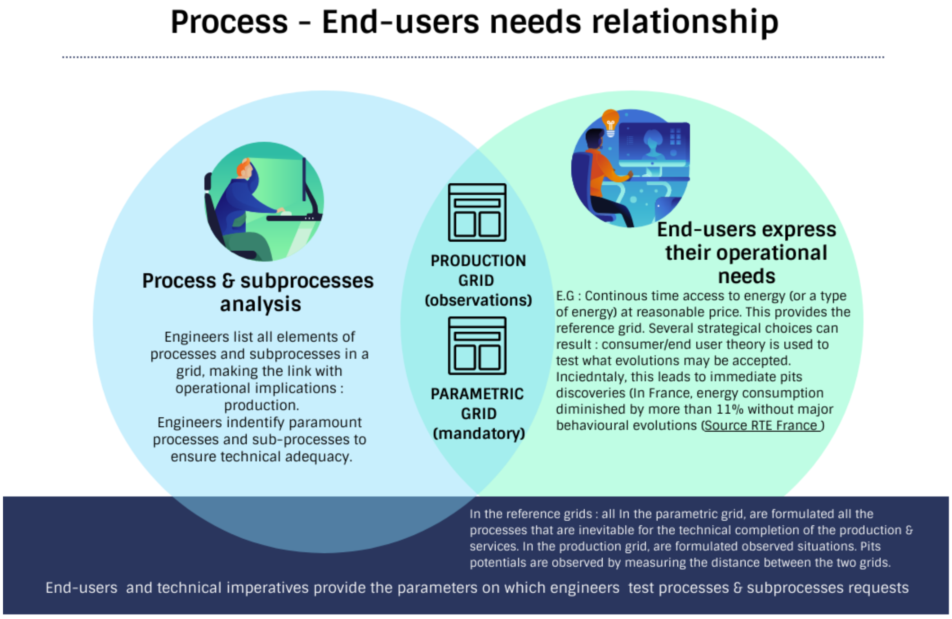

Figure 2: Process – End-Users Relationship

First, we analyse each production cycle's components and subcomponents. Processes are the sum of productive chains. We use requirement engineering to link (Figure 2) end-user expectations with process reality (Cheng & Atlee, 2009). Repertory grids can be used (Sadiq, M., & Jain, 2012). We assume that f(x) and g(x) are parametric grid functions for production and observation variables, respectively.

All necessary production and service processes are formulated in the parametric grid. Production grid situations are observed. Measurements between grids reveal pit potentials.

The ABC (activities best costing) method breaks down activities into cost drivers to determine their financial and operational existence. Activities are processes, and sub-processes are cost drivers (Tsai, 1996). The processes exist if the expenses do, but if they do not, there is a loss and a sobriety pit.

Well-known calculation theorems estimate the area between two curves and between the curve of an odd or even function and the x-axis (Armatte, 2010)

As a reminder, though this might appear trivial, for two functions, $f(x)$ and $g(x)$, where $f(x)\geqslant g(x)$ on the interval $[a;\ b]$, the area bounded by the two curves of equations y=$f(x)$ and y=$g(x)$, and the two vertical lines of equations =a and x=b, is given by: $\int_a^b \big(f(x) - g(x)\big)dx$

Whereas if $f(x)$ is an odd function, i.e., such that $f(-x)$ =-$f(x)$,then the area bounded by the curve of $f(x)$ and the x-axis in an interval [-a;a] is twice the area between the curve of $f(x)$ and the x-axis in the interval [0;a].More precisely,$\int_{-a}^{a} f(x)dx = 2\int_0^a f(x)dx$. The same is true for an even $g(x)$ function, i.e. such that $g(-x)$ =$g(x)$. We have: $\int_{-a}^{a} g(x)dx = 2\int_0^a g(x)\,dx$

For the current analysis, elements where the f(x) curve is above the g(x) curve have a positive algebraic area but involve ideal, i.e., too much use of resources compared to end-user expectations, and inversely, when it is below, the algebraic area is negative, indicating a non-optimal process.

2.3 Explaining satisfaction.

But what about user satisfaction? Economic theory offers three answers: utility, in a cardinal or ordinal reading, or the "choices" theory, which emphasises purchase decisions over satisfaction (Mattei, 2000). However, these three theoretical frameworks assume end-users express satisfaction by arbitrating a price/quantity trade-off (Chiappori, 1990), which is partially observed but not a unique decision point. Product innovation may increase appetite, which is more important than satisfaction.

Consumer satisfaction is called utility. Marginal utility measures the utility change from a one-unit change in consumption/use of a good/service. Such economists (Hugon, 2004) value marginal utility (the scarcity of a good). The utility function is subject to market biases because scarcity can be artificially induced, such as stockpiling mustard seeds in winter 2022 to artificially raise prices (Cuissard, 2023). This neoclassical reading links value to the utility of the last unit exchanged. Gossen's first law (Jolink & Van Daal, 1998) states that consumer desire decreases with each unit consumed. Thus, each subsequent unit has less utility. Marginal utility (first consumed unit) > Marginal utility (second consumed unit) > Marginal utility of n consumed units.

The total utility function shows how the consumer feels when using x units of good X and y units of good Y. The total utility of goods X and Y is U(x; y). Marginal utility is the utility of consuming another good. This is standard. Um(x)=U/x, where U is utility variation and x is good/service variation. Only marginal utility determines price. Pareto and Slutsky (Katzner, 2014) believed utility quantification is more complicated than par ordinal theorists thought. They proposed measuring utility by end-user importance rather than numbers. Substantial rationality underpins this theory. Substantive rationality means people seek maximum satisfaction with minimum resources (at the lowest possible price). This is known as the Ordinal approach.

Both theories assume the consumer is rational and seeks maximum satisfaction or utility. Thus, consumers can use a precise quantitative index to measure their utility from consuming a good/service. This approach is supposed to represent the preferences of economic agents between several options (baskets of goods/services, financial portfolios) over a potentially infinite period, where they all have the same information, all derive satisfaction from their consumption (or use, we speak of positive utility), are limited in their purchasing capacity (they cannot borrow), and allocate all of their money to realising this utility (arbitrage, e.g. investment, distribution). These assumptions rarely hold true. This reading attempts to answer the question: how does an economic agent allocate their budget between goods and services?

Aware of the shortcomings of this approach, economic theory has attempted to develop a "new theory of the consumer" (Barnett, 2003) that emphasises the existence of a consumption process similar to the production process, allowing the consumer/end-user to act with the goal of achieving explicit ends rather than in an impulsive/irrational way whose role is limited to "consuming" goods to satisfy his needs. This view makes household behaviours tangible and objective. However, it has obscured a second novel aspect of the new theory, which is to provide a framework for studying subjective choice formation. This vision is absent from the traditional theory of utility, but it is essential if the consumer must determine his ends and seek information to arbitrate choices (Fustier & Rouget, 1979).

Arbitrage is hence crucial because it drives consumer choice. If two products perform the same function, consumers do not care which one they buy. As long as the services are the same, the latter will accept both a wasteful and an environmentally harmful product. This is the indifference function.

Demonstrating a product/identity service's and functionality can increase end-user acceptance of one choice over another (de Lima Salem & Picot-Coupey, 2020). To maintain satisfaction if the service supports it. Users are committed to satisfaction, not products (Dufer & Moulins, 1989).

Thus, regardless of approach, trade-offs revolve around goods/services availability and price as an attribution of value, all within a volumetric logic (a price corresponds to a given quantity). The Maslovian logic of moving from one state of societal achievement to another and from one product/service life cycle to another never addresses consumer satisfaction but the ability to produce more after buying a product/service.

Our AI work (Gans-Combe, Jun Kim, Mouhali tbp 2023) and social media testing have this meaning. We found the source of economic agent satisfaction. It comes from transitioning from level x to level y in product access through integrated functions. I want to train a fruit recognition algorithm. Only 68% of my database images were used to train the algorithm, but it correctly identifies fruits. My algorithm training requires 68% of the resources. End-user satisfaction is not improved by using more resources. I can deploy this algorithm without consuming resources, as noted ~C. (or non-C). Contrary to theory, utility can be negative. Thus, a sobriety function generates end-user satisfaction from non-consumption. Thus, satisfaction (S) is linked to accessibility (supply chain or a) and product life cycle (existence or e). $S = f(a) + f(e)$. We also know that any product/process service (P) depends on these two functions at the right time (t). $P = \frac{f(a)+f(e)}{t}$ and S=P/t.

Thus, end-user satisfaction depends on economic agents' ability to implement processes that meet my needs. Each element of f(a) and f(e) can be broken down into activities, drivers, resources, and costs through “Activity best costing” applied to production (Chea, 2011). We also know we don't need to use all resources to reach a satisfaction level that allows end-users to continue production/usage.

Thus, S and P converge, meet, and diverge at a limit. How do I determine my non-consumption point (my optimum trade-off between satisfaction and efficiency) and decide which variable to satisfy? Safety, deployment simplicity, and (Kitchenham & Pfleeger, 1996). or price trade-off. Three functions converge until the decision point, then diverge.

Adequacy models as arbitrage tools are widely used in AI, but are they applicable to social network architectures?

3. Social media sobriety pits

Social media have a complex sobriety pool detection profile. Their architectures and productive cycles are fragmented and not fully dematerialised (Bossetta, 2018). The diversity of services these structures offer—messaging, video, search, affinity or relevance networking—consume fluids, but not exclusively.

3.1 Complex architectures, but shared resources needs.

Figure 3: Resource needs per social networks transaction types

Indeed, without the physical media that enable their distribution—smartphones, computers, etc.—none of these tools or offers would exist (networks, servers, but also algorithmic capacities, etc.). Despite their energy needs, these offers incrementally consume rare earth, human resources, and programmatic skills (see Figure 3 - resource needs per social networks transaction types).

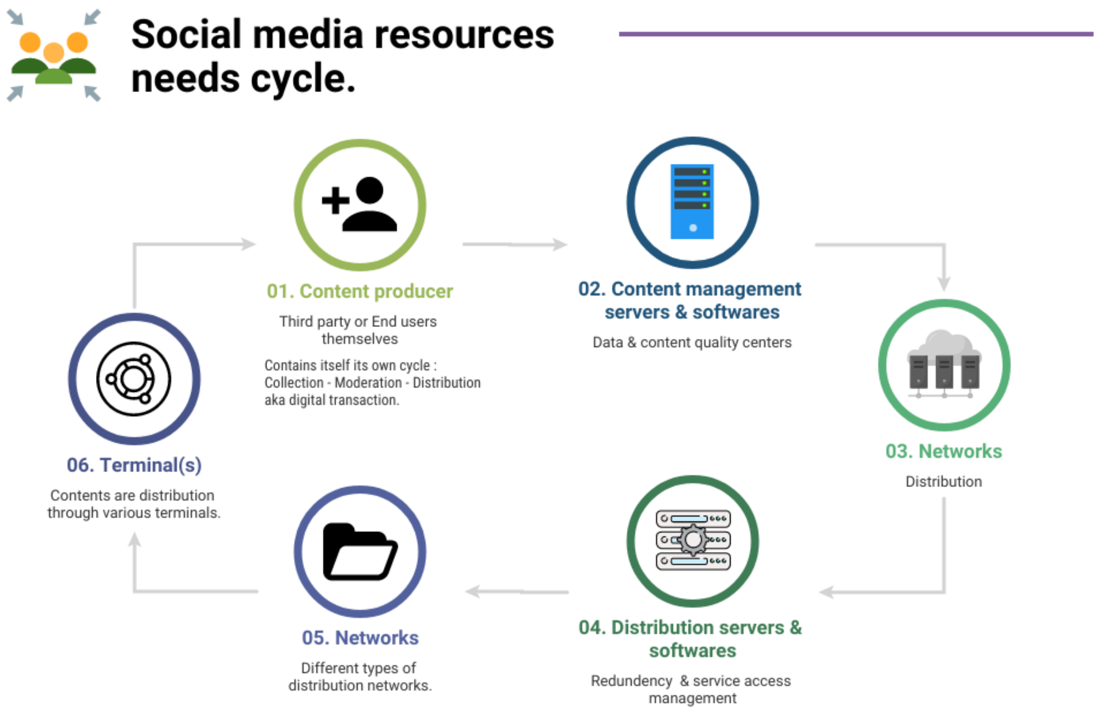

Figure 4: Social media resources needs cycle

However, resource analysis shows a homogeneity of goods and services needed to build, implement, and deploy this type of service (Figure 4).

We have a resource-only backend for multiple frontends. Resource concentration, according to stakeholders, differentiates resource needs. Thus, from the perspective of sobriety and the model to be implemented, knowledge of a process associated with business concentration ratios could help identify areas for improvement by establishing business resource profiles.

3.2 Social media and digital "overconsumption"

This accumulation of usages (Figure 4) affects resources, their use, and the planet (Kliem & Kao, 2015). "Digital over-consumption" refers to a connected device's life cycle's environmental impact. From manufacturing to disposal, a device emits CO2, creates waste, and degrades biodiversity. Every end-user action—using an app, sending an email, or watching a video—impacts the environment. Three factors affect this.

3.2.1 Digital device production.

Connected devices use 79% water and fossil fuels. This process pollutes the earth and accounts for 70% of France's digital technology's carbon footprint. Smartphones require global imports of lithium, gold, and metal. Transport increases CO2 emissions. Miniaturization may not work because smaller components require more energy, rare metals, and chemicals to make (Barney, 1995).

3.2.2 Communication infrastructure operations

"Pipes" and social media overconsume content, which must be stored in clouds or data centres. Since they need coolants and electricity to run, these massive physical storage centres pollute a lot (Rong, Zhang, Xiao, Li & Hu, 2016). In 2021, social networks used 30% of global data centre electricity, which was 220-320 TWh or 0.9-1.3% of global final electricity demand (IEA, 2022). In 2021, cryptocurrency mining consumed 100-140 TWh: "Over the past several years, large data centres have used 10-30% more energy due to rapid workload growth. Data centre energy use (excluding crypto) is expected to grow moderately in the coming years, but longer-term trends are uncertain. Coolants are another example (including water: Mytton, 2021).

3.2.3 Equipment's' End-of-life.

A recent study (Magazzino, Mele, Morelli & Schneider, 2021) examined the link between poorly deployed information and communication technologies and waste ending up in open dumps where some raw materials cannot be recycled due to infrastructure or design issues.

4. Recalculating to find sobriety pits

According to the global web index (GWI 2022), personal (the primary use) and economic imperatives drive social media use and growth (job search, visibility) ... It is about sharing interesting content with friends or strangers (Krishen, Berezan, Agarwal & Kachroo, 2016) or showing activism. These social tools are among the most widely used (Pearce, Niederer, Özkula, & Sánchez Querubín, 2019).

Overconsumption is obvious: 4.33 billion mobile users consume 262 million Tons of EqCO2 per year, accounting for 0.61% of global EqCO2 impacts in 2019 and 56% of France's carbon emissions. Additionally, superimposing social network layers requires additional energy and resources. Thus, TikTok leads with 15.81 mAh/min, followed by Facebook (12.36) and Snapchat (11.48). These use 10% of France's annual electricity consumption. The energy efficiency of established platforms like LinkedIn, YouTube or Instagram would be interesting to investigate as they use the least energy while being quite client efficient.

Maintaining the user experience while finding a critical path for improving the links between production layers that could lead to sobriety is the challenge. Thus, intimate knowledge of social network production processes is essential.

What makes a social network? Schematically this is known, but in detail, this is less evident. In contrast, detecting areas of sobriety requires this knowledge, the ability to identify in a production process when the resource is overused in relation to the expected customer experience.

Therefore, any actor tempted by an approach to make its production practises lean should first question the auditors to see if they can do this work. This requires a detailed understanding of each social network's productive continuum, which breaks down each product/service into activities and cost drivers using accounting standards guidelines. Without a clear picture of the processes and their costs, it seems compromised to look for resource usage savings.

It is worth repeating that the customer experience determines a user's satisfaction with using a social network, even to satisfy useless needs. According to research, Twitter loses 0.5% of its daily users monthly, directly impacting customer experience (Stokel-Walker, 2022).

Thus, even elites use social media for satiety and psychological belonging (Bao, Sun, Han, Lin, and Lau, 2023). They are also very high on the Maslovian scale (Ghatak and Singh, 2019). Due to overconsumption and customer experience, the social media ecosystem seems like a textbook example of how to find sobriety pits. However, we must consider resource stacking. Establishing a model on a horizontal process is different from analysing this issue in a chain of N superimposed functionalities or N consecutive processes. N is 6.

We previously demonstrated that sobriety lies in optimising a process while satisfying the end user. At least six simultaneous processes satisfy social media users. Therefore, it is necessary to identify the points of convergence of these processes to express them in a way that makes the search for sobriety wells possible in a continuous manner (in a single approach) rather than subsequently, which would make the analysis tedious. Restate: $S = P/t$ with: $P = \frac{f(a)+f(e)}{t}$ .This expresses social media satisfaction. $S = \sum_{i=0}^{5} \frac{P_i}{t}$

P2's resource knowledge is limited to what is not in P1 and later. If the usage structure of the previous resource phase is known, only the unknown elements need to be explored, greatly reducing the work. The resources are used concurrently in phase t.

So: $P = \frac{f(a)+f(e)}{t}$

$$P_1 = \frac{(f(a) + f(a_1)) + (f(e) + f(e_1))}{t} = \frac{f(a) + f(e)}{t} + \frac{f(a_1) + f(e_1)}{t}$$

(….)

$$P_6 = 6\frac{f(a)+f(e)}{t} + 5\frac{f(a_1)+f(e_1)}{t} + 4\frac{f(a_2)+f(e_2)}{t} + 3\frac{f(a_3)+f(e_3)}{t} + 2\frac{f(a_4)+f(e_4)}{t} + \frac{f(a_5)+f(e_5)}{t}$$

$$P_6 = 6P + 5\frac{f(a_1)+f(e_1)}{t} + 4\frac{f(a_2)+f(e_2)}{t} + 3\frac{f(a_3)+f(e_3)}{t} + 2\frac{f(a_4)+f(e_4)}{t} + \frac{f(a_5)+f(e_5)}{t}$$

This shows that social media users' needs and resources are redundant. Finding and discarding these unnecessary items may lead to sobriety pits.

5. Deploying the model: a ten components example.

Suppose a network consists of n components, each of which corresponds to a given use of resources (monetary or otherwise). Let the marginal utility (µ) of each component be given by:

$$\begin{aligned} \mu_1 &= x - y \times Q_1 \\ \mu_2 &= x - y \times Q_2 \\ &\dots \\ \mu_n &= x - y \times Q_n \end{aligned}$$

where x and y are constants and Qi is the quantity of component i consumed. Here, x and y are treated as constants to simplify the mathematical representation and analysis of the problem. Constants being fixed values that do not change within the context of the problem being analyzed, they are in the present case used to represent the underlying factors or characteristics of the components in the network that remain consistent across all components. If the costs of products i are given by Ci, and the resources (budgetary or else) constraint is fixed at R, then, to find the end user equilibrium, we need to set the marginal utility per monetary unit (let say euros) spent on each component equal to each other and tending to 0. This gives us the following equation:

$$\frac{\mu_1}{C_1} = \frac{\mu_2}{C_2} = \dots = \frac{\mu_n}{C_n}$$

$$\frac{((x-(y\times Q_1))}{C_1} = \frac{((x-(y\times Q_2))}{C_2} = \dots = \frac{((x-(y\times Q_n))}{C_n}$$

Solving for Qi, we get:

$$\text{Qi} = \frac{(x-(C_i\times\mu_i))}{y}$$

Substituting this expression for Qi into the resources' constraint: $C_1Q_1 + C_2Q_2 + \dots + C_nQ_n = R$

We get:

$$\frac{C_1(x-(C_1\times\mu_1))}{y} = \frac{C_2(x-(C_2\times\mu_2))}{y} = \dots = \frac{C_n(x-(C_n\times\mu_n))}{y} = R$$

Now, we can solve for Ci in terms of R. This gives us the resources that will set the marginal utility vector to zero:

$$C_1 = \frac{((x-(y\times\mu_1))\times R)}{(\mathrm{x} * \mathrm{y} + \mathrm{y} * \mu_1 + \mathrm{y} * \mu_2 + \dots + \mathrm{y} * \mu_n}$$

$$C_2 = \frac{((x-(y\times\mu_2))\times R)}{(\mathrm{x} * \mathrm{y} + \mathrm{y} * \mu_1 + \mathrm{y} * \mu_2 + \dots + \mathrm{y} * \mu_n}$$

…

$$C_n = \frac{((x-(y\times\mu_n))\times R)}{(\mathrm{x} * \mathrm{y} + \mathrm{y} * \mu_1 + \mathrm{y} * \mu_2 + \dots + \mathrm{y} * \mu_n}$$

Thus, we have demonstrated the pathway to set the marginal utility vector to zero in the context of a network with n components. In general, the end-user equilibrium condition can be used to find the costs that will set the marginal utility vector to zero for any network with n components.

As explained before, ABC gives us the precise costs for each component of a network. By comparing the calculated marginal utilities and the real costs, we can establish the optimal quantity of resources necessary to satisfy the users, and the distance between the real costs observed and this optimum. It is in this interval, which is repeated for each network, that the wells of sobriety can be found, making it possible to perpetuate user satisfaction with the services offered while improving operational margins.

Let us now assume that there are two production pathways resulting in the same service, each composed - for the purpose of this example - of ten components. These methodologies ultimately provide the same service, and each pair of components performs the same service: component 1 of set 1 delivers the same service as component 1 of set 2. We note that this approach is valid for n elements as mentioned above, but we limit the number of components for the purpose of the example. Each service component has its own balanced marginal utility, i.e., the point where users get what they want for a given resource usage (which can be monetary or otherwise). Comprehensive Activity-Based Costing (ABC) matrixes provide for each component used in a digital service, on one hand the volume of resource used, and on the other hand the associated costs (Shaffi & Al-Obaidy, 2013). The process consists of eight essential steps. initially pinpointing the primary activities within the network that contribute to overall costs, such as servers setup, service quality, and more as well as determine the cost objects, which are the products or services for which costs will be allocated (Kamiya, 2020). Next, the identified activities are categorized into cost pools to ascertain a cost driver for each cost pool. After calculating the total cost of each cost pool by aggregating the associated direct and indirect costs of the activities within the pool, an activity rate can be derived by dividing the total cost of each cost pool by the total quantity of the cost driver.

With this information, a matrix can be formulated wherein rows symbolize cost pools and columns represent cost objects. Within each cell, input the product of the activity rate for the corresponding cost pool and the quantity of the cost driver utilized by the cost object. Subsequently, for every cost object, the allocated costs must be consolidated from all cost pools to derive the total indirect cost for that particular object.

Finally, direct costs must be combined with the allocated indirect costs from the Activity-Based Costing matrix to ascertain the total cost for each cost object.

By comparing the costs and marginal utilities of the components in the two production pathways, we can determine the most efficient pathway to achieve the desired level of user satisfaction while minimizing resource consumption. This analysis can help organizations optimize their service offerings, reduce waste, and ultimately improve their bottom line.

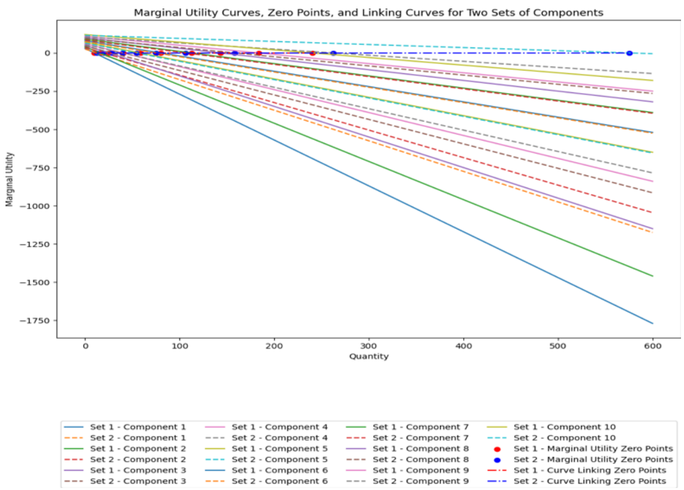

Figure 5: Marginal utility curves and links for two sets of resources components used in a network production process.

From these elements we calculate (Figure 5):

(1) the marginal utility of each component. This allows us to demonstrate that - for an identical activity - one set of components requires significantly more resources than another, the marginal utilities for components 5 and 10 of the second set being above 250 resource units,

(2) the distance between marginal utilities of each set (or couple) of components with a given volume. This approach makes it possible to carry out an arbitration between components, thus, to test the subsidiarity of the components, which is called homogeneity in economics. Having done this, we can extrapolate the optimal component basket to render the desired service, thus highlighting both the sobriety wells per component and components group.

We note that in our example, the marginal utility holding towards 0 is fast reached, which indicates an important propensity of the networks processes to waste resources if not optimized.

6. Recommendation as conclusion

Due to technical layers and different expectations and operations in comparable instruments, streamlining industrial methods for resource consumption efficiency in the social media industry is complex. They combine institutional and family communication, and commercial and personal interests on the same platforms. This operational confusion results in polymorphous expectations, which serve as a vector for resources over usage. In fact, the more numerous and diverse the expectations, the more the associated processes are plagued by the same flaws, as demonstrated above.

Consequently, there are multiple satisfaction curves with increasing expectations. The modeller's response can only be matrix-based in this instance. Also, in such a framework, work on harmonising processes and expectations appears necessary, mainly because we can observe that the social media platforms with the most dedicated channels are the ones that have discovered their economic model and are the most environmentally responsible (Dunia, Rambe & Fauzi, 2018, March).

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