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A framework for evaluating the business deployability of digital footprint based models for consumer credit

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ABSTRACT

Every time we interact with online digital services, we generate large amounts of data that reveal our shopping habits, social interactions, and much more. We refer to these data collectively as the user-generated digital footprint (UGDF). Today, there is growing interest in using UGDF data as an alternative to conventional financial data in building consumer credit models—UGDF models. Unfortunately, we also observe a hype where the models' business deployability is reduced to simplistic technical metrics, namely, the model's prediction accuracy. This study argues that this is a misleading oversimplification of the financial sector's business realities as it ignores vital dimensions such as the model's economic viability. Therefore, we develop a framework for evaluating the business deployability of UGDF models for consumer credit using a design science research methodology. The framework is composed of seven criteria: Data accessibility, data coverage, data timeliness, data authenticity, cost of deployment, interpretability, and compliance.

1. Introduction

Consumer credit, such as credit cards and personal loans, have always been data-driven. In fact, their delivery relies heavily on data to assess consumers' credit worthiness and build models that can predict their payment default probability.

Over the past decade, data used in building models for consumer credit has undergone an unprecedented revolution, driven by three main pillars. First, modern societies have become greatly digital, and have moved their most fundamental workloads online. Today, we pay our bills digitally, meet new friends on digital social platforms, share our most intimate thoughts with a search engine, and track our heart rate with a smartwatch (Lehdonvirta, 2012). Therefore, each one inadvertently generates huge amounts of data through the simple routines of everyday life. We refer to such data as user-generated digital footprint (UGDF) and formally define it as: "The trail of data that individuals create while using digital services". UGDF data are considered active when users intentionally share it with their online service providers (e.g., picture, video, tweet, and purchase amount) and passive when they unintentionally share it as an unavoidable artifact of their digital transaction (e.g., IP address and credit card issuer). Across all categories, the cumulative power of millions of UGDF data has given rise to unique datasets, both quantitatively and qualitatively (Weaver & Gahegan, 2007). The second enabler of the data revolution is the advances within machine learning, which allow us to process large high-dimensional UGDF datasets made up of various data types (e.g., digits, natural language, signals, and images) (Qiu et al., 2016). The third and final enabler is the advances in the computational infrastructure that allow us to train and deploy computation-intensive machine learning algorithms both efficiently and cost-effectively (Jordan & Mitchell, 2015; Pop, 2016).

The business opportunities created by these three advances in data and the UGDF data it generates, were swiftly leveraged by various industries, such as digital marketing and cybersecurity (Gavriluţ et al., 2009; Verhoef et al., 2016). However, since UGDF data fall outside the data categories conventionally used in consumer credit, many initially deemed it irrelevant. This could not have been further from the truth. In fact, it was only a matter of time before technical practitioners started experimenting with UGDF data as an alternative to conventional data in building models for consumer credit, such as credit scoring. Early UGDF models that were successfully deployed made use of telecommunication usage patterns data, utility consumption data, and social media posts

Abbreviations: UGDF, User-Generated Digital Footprint; P2P, Peer-2-Peer; FinTech, Financial Technology; DSRM, Design Science Research Methodology; GDRP, General Data Protection Regulation.

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data to predict consumers' default on payments (Zhang & Meng, 2010). The significance of such early technical results cannot be overstated. First, they bootstrapped new viable credit business models, such as Peer-2-Peer (P2P) lending (Ma et al., 2018). Second, they successfully extended the offering of credit to millions of unbanked consumers who would otherwise be considered thinly scored or invisible. "Jagtiani and Lemieux (2018) find that most of the "invisible prime" borrowers, who have been rated poorly by the traditional credit scoring process, have a very low default probability that is similar to the default probability of (traditional) super-prime borrowers." (Croux et al., 2020, p. 22). Finally, they challenged the long-standing monopoly of traditional financial institutions over the delivery of consumer credit and gave rise to new players, which would come to be collectively known as the Financial Technology (FinTech) industry (Li et al., 2017).

Today, the financial sector has embraced the power of UGDF models for consumer credit, so much so that its value has become hyped (Maurer, 2014). A case in point is the exponential surge in the number of academic publications and investment-white papers that advertise their models as viable business solutions based only on the prediction accuracy of their models (Cm, 2018; Hurley & Adebayo, 2016). In this study, we argue that this is a misleading oversimplification of the business realities of the financial sector. The prediction accuracy of a UGDF model is a necessary, but not a sufficient criterion in evaluating its business deployability within a real-world business setting. Within this context, we define business deployability as the ability to deliver a UGDF model at a scale, cost, and accuracy that meets the business profitability requirements of a real-world setting. In fact, we argue that other technical, economic, and compliance criteria should be met before we consider a UGDF model viable for business deployment.

The primary research question of this paper is as follows: What criteria should we use to evaluate the business deployability of UGDF models for consumer credit? To answer this research question, we followed a design science research methodology, where we performed a systematic review of the literature, as well conducted interviews with both industry practitioners and academic experts.

The main result of this study is a framework for evaluating the business deployability of UGDF models for consumer credit, composed of the following seven criteria: Data accessibility, data coverage, data timeliness, data authenticity, cost of deployment, interpretability, and compliance.

As part of this study, we also performed a semantic categorization of 184 UGDF variables that were collected throughout this study, such as telecommunication usage pattern data (e.g., number of calls and their frequency and reciprocity), social media content data (e.g., tweets, pictures, and videos), and silent metadata (e.g., time spent on applications, typos, and device brand). We also showcased how to use the proposed framework to evaluate the business deployability of UGDF models. This allowed us to draw insights into the potential impact of UGDF models adoption on the future evolution of consumer credit market.

The remainder of this paper is organized as follows. In Section 2, we provide an overview of the relevant background concepts and prior literature. Section 3 we describe the methodology used. In Section 4, we present the framework and then analyze its evaluation criteria. In Section 5, we showcase how the framework can be used. Finally, we conclude the paper in Section 6 with a discussion and reflection on the study's results.

2. Background and preliminaries

2.1. The evolution of consumer credit

2.1.1. Consumer credit

Columbia Encyclopedia defines credit as "granting of goods, services, or money in return for a promise of future payment" (Kamleitner & Kirchler, 2007, p.2). Consumer credit is a type of credit defined as "credit obtained [by private households] to finance any purchase other than property (Guardia, 2002, p.2)" (Kamleitner & Kirchler, 2007, p.2). Therefore, it includes all types of installment credit (e.g., credit cards) and non-installment credit and excludes mortgages. Consumer credit also includes home equity loans that are used for purposes other than real estate but can nonetheless be secured by real estate (Kamleitner & Kirchler, 2007).

2.1.2. Traditional models in consumer credit

Consumer credit have been traditionally provided by traditional financial institutions (e.g. commercial banks) that have relied on a predefined set of conventional data to build their models. Most notably, their models often used data that fit within the once popular 5C model (Rosenberg & Gleit, 1994; Thomas et al., 2017):

Capacity. This category is represented by data that capture applicants' past financial performance, such as their payment history, length of credit history, outstanding debt, applications for new credit, and debt-to-credit ratio (Rosenberg & Gleit, 1994; Vidya, 2018).

Capital. This category is represented by data that capture applicants' number of employment years, financial backups, and any property/ mortgage papers (Rosenberg & Gleit, 1994; Vidya, 2018).

Collateral. This category is represented by data that capture applicants' assets (e.g., property),) or a third party's guarantee that can be liquidated in case of default on payment (Rosenberg & Gleit, 1994; Vidya, 2018).

Conditions. This category is represented by data that capture applicants' credit characteristics such as the purpose and amount of credit as well as the state of the economy (Rosenberg & Gleit, 1994; Vidya, 2018).

Character. This category is represented by data that capture applicants' professional experience, references from third parties, and educational level (Vidya, 2018).

2.1.3. UGDF models in consumer credit

The last decade has witnessed a sharp interest of new players in competing with traditional financial institutions in the delivery of consumer credit. They relied mainly on using UGDF data as an alternative to conventional data in building their models. For instance, the Swedish payment provider Klarna trains its models on novel UGDF variables such as consumers device type, operating system version, screen resolution, browser settings, and time of performing the transactions. This allows it to accurately predict the most optimal credit payment modalities to offer to each of its 60 million users (Berg et al., 2019). Furthermore, LenddoEFL uses telecommunication UGDF variables to offer credit to emerging markets where many consumers are considered thinly scored. Their variables include the battery lifetime of the device, its connected broadband network, its browser settings, and the length and semantics of the credit application submitted by each user (Berg et al., 2019). Similarly, Cignifi also targets emerging markets using telecommunication UGDF variables, such as the number of calls users make/receive and their duration, frequency, and reciprocity (Berg et al., 2019). Additionally, KrediTech augments its models with behavioral UGDF variables, such as the time a user takes to fill out their application form and whether its content is typed or copy-pasted (Berg et al., 2019).

Overall, we observe that UGDF models change the landscape of consumer credit, create completely new business models, and extend their reach to new customers. A case in point is that consumer credit providers that use UGDF models whose variables are more universally applicable can serve customers with little to no past documented financial transactions. Such financial inclusion has far-reaching societal and economic implications. On the one hand, it financially empowers vulnerable individuals and gives them the tools to lift themselves out of poverty (Dostov et al., 2019). On the other hand, it expands the portfolios of financial institutions and increases their revenue (Mostak & Sushanta, 2019).

These new players that challenged the long-standing monopoly of

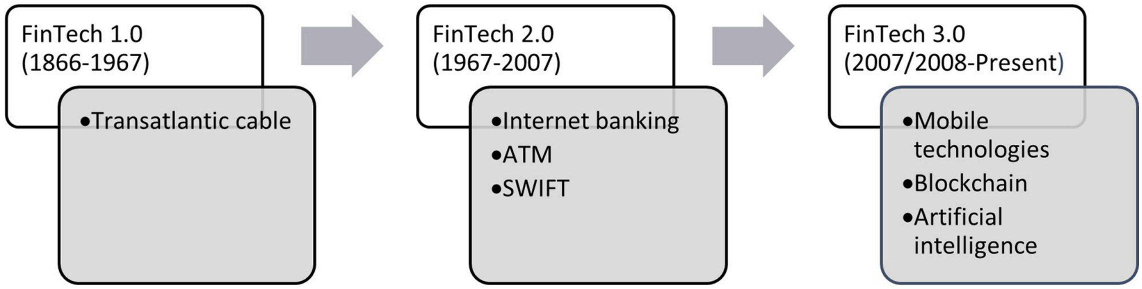

Fig. 1. Evolution of FinTech: How the use of technologies in the delivery of financial services has evolved through the years.

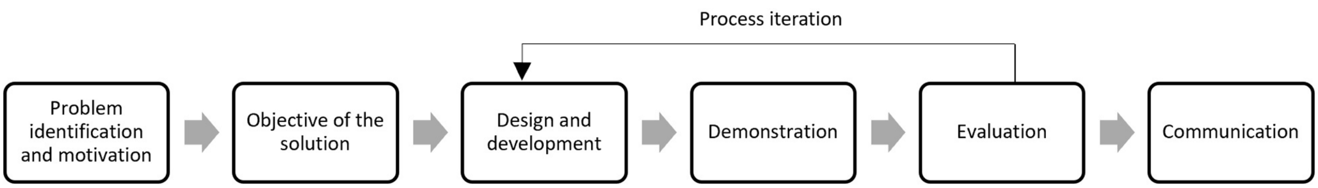

Fig. 2. The six-step DSRM process proposed by Peffers et al. (2007).

traditional financial institutions over the delivery of financial services, including consumer credit, would come to be collectively known as the FinTech industry.

2.2. Evolution of FinTech

FinTech can be formally defined as "technology-enabled innovation in financial services that could result in new business models, applications, processes, or products with an associated material effect on the provision of financial services" (Financial Stability Board, 2019, p.1). While the term FinTech is quite recent, the use of technologies in the delivery of financial services can be traced back to 1867. FinTech has evolved through three main historical stages, as discussed by Leong & Sung (2018) and shown in Fig. 1. First, FinTech 1.0 was ushered in by the birth of the business computerization era in 1866, as well as the invention of the transatlantic cable. These inventions facilitated global telecommunications and reduced the communication time between Europe and North America from 10 days to 17 h. For the first time in history, we had financial services that were truly global, namely within payment, trade, and investment (Nicoletti, 2017). Subsequently, FinTech 2.0 was triggered in 1967 by the invention of the Internet, resulting in the development and proliferation of Internet banking services, the society for worldwide interbank financial telecommunications protocol (SWIFT), and automated telling machines (ATMs). The rest of the century marked a golden age for financial institutions, where they were at the forefront of implementing emerging technologies and innovations.

However, this came to an abrupt halt in 2007/2008, when the financial crisis erupted in the United States and then spread swiftly across the globe. For the next decade, traditional financial institutions would be left to grapple with the repercussions of the crisis: Technology innovation projects were deprioritized, and resources were mostly allocated for compliance and crisis management.

Meanwhile, the technology industry was moving ahead and making fundamental breakthroughs across several disciplines, including artificial intelligence, blockchain technologies, and mobile computing (Bataev, 2018). While these innovations were quickly deployed by several industries such as retail, marketing, and manufacturing, the financial sector lagged behind. This created an acute gap between customer expectations and the antiquated user experience offered by most consumer credit providers. Customers could no longer understand why their international bank transfers were slow and expensive, why they could not pay using their smartphones, and why no tailored financial advice was provided to them. In turn, this created a market opportunity that was soon seized by new entrants, both start-ups and big tech companies (e.g., telecommunication companies and GAFAA: Google, Apple, Facebook, Amazon, and Alibaba and), who listened to customers and then used technology to deliver services that met their expectations. Their innovative solutions and business models unleashed the third wave of financial technologies, Fintech 3.0. Notable early successes of the latter are the proliferation of user-friendly mobile/Internet of things payment solutions, the extension of financial services towards the unbanked and thinly scored using alternative data (e.g., social media data), crowdfunding platforms, and the deployment of real-world scalable P2P digital cryptocurrency networks and trade platforms.

Throughout this article, the term FinTech is used to refer to the following FinTech 3.0 companies that provide consumer credit: 1) FinTech start-ups and 2) FinTech incumbent challengers that are made up of established organizations that want to deliver consumer credit to their individual customers as an extension to their core business, namely BigTech such as Amazon and telecommunication companies (telcos) such as Vodafone.

2.3. Evaluation frameworks

To the best of our knowledge, this study is the first to formally pause the business deployability question of UGDF models for consumer credit and then provide a systematic answer. Other studies have focused on presenting different frameworks for evaluating the models' input data quality. Taleb et at. (2021) focuses on the problem of big data losing its quality over its lifecycle, and how the current approaches to verifying it are both lengthy and costly. To resolve this, they develop a framework based on "Big Data Quality Profiles", where they propose the in-between pre-processing to be both preceded and followed by better optimized data quality estimations (Taleb et at., 2021). In Warwick et al., (2015), the authors review the available frameworks for evaluating the quality of research data, and then propose a new framework that draws from different disciplines, and which can assist researchers in deciding whether to use a given dataset or not.

3. Methodology

3.1. Overview of the design science research

The design science research has become an important tool for conducting research in the field of information systems for various reasons that make it suitable for this study, namely its focus on building original artifacts and using them to impact a given practice or ecosystem (Hevner, 2007; Simon, 1996).

There currently exists different practical approaches to using the design science research (Hevner, 2007; Peffers et al., 2007). While each has its own merits, we have chosen to adopt the six-step Design Science Research Methodology (DSRM) as outlined by Peffers et al. (2007) for four main reasons: First, it outlines a straightforward process that has clear and distinct steps that make it easy for the reader to understand. Second, it inherently lends itself to multidisciplinary research as it is itself the result of the contributions of several researchers in information systems and other disciplines. Third, it has already been successfully used in numerous other studies and for building frameworks that are functionally comparable to the one we want to propose in this study (Geerts, 2011; Labazova, 2019; Poels, 2013). Fourth, it keeps the focus throughout its six steps, on producing artifacts that have a practical impact, which is a goal that corresponds to the objectives of this study. The six steps proposed by Peffers et al. (2007) as shown in Fig. 2 are as follows: 1) Problem identification and motivation, 2) Definition of the objectives for a solution, 3) Design and development, 4) Demonstration, 5) Evaluation and 6) Communication.

3.2. Implementing the DSRM

To meet the rigorous design science research principles, this study follows the comprehensive six-step DSRM process described by Peffers et al. (2007).

Step 1 – Problem identification and motivation. Using UGDF data as an alternative to conventional data in building models has been positively embraced by consumer credit providers. Unfortunately, we find that the business deployability of UGDF models is often reduced to simplistic technical metrics, namely, the prediction accuracy of the model (Cm, 2018; Hurley & Adebayo, 2016). We argue that this is a misleading oversimplification because it completely disregards many important business realities of the financial sector, such as compliance, economic viability, and scalability.

Step 2 – Objective of the solution. To develop a comprehensive evaluation framework that can be used to assess the business deployability of UGDF models within realistic business settings.

Step 3 – Iteration I: Design and development.

Step 3.1 - Data collection. We conducted a literature review of previously published studies. Our research mainly spanned three academic databases, 'Google Scholar,' 'Web of Science,' and 'Scopus,' where we used the Boolean operators 'And' or 'Or' inclusively and exclusively (e.g., ('digital footprint' Or 'alternative data' Or 'big data') And ('FinTech' Or 'financial technology') And ('consumer credit' Or 'credit scoring),' and applied them to the title, abstract, and keywords. We also performed a backward search to identify relevant manuscripts. Overall, we compiled a final list of 35 journal articles, conference papers, books, and book chapters. Since our topic of study is relatively recent and practice-oriented, it was also important to include white papers and industry reports.

Step 3.2 – Data analysis.

Open coding. While going through the literature, we highlighted all the sections that were relevant to the evaluation of deployability and added a descriptive name or a "code" to it as shown in Table A1 in the Appendix. Most codes are related to the model's UGDF data rather than to its algorithm. Therefore, acquiring a deep understanding of the semantics of UGDF data became a per-requisite for properly identifying the framework's evaluation criteria. We decided to also use the literature review step to compile a list of the UGDF variables that are relevant to consumer credit.

Axial coding. We used axial coding to aggregate the codes. By the end of this step, we had identified four initial evaluation criteria: Interpretability, data coverage, data authenticity, and data timeliness.

Step 3.3 – Data visualization. We transcribed the evaluation criteria into a decision framework.

Step 4 – Iteration I: Demonstration. The study was presented during an event held at the Norwegian business hub, NextDigital.

Step 5 – Iteration I: Evaluation. This first set of interviews was conducted with eight interviewees who were each selected based on their professional experience and its relevance to this study as shown in Table A2 in the Appendix. At a high level, the interviewees were experts in the following disciplines: FinTech, banking, information systems, finance, cybersecurity, computer science, data science, machine learning, and artificial intelligence. They also each had at least five years of professional experience within their respective area of expertise. As such, the interviewees had a complementary set of expertise as well as deep knowledge within their respective fields. The interviews were semi-structured, lasted an average of 45 min, and were held either face-to-face or digitally. The interview guide was organized into four sections:

Section 1. The interviewees were introduced to the context of the research, its motivation, problem statement, and its expected outcomes.

Section 2. The interviewees shared and discussed their experience using UGDF data in building models for consumer credit. We noted that five of them have had direct hands-on experience with it. Examples of questions that were asked are "Which UGDF data do you consider relevant in building models for consumer credit? And why?".

Section 3. We presented the UGDF variables compiled during the literature review to the interviewees so as to discuss their semantics and usage. The list of UGDF variables was also extended based on the interviewees feedback about what other variables were missing and which they found useful in their experience. An example of the questions asked is "Which UGDF variables do you think are most often used in building models for consumer credit?".

Section 4. We discussed the concept of business deployability of UGDF models and what it means to the interviewees. Examples of the questions asked are: "What do you think of this statement: "A UGDF model's prediction accuracy is a necessary, but not a sufficient factor in evaluating its business deployability in real-life business setting?" "Are there any criteria that you think about before deciding on the business deployability of a UGDF model?".

Section 5. We introduced the proposed framework and discussed how it could be augmented with other relevant evaluation criteria. An example of the questions asked is "Do you think there are other evaluation criteria which we should consider? If so, which ones?". At a high level, the interviewees were very open and discussed at length all of the questionnaire's questions. However, three interviewees who were industry practitioners were reluctant towards going into the details of the UGDF variables they have deployed in their real-life commercial UGDF models. This is due to their need to maintain the confidentiality of their UGDF models and any non-disclosure agreements they might have signed with their organizations. The interviews were transcribed using NVivo. Overall, we gathered 31 pages of interview transcriptions. For data analysis, we followed the same process previously outlined in the "Design and development" step. By the end of this step, we had identified three new criteria: Cost of deployment, compliance, and data accessibility.

This effectively marked the end of the first DRSM iteration. We then continued the study by starting the second iteration of the DRSM "Design and development", "Demonstration" and "Evaluation" steps.

Step 3 – Iteration II: Design and development. The results from the first set of interviews were used to refine the proposed framework, by augmenting it with the three newly identified criteria.

Step 4 – Iteration II: Demonstration. The developed deployability

Table 1
A Framework for Evaluating the Business Deployability of UGDF Models for Consumer Credit.

Criteria	Explanation	Potential effects if the criteria are not met
Data accessibility	UGDF data can be acquired through three main channels: 1) Fully owned. 2) Purchased from third parties. 3) Collected from public sources. Each channel presents different levels of risk and control.	1) Fully owned UGDF data presents no accessibility risks. 2) Third party data providers might decide to stop selling UGDF data. 3) Public UGDF data sources might become private or only available for a fee.
Data coverage	The UGDF data is available at a scale that can ensure the sustainable profitability of the consumer credit providers.	When the coverage of a UGDF data is limited, organizations deploying models based on it may not be able to achieve the needed scale to become profitable.
Data timeliness	The UGDF data new value can be updated swiftly and efficiently, upon the occurrence of unexpected life events that alter the user's risk metrics computed during their initial service registration.	The slower the change notification process of UGDF data values, the longer it takes to implement actions that can mitigate the potential risks.
Data authenticity	The UGDF data is difficult or impossible to manipulate.	When UGDF data can be easily altered, it might get manipulated in order to influence the model's results.
Cost of deployment	Cost of data collection + cost of algorithm acquisition + cost of computing.	Using a UGDF model whose cost of deployment exceeds its revenue is not economically viable.
Interpretability	Humans can explain the rationale for the results of the UGDF model and articulate how its UGDF input data relates to its output results.	Non-interpretable UGDF models breach the "right of explanation" regulation that is mandated by several jurisdictions.
Compliance	The UGDF model needs to comply with the financial sector's laws and regulations.	A UGDF model that breaches the financial industry's laws and regulations can cause the organization deploying it to become liable to legal action and fines.

framework was demonstrated during different relevant events held at the Norwegian University of Science and Technology.

Step 5 – Iteration II: Evaluation. We conducted a second round of five semi-structured interviews, to evaluate the refined framework which included seven evaluation criteria. The interviewees were both industry practitioners and academic experts who also participated in the first interviews round. The interviews were held digitally and lasted twenty minutes on average. The final form of the framework was approved by the interviewees.

Step 6 – Communication. The final framework was shared and presented to an incumbent Norwegian bank.

4. Deployability evaluation framework

After completing the DSRM process, we identified seven evaluation criteria to assess the business deployability of UGDF models for consumer credit as shown in Table 1: Data accessibility, data coverage, data timeliness, data authenticity, cost of deployment, interpretability, and compliance.

4.1. Evaluation criteria

4.1.1. Data accessibility

Consumer credit providers can acquire UGDF data through three main channels, each with different levels of risk and control. First, they can own UGDF data and have full access to it. Second, they can buy it from third parties, who can later decide to stop selling it for strategic or compliance reasons. Third, they can collect data from public sources, which can then become private or only available for a fee. Hence, evaluating the level of accessibility of UGDF data is important for assessing the business deployability of their associated UGDF models. For instance, while it has been empirically demonstrated that a user's telecommunication behavior (e.g., how often a user communicates with their contact list and communication reciprocity, length, and frequency) can accurately predict their default on payment (Ma et al., 2018; San Pedro et al., 2015), this is irrelevant for consumer credit providers who cannot buy the variable values from the telecommunication company who owns them. Other UGDF variables, such as the content of private messages exchanged between users on social media, can never be shared with commercial third parties for privacy protection and compliance reasons. In the context of this work, accessibility refers to the three possible UGDF data acquisition channels and their associated risk and control levels:1) Fully owned, 2) Purchased from third parties, and 3) Collected from public sources.

4.1.2. Data coverage

Empirical research shows that the profitability of financial institutions is influenced by the rules of economies of scale, where organizations exhibit increasing returns to scale when an increase in firm size results in a decrease in the per-unit cost of production (Bernstein, 1996; Campbell, 2018). Furthermore, numerous studies that have analyzed a large sample of banks of varying sizes have concluded that the largest banks exhibit the largest returns to scale, with banks with total assets in excess of $100 billion experiencing only a 7 percent increase in cost in response to a 10 percent increase in output (Campbell, 2018; Hughes & Mester, 2013). In other words, start-ups are more sensitive to the scale of their market and capital, and they need to bootstrap a substantial critical mass of users to become economically profitable.

Overall, consumer credit providers need to ensure that their UGDF models are built using UGDF data that include values for most of their target users to scale their businesses and maintain them at profitable levels. However, it is up to the discretion of each financial institution to determine its specific break-even target and then map it back to the coverage value that its UGDF data needs to meet.

Last but not the least, the extent of coverage of UGDF data can have significant societal implications: If consumer credit providers deploy models built using UGDF variables that do not include a given segment of society, the latter will be excluded from benefiting from its corresponding consumer credit. Failing to remedy this can be alarming as access to consumer credit is a prerequisite for empowering individuals across all modern societies, and its absence robs them from their right to equality of opportunity and hopes for a better future (Guo et al., 2016).

4.1.3. Data timeliness

Every-one is prone to unexpected life events that can impact their financial situation, such as job loss, change of employer, disease, relocation, or divorce. The occurrence of such events can impact consumers' risk metrics, which are computed during their initial service registration. Therefore, a user's profile should be regularly monitored and swiftly updated whenever a relevant event occurs. Furthermore, the slower the change-notification process, the longer it takes to implement the actions needed to mitigate potential associated risks (Fei et al., 2010; Guo et al., 2016). For instance, consumer credit providers with direct access to consumers' mobility patterns can detect any changes in their home location or relationship status much earlier than any public record would. They can also efficiently detect changes in the employment status of a user when their employer terminates their business subscription. Similarly, semantic analysis of browsing history data can efficiently detect whether a person is anticipating any major life-changing events, such as divorce or job change.

We further note that timeliness is a particularly important business deployability criterion for consumer credit providers that are experimenting with new UGDF business models, such as P2P lending, as they often struggle with higher risks and lower initial revenue margins. In fact, an empirical study on Chinese P2P lending platforms demonstrated that their number is expected to drop from 2,000 + to a couple hundred in the next few years due to the slow response to unexpected credit risks (Oster & Stephen, 2016).

4.1.4. Data authenticity

As its definition indicates, the UGDF is data generated by individuals. Therefore, it is important to account for the fact that some UGDF variables might be manipulated to influence the model's decision in one way or another. For instance, we have all heard of people who carefully curate their social media content to project a certain image of wealth or influence. While such manipulation might appear harmless, it can be very costly for a P2P lending platform to base its credit scores on such non-authentic UGDF data values.

To avoid such manipulations, we have noted an increasing interest in authentic metadata variables that are inherently impossible to manipulate, such as the behavioral biometrics of users (their pattern of typing) (Ma et al., 2018). We also consider other UGDF variables as authentic, when their cost of manipulation exceeds their associated potential financial gains. To illustrate the latter point, we consider a short-term credit provider that uses the user's phone brand and telecommunication subscription type in predicting their payment default; for example, while a user can acquire an iPhone in theory and pay for a premium subscription, such manipulation would not be economically viable if the credit amount is less than the phone and subscription costs.

4.1.5. Cost of deployment

Financial service providers are mainly driven by profit. In this section, we focus on evaluating the direct cost of deploying UGDF models in a real-world business setting. As highlighted by the interviewees who have hands-on experience with UGDF models, the direct cost can be defined as the sum of the following three variables:

C1- Cost of data collection. As discussed in Section 4.1.1, UGDF data can be 1) fully owned, 2) purchased from third parties, or 3) collected from public sources. Each channel has a different cost associated with the data-collection process. Furthermore, our cost computation also differentiates between variables that need to be acquired once (e.g., date of birth) and those that need to be regularly updated (e.g., employer). Therefore, we compute C1 as follows:

$$C1 = \sum_{i=1}^{n=size\ of\ the\ UGDF\ dataset} (cost\ of\ collecting\ one\ UGDF\ data_i + (cost\ of\ one\ UGDF\ data\ update_i \times update\ frequency\ of\ one\ UGDF\ data_i))$$

C2– Cost of algorithm acquisition. While some machine learning algorithms can be distributed under open-source licenses, many are proprietary to developers who prefer to keep their algorithms' hyper-parameters private, "because of their commercial value and the confidentiality of the proprietary algorithms that the learner uses to learn them." (Wang & Gong, 2018, p. 1) (e.g., Amazon Machine Learning).

C3– Cost of computing. This refers to the cost of the computing infrastructure required for training and running the machine learning algorithms.

Thus, the overall cost of deployment (C) can be computed as follows:

$$Cost\ of\ deployment\ (C) = cost\ of\ data\ collection\ (C1) + cost\ of\ algorithm\ acquisition\ (C2) + cost\ of\ computing\ (C3)$$

Finally, we note that UGDF data constitute a dynamic marketplace, where the cost of different variables can fluctuate depending on the market rules of supply and demand. Therefore, it is especially important for consumer credit providers that acquire their UGDF data from third parties to regularly update the value of their cost of deployment, as well as account for its volatility.

4.1.6. Interpretability

Recent advances in machine learning have led to the development of complex non-linear models. While such complexity has certainly increased the accuracy of the models, it has also turned them into mysterious black boxes that cannot be interpreted; we accept and use their results without any understanding of the rationale behind them. This is in contrast to older linear models, where one could intuitively explain how the input data correlate with the output, as well as provide a humanly understandable explanation for their results. Neural networks are a notorious example of non-interpretable machine learning algorithms (Zhang & Zhu, 2018).

Furthermore, model interpretability depends not only on the underlying algorithm, but also on the type and semantics of the data variables used (Dubina et al., 2019). For instance, while we can intuitively understand the relationship between income and credit score, it is not clear why "the time a user spends on applications" should impact their credit score, even if we can experimentally prove that it accurately does.

Unfortunately, this lack of interpretability can hinder the business deployability of UGDF models. This is especially true for traditional financial institutions, which are mandated by law to provide a rational explanation for their business decisions, including those that are the result of machine-learning algorithms. For instance, the Equal Credit Opportunity Act of the United States of America states that every individual has the right to contest any decision made about their credit score, and that financial institutions, in turn, must provide an explanation that consists of a quantitative numerical value as well as a logical explanation of its interpretation (The United States Department of Justice, 1974). Within the European Union, such a "right of explanation" is not strongly mandated by the General Data Protection Regulation (GDPR) as it was written as part of Section Recital 71, which only provides guidance rules and not legally binding laws. Therefore, the GDPR is likely to only grant individuals "an explanation of automated decision-making addressing system functionality, not the rationale and circumstances of specific decisions." (Wachter, 2017, p.83).

Regardless of how strongly the right of explanation is mandated by different laws, the intention behind it is the same: To prevent unintentional technical failures, such as overfitted models and non-representative datasets, as well as prohibit "creditors from discriminating against credit applicants on the basis of race, color, religion, national origin, sex, marital status, age, because an applicant receives income from a public assistance program, or because an applicant has in

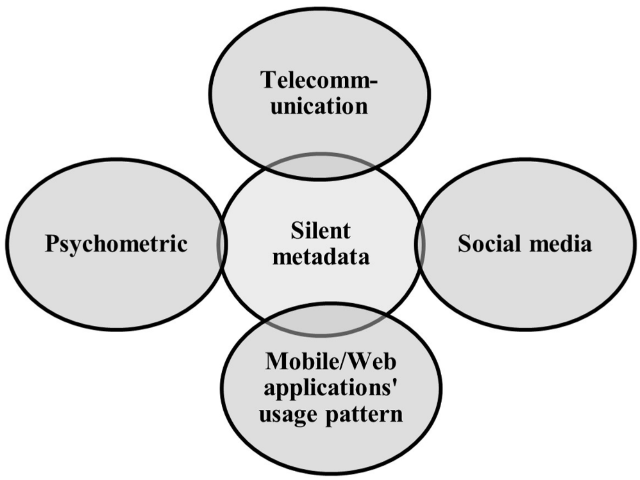

Fig. 3. The five semantic categories of the UGDF data in consumer credit collected throughout this study.

good faith exercised any right under the Consumer Credit Protection Act." (The United States Department of Justice, 1974).

4.1.7. Compliance

Financial services are among the most heavily regulated industries (Demirguc-Kunt et al., 2003). Therefore, it is critical to ensure that the UGDF models do not breach relevant laws or regulations. As it is outside the scope of this study to present a complete overview of all such regulations, we focus in this section on forgetfulness and privacy.

In fact, the U.S. Federal Reserve System has a mandate of forgetfulness that regulates the data look-back time and limits micro-loan providers and credit scoring companies to using data no older than three months and 10 years, respectively (Dubina et al., 2019). Furthermore, there exist several data protection regulations, such as the European GDPR, which regulate how personal data are to be handled and impose heavy fines for its breach. For instance, it is illegal under the GDPR to collect users' data without their consent (European Parliament and Council of the European Union, 2016).

However, assessing the compliance of the UGDF models is not always straightforward. For instance, consumer credit providers who acquire their UGDF datasets from third parties cannot always guarantee the data's provenance and compliance level.

4.2. Semantic categories of UGDF

Understanding the semantics of UGDF data is a prerequisite for properly using the proposed framework and evaluating the deployability of the corresponding UGDF models. In this study, we compiled a list of 185 UGDF variables, and we semantically categorized them into five groups, as illustrated in Fig. 3.

4.2.1. Social Media data

The proliferation of digital social media platforms has reshaped how human beings experience social connectivity and sharing. Today, it is common for people to connect with friends online, video-log (Vlog) their everyday lives, and then broadcast it publicly and share their commentary on various personal and societal events. In fact, the wealth of insight that social media generates about a person's behavior is unique, both quantitatively and qualitatively. To put things into perspective, Meta alone generates four new petabytes of data per day and takes up 22 % of the Internet time Americans spend on mobile devices (Facebook's Top Open Data Problems, 2014). Social media data can reveal important attributes of a user's economic status, spending habits, political views, personality traits, tastes, and risk appetite. Unsurprisingly, many industries, such as marketing, online retail, public relations management, and news broadcasting, have used UGDF data to better understand their customers' needs (Agarwal et al., 2020; Erevelles et al., 2016; Sivarajah et al., 2017; Vanhala et al., 2020).

In consumer credit, interest in using social media UGDF data has increased sharply over the last decade (Chorzempa et al., 2018; Devereaux & Peng, 2018; Guo et al., 2016; Meadows et al., 2004; Niu et al., 2019).

Social media data UGDF can be classified into 5 subcategories:

Social capital. These variables are related to the depth and breadth of a user's social network, such as their contact entropy, size, and growth rate. This category also includes other behavioral variables, such as the number of interactions the user has with their network, the time of these interactions, their reciprocity, and variation. The underlying intuition behind using these variables is that positive social media data signal stability and a healthy support system.

Transitive-Social-Similarity. Within the financial sector, it is assumed that users tend to associate with people who exhibit similar financial behavior (McPherson et al., 2001; Niu et al., 2019). Such transitive assessments can be easily captured through the social media UGDF, where a user's social graph can be constructed by tracing their online contacts.

Content shared. This category includes all content shared by users, such as their pictures, likes, shares, subscriptions, and comments. These variables are analyzed across several metrics, such as expressiveness, emotional polarity, volatility of expressed opinions, and conformity. Other relevant quantitative variables are the amount of shared content and their type, frequency, and variance (Agarwal et al., 2020).

Self-reported data. These are mostly simple personal data variables such as username, age, location, occupation, and phone number.

Metadata. These variables include all the data that a user inadvertently generates as an unavoidable artifact of using digital social media platforms, such as the time they spend reading or watching a specific type of content, hesitance before sharing content (e.g., writing and deleting a status update), and typos.

In this study, we collected 88 social media UGDF variables (see Table B1 in the Appendix).

4.2.2. Telecommunication data

Globally, telecommunication penetration rates are high in both developed and developing countries. Telecommunication companies harness immense amounts of UGDF data from their users, with AT&T Inc. storing 300 million records per day for long-distance calls alone. These companies have to deal with financially fraudulent customers who use subscriptions without paying for them or who buy preferential deals that they are not entitled to (residential vs commercial) (Cortes et al., 2003; Farvaresh & Sepehri, 2011; Paredes, 2005). To combat this, some telecommunication companies use UGDF telecommunication data to detect, predict, and prevent fraud. This has proven to be highly efficient because a user's mobile usage behavior reveals much about their economic status, social status, and personality traits (Farvaresh & Sepehri, 2011).

Today, several FinTech companies have also started using telecommunication UGDF data to extend consumer credit to users with little or no financial history. In fact, a mobile subscription is in many ways similar to a bank account, with typical deposit and payment transactions. Therefore, it is unsurprising that telecommunication datasets have achieved great success in consumer credit (Berg et al., 2019).

Telecommunication UGDF can be classified into 4 sub-categories:

Billing. This primarily includes users' history of payment transactions, such as their subscription type, payment regularity, default history, deviation from subscription terms, and any changes in their consumption behavior. If the subscription is prepaid, then we can also include other variables, such as how long a user waits before topping up their account, the amount of the top-ups, and their variability (Ma et al., 2018).

Social capital. This includes all variables related to the user's social interactions, such as the entropy of their contacts, the number of their voice calls, their reciprocity, and variability over time.

Transitive-Social-Similarity. A complete social graph of users can be constructed by tracing their list of contacts.

Mobility patterns. Location and mobility can model the socioeconomic status, shopping habits, and employment status of users. For telecommunication companies, the location of a user can be inferred from their position relative to the service tower to which they are connected. Examples of such relevant UGDF variables are the number of locations where phone calls take place over a day and the variability of these locations (Ma et al., 2018).

In this study, we collected 74 telecommunication UGDF variables (see Table B1 in the Appendix).

4.2.3. Psychometric data

"Psychometrics is a field of study concerned with the theory and technique of psychological measurement… The field is concerned with the objective measurement of skills and knowledge, abilities, attitudes, personality traits, and educational achievement. Some psychometric researchers focus on the construction and validation of assessment instruments such as questionnaires, tests, raters' judgments, psychological symptom scales, and personality tests." (Wikipedia, 2020). Psychometric theory is widely used in corporate job screenings to match an applicant's capabilities with the job's requirements and company culture. Over the years, psychometric tests have proven to be useful in better predicting the "overall job performance than a review of the candidate's job experience, level of education, employment interview results, peer ratings, and reference checks (Schmidt and Hunter, 1998)" (Arraiz et al., 2015, p.8).

In consumer credit, psychometric UGDF data have been recently proposed and used as a tool to predict users' payment default risk. Such an unconventional application of psychometrics is based on the assumption that "there is a trait or set of traits that characterize low versus high-risk loan applicants, the psychometrician's task is to identify those traits" (Arraiz et al., 2015, p.8). Most psychometric tests aim to measure three main traits: 1) Personality, 2) Intelligence, and 3) Integrity and honesty (Klinger et al., 2013). Therefore, their design and analysis are deeply anchored within well-studied psychology theories, such as the Big Five model for personality testing (Judge et al., 1999); Digit Span Recall, which is a component of the Wechsler Adult Intelligence Scale (Wechsler, 1955); Raven's Progressive Matrices test for intelligence (Spearman, 1946); and Bernardin and Cooke test for integrity assessment (Arraiz et al., 2015). Psychometric testing of consumer credit was first conceptualized at the Harvard Business School and later deployed by its Entrepreneurial Finance Lab within several communities across the developing world, namely Ethiopia, Kenya, Nigeria, and Peru (Klinger et al., 2013).

In this study, we collected 3 psychometric UGDF variables (see Table B1 in the Appendix).

4.2.4. Mobile/Web applications' Usage pattern data

Several studies have demonstrated that the usage pattern of mobile/web applications can accurately predict two important personality traits: Consciousness and agreeableness. For instance, the number of installed applications, their access frequency, and time spent on entertainment applications have been found to be strongly inversely correlated with users' conscientiousness (Ma et al., 2018). Such findings are important for consumer credit because both agreeableness and conscientiousness are highly correlated with users' credit worthiness. Several studies have shown that individuals high in conscientiousness tend to make more rational financial decisions (Bernerth et al., 2012; Tokunaga, 1993), while those high in agreeableness tend to be too altruistic and more likely to sacrifice personal resources to keep their promises to others (Bernerth et al., 2012; Judge et al., 1999; Ma et al., 2018).

In this study, we collected 33 mobile/web application usage pattern UGDF variables (see Table B1 in the Appendix).

4.2.5. Silent Metadata

We define silent metadata as the trail of bits that a user inadvertently and passively generates online as an unavoidable artifact of their online digital interactions. In fact, even when a user simply browses through a given website, its service provider can collect numerous data points, such as the type of device from which they are connected, its operating system, system update status, browser settings, how long they spend reading a given piece of content, and the speed at which they scroll through the page. Furthermore, when they actively interact with a website, as is the case for account registration, users inadvertently release further metadata such as their behavioral biometrics (e.g., pattern typing or scrolling), email hosting services, and typos.

Several studies have demonstrated that silent UGDF metadata variables can predict consumers' creditworthiness with surprisingly high accuracy. For instance, Berg et al. (2019) and Agarwal et al. (2020) experimentally demonstrated that users who own an iPhone have lower default rates. In the context of our study, we noted that the silent metadata category can intersect with all other semantic categories.

In this study, we collected 42 silent metadata UGDF variables (see Table B1 in the Appendix).

5. Putting the framework to work

In this section, we showcase how consumer credit providers, be it traditional financial institutions, FinTech incumbent challengers or Fintech start-ups, can each use the proposed framework to evaluate the business deployability of a given UGDF model, while considering the UGDF variables collected through this study.

For brevity, we refrain from presenting our entire process regarding every UGDF variable. Instead, we illustrate this by focusing on one UGDF variable. We choose the UGDF variable "The distribution of locations from which the user conducts telecommunication call" (call-dist-*per*-location) because of its relevance to both developing and developed countries, as well as its widespread use in UGDF models. The "call-dist-*per*-location" variable refers to telecommunication calls made from mobiles phones or applications.

Data Accessibility. FinTech that own the "call-dist-*per*-location" variable, can maintain full control over its availability. However, traditional financial institutions and FinTech that do not own it cannot access it without signing commercial agreements. Therefore, they need to consider the risk associated with the data owners stopping its sale.

Data Coverage. FinTech that have full access to the whole range of values of the "call-dist-*per*-location" variable can cover all of their target customers. However, traditional financial institutions and FinTech which rely on third parties for the UGDF variable acquisition, need to successfully and continuously negotiate commercial agreements that can give them access to the variable values that include their target customers.

Data Timeliness. FinTech that own "the call-dist-*per*-location" variable can have immediate access to changes in its value. However, traditional financial institutions and FinTech that do not own it can only receive such updates periodically after the variable has been properly cleaned, processed, and made available by third parties that own it through APIs or other data acquisition channels.

Data Authenticity. The "call-dist-*per*-location" is a metadata variable that is difficult to manipulate. Therefore, FinTech that own it can trust its authenticity. However, traditional financial institutions and FinTech that do not own it need to further assess whether their provider might have maliciously altered the UGDF variable.

Cost of deployment: FinTech companies that own communication data have free unlimited access to the "call-dist-*per*-location" variable. Therefore, they only need to account for the cost of algorithm acquisition (*C*2) and computing (C3). In contrast, traditional financial institutions and FinTech that do not own it need to account for the full cost of deployment: Cost of data collection (C1), cost of algorithm acquisition (*C*2), and cost of computing (C3). Furthermore, since FinTech companies are often run by tech-savvy teams that usually possess the needed machine learning expertise to build and train UGDF models, their cost of algorithm acquisition ($C2$) can be considered negligeable.

Interpretability: The pattern of users' telecommunication activities is highly correlated with their social connectivity and consciousness. Furthermore, when augmented with other location data, it can also accurately predict a person's economic status. Finally, any changes to the user's telecommunication patterns in relation to their location can signal important events, such as a job change or divorce. While such abstract interpretations of how the input variable "call-dist-*per*-location" correlates with the output of the model's results can be sufficient for FinTech, traditional financial institutions need to ensure that they are not in breach of "the right of explanation" regulations.

Compliance: Traditional financial institutions need to ensure that their UGDF model is compliant with all of the financial industry's laws and regulations, regarding both the model itself and the data used to build it. For instance, the deployability of the "call-dist-*per*-location" variable depends on its compliance with the Equal Credit Opportunity Act of the United States of America and the GDPR of the European Union. To the best of our knowledge, FinTech could use the UGDF variable without any compliance constraints at the time of conducting this study.

5.1. Discussion

When we assess how consumer credit providers (traditional financial institutions, Fintech incumbent challengers, and Fintech start-ups) can use the framework to evaluate the business deployability of UGDF models for consumer credit while considering the UGDF variables collected through this study, we find that FinTech incumbent challengers are at advantage. This is primarily because of the big amount of UGDF variables they already own, its high coverage, and fast update rate. Also, their cost of deployment tends to be low as they usually have access to advanced computational infrastructure and the technical knowhow needed to build and train their UGDF models. These insights are consistent with the FinTech incumbent challenger trend of the last five years, where Big Techs such as Amazon and telecommunication companies such as Vodafone have successfully offered consumer credit (King, 2019; Zetsche et al., 2017).

Furthermore, this assessment shows that FinTech start-ups are often at a disadvantage compared to FinTech incumbent challengers. This is primarily because they do not fully own the majority of the UGDF variables, they need high-coverage datasets to reach sustainable profitability scales, and they rely on fast data-update channels to implement proper risk mitigation strategies. In contrast, FinTech start-ups tend to only incur a medium cost for model deployment as they are often run by tech-savvy innovative teams that possess the machine learning expertise needed to build and train UGDF models. However, it is unclear whether this is sufficient to offset their high data acquisition cost from third parties which increases their operating expenses, susceptibility to market volatility, and bankruptcy risk. These insights are in line with other findings, such as an empirical study on Chinese P2P lending platforms that concluded that the number of P2P lenders is expected to drop from 2,000 + to a couple hundred in the next few years because of their slow response to unexpected credit risks (Oster & Stephen, 2016).

Finally, the position of traditional financial institutions depends greatly on the regulations mandated by the jurisdictions where they operate. For instance, the US "right of explanation" would prevent banks from deploying UGDF models that used machine learning algorithms to train their UGDF datasets because of the lack of interpretability of such complex non-linear models. Fortunately, most traditional financial institutions have sufficient liquidity to withstand the potential downsides of increased competition within the consumer credit industry.

5.2. Open banking and the new information asymmetry

Over the last decade, several countries have rolled out legal frameworks that mandate that traditional financial institutions, such as commercial banks, must share their customers' financial transaction data with other third parties. In fact, regulations such as the European Union Payment Service Directive Two (PSD2) and British open banking are finally putting an end to the monopoly of banks over users' financial data and transactions. This will be implemented through a set of application programming interfaces (API) that banks must deploy and maintain (Cortet et al., 2016; European Commission, 2015; Zachariadis & Ozcan, 2017).

In such a post-open-banking world, FinTech incumbent challengers, and FinTech start-ups will all have access to banks' user transactions while maintaining their right to keep their own UGDF data private. Consequently, such regulations are expected to create new market dynamics in the consumer credit industry, which will give rise to a new type of information asymmetry that disfavors banks.

6. Conclusion

This study provides an evaluation framework for the business deployability of UGDF models for consumer credit. The proposed framework, which considers the intricate business realities of the financial sector, is built around seven main deployability evaluation criteria: Data accessibility, data coverage, data timeliness, data authenticity, cost of deployment, interpretability, and compliance. As part of this study, we also showcased how consumer credit providers can use the framework to evaluate the business deployability of UGDF models. This allowed us to draw insights into the potential impact of UGDF models adoption on the future evolution of consumer credit market.

What is certain is that UGDF models are steadily restructuring the consumer credit industry: This once blue ocean which was controlled by traditional financial institutions, is slowly turning red due to fierce competition by the new players—FinTech. Furthermore, the latter also use UGDF data to create completely new blue oceans of leading consumer credit, such as extending credit to consumers with little or no past financial transactions and deploying global P2P credit service platforms.

Ultimately, we believe that these new market dynamics will benefit end-users in the long run, as they will likely motivate competing consumer credit providers to improve their customer experience and lower their fees.

Overall, this work contributes to consolidating the knowledge scattered across the literature and augments it with additional findings uncovered through interviews and further analysis. This contributes to bridging the gap between academia and practice and provides an evaluation tool that is recommended for practical use in consumer credit.

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CRediT authorship contribution statement

Ahmad Amine Loutfi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See the Table A1 and A2.

Table A1
Open and axial coding process followed in the design and development step of the DSRM process- Literature.

References	Open coding	Axial coding			
		Criteria 1	**Criteria 2**	**Criteria 3**	**Criteria 4**
		Data timeliness	Data authenticity	Data coverage	Interpretability
Agarwal et al., 2020 Arraiz et al., 2015 Bataev, 2018 Berg et al., 2019 Bernerth et al., 2012 Campbell, 2018 Chorzempa et al., 2018 *Cm, 2018* Croux et al., 2020 Devereaux & Peng, 2018 Dostov et al., 2019 Dubina et al., 2019 Erevelles et al., 2016 Farvaresh & Sepehri, 2011 Fei et al., 2010 Guo et al., 2016 Hurley & Adebayo, 2016 Jagtiani & Lemieux, 2019 Kamleitner & Kirchler, 2007 Ma et al., 2018 Maurer, 2014 Meadows et al., 2004 Niu et al., 2019 Qiu et al., 2016 San Pedro et al., 2015 Sivarajah et al., 2017 Thomas et al., 2017 Tokunaga, 1993 Vanhala et al., 2020 Vidya, 2018 Wang & Gong, 2018 Weaver & Gahegan, 2007 Zetsche et al., 2017 Zhang & Meng, 2010 Zhang & Zhu, 2018	Code 1. *Data update frequency* Code 2. *Risk of data manipulation* Code 3. *Data cannot represent some users* Code 4. *Maneuvering data to influence the score* Code 5. *Blackbox models* Code 6. *Data values can cover the full customer base* Code 7. *Update cadence* Code 8. *Can the input data explain the output of the model?* Code 9. *Data difficult to alter* Code 10. *Accurate data points* Code 11. *Speed at which data is updated* Code 12. *Scalable data* Code 13. *Humans need to understand the model output* Code 14. *Users attempt to influence the score*	Code 1. *Data update frequency* Code 7. *Update cadence* Code 11. *Speed at which data is updated*	Code 2. *Risk of data manipulation* Code 4. *Maneuvering data to influence the score* Code 9. *Data difficult to alter* Code 10. *Accurate data points* Code 14. *Users attempt to influence the score*	Code 3. *Data cannot represent some users* Code 6. *Data values can cover the full customer base* Code 12. *Scalable data*	Code 5. *Blackbox models* Code 8. *Can the input data explain the output of the model?* Code 13. *Humans need to understand the model output*

Table A2
Interviewees' profile.

Title	**Industry**
Head of innovation	Banking
Innovation team	Banking
Chief executive officer	FinTech
Chief executive officer	FinTech/Banking
Founder	FinTech
Product manager	FinTech
Scientific researcher	Research
Scientific researcher	Research

Appendix B

See the Table B1.

Table B1
UGDF variables compiled during this study.

	Semantic Groups	UGDF variables
1	Social Media (SM)	Social media presence
2	Social Media (SM)	Number of followers
3	Social Media (SM)	Number of followings
4	Social Media (SM)	Fraction of followers that are also followings
5	Social Media (SM)	Number of friends
6	Social Media (SM)	Number of default borrowers in a borrower's network of friends
7	Social Media (SM)	Interactions per network friends
8	Social Media (SM)	Aggregated features of one-hop neighbors' degree features
9	Social Media (SM)	Aggregated values of the user one-hop neighbors' social media network features
10	Social Media (SM)	Social media ego network structures
11	Social Media (SM)	Growth of the social media network
12	Social Media (SM)	Groups joined on social media networks
13	Social Media (SM)	Movement on the social media platform
14	Social Media (SM)	Time spent online using the social media platform
15	Social Media (SM)	Active level of the user on the social media platform
16	Social Media (SM)	Time of posting
17	Social Media (SM)	Frequency of posting
18	Social Media (SM)	Type of content posted
19	Social Media (SM)	Length of content posted
20	Social Media (SM)	Language styles of content posted
21	Social Media (SM)	Spirituality in the content posted
22	Social Media (SM)	Posts that can reveal the user financial situation
23	Social Media (SM)	Strong readability of content posted
24	Social Media (SM)	Number of duplicate posts
25	Social Media (SM)	Fraction of posts at each of 24 h of a day
26	Social Media (SM)	Hash tags supported
27	Social Media (SM)	Number of mentions in the user posts
28	Social Media (SM)	Average number of mentions per post
29	Social Media (SM)	Fraction of posts that contain mentions
30	Social Media (SM)	Standard deviation of number of mentions in the user posts
31	Social Media (SM)	Type of content liked
32	Social Media (SM)	Time of liking
33	Social Media (SM)	Spirituality in the liked content
34	Social Media (SM)	Likes that can reveal the user financial situation
35	Social Media (SM)	Frequency of liking
36	Social Media (SM)	Time of resharing posts
37	Social Media (SM)	Type of content of reshared posts
38	Social Media (SM)	Spirituality in the reshared content
39	Social Media (SM)	Reshared content that can reveal the user financial situation
40	Social Media (SM)	Frequency of resharing posts
41	Social Media (SM)	Maximum depth of reshared posts chains
42	Social Media (SM)	Depth deviation of reshared posts chains
43	Social Media (SM)	Number and fraction of reshared posts with no comments
44	Social Media (SM)	Number and fraction of reshared posts of the user posts
45	Social Media (SM)	Average length of reshared posts chains
46	Social Media (SM)	Usage of emoticons in the user posts
47	Social Media (SM)	Type of emoticons in the user posts
48	Social Media (SM)	Number of emoticons in the user posts
49	Social Media (SM)	Average number of emoticons per post
50	Social Media (SM)	Fraction of posts that contain emoticons
51	Social Media (SM)	Standard deviation of number of emoticons in the user posts
52	Social Media (SM)	Sentiments expressed in the content of posts
53	Social Media (SM)	Sentiment vocabulary of posts (e.g., vulgar language)
54	Social Media (SM)	Number of positive/negative sentiment words in the user posts
55	Social Media (SM)	Fraction of positive/negative sentiment words in the user posts
56	Social Media (SM)	Number of positive/negative sentiment word occurrences in the user posts
57	Social Media (SM)	Sentiment polarities of posts
58	Social Media (SM)	Number and fraction of posts whose sentiment polarities are positive/negative
59	Social Media (SM)	Fraction of posts whose sentiment polarities are positive/negative
60	Social Media (SM)	Standard deviation of the sentiment polarity values among the user posts
61	Telecommunication (T)	Content of text provided during an application for a telecommunication service provider
62	Telecommunication (T)	Entropy of contacts
63	Telecommunication (T)	Number of contacts
64	Telecommunication (T)	Number of default borrowers in a borrower's contacts list
65	Telecommunication (T)	Connectiveness with the contacts
66	Telecommunication (T)	Interactions per contacts
67	Telecommunication (T)	Mobile SMS exchanged with contacts
68	Telecommunication (T)	Mobile phone usage
69	Telecommunication (T)	Mobile phone data consumption
70	Telecommunication (T)	Duration of the call/SMS
71	Telecommunication (T)	Length of mobile calls
72	Telecommunication (T)	Location of most calls
73	Telecommunication (T)	The distribution of locations from which the user conducts telecommunication call
74	Telecommunication (T)	Number of locations where phone calls occurred in one day
75	Telecommunication (T)	Regularity of locations from phone calls and data use
76	Telecommunication (T)	Sum of locations that phone calls and data use occurred
77	Telecommunication (T)	Tower location of the call/SMS
78	Telecommunication (T)	Mobile phone payment
79	Telecommunication (T)	Type of payment mean
80	Telecommunication (T)	Mobile phone plan
81	Telecommunication (T)	Changes in mobile phone plan
82	Telecommunication (T)	Presence or absence of a denial of a tentative telecom payment plan
83	Telecommunication (T)	Amount of money being added to the phone account (or recharge amount)
84	Telecommunication (T)	Phone user's new balance after the recharge
85	Telecommunication (T)	Date and time when the phone recharge occurred
86	Telecommunication (T)	Time of exchange (call, SMS/MMS…etc.)
87	Telecommunication (T)	Frequency of exchange (call, SMS/MMS…etc.)
88	Telecommunication (T)	Type of messages (SMS/MMS)
89	Telecommunication (T)	Length of messages (SMS/MMS) sent
90	Telecommunication (T)	Language styles of messages (SMS/MMS)
91	Telecommunication (T)	Spirituality in the messages (SMS/MMS)
92	Telecommunication (T)	Messages (SMS/MMS) that can reveal the user financial situation
93	Telecommunication (T)	Usage of emoticons in messages (SMS/MMS)
94	Telecommunication (T)	Type of emoticons in messages (SMS/MMS)
95	Telecommunication (T)	Number of emoticons in the user feedback
96	Telecommunication (T)	Average number of emoticons per messages (SMS/MMS)
97	Telecommunication (T)	Fraction of messages (SMS/MMS) that contain emoticons
98	Telecommunication (T)	Standard deviation of number of emoticons in messages (SMS/MMS)
99	Telecommunication (T)	Sentiments expressed in the messages (SMS/MMS)
100	Telecommunication (T)	Sentiment vocabulary (e.g., vulgar language) of messages (SMS/MMS)
101	Telecommunication (T)	Number of positive/negative sentiment words in messages (SMS/MMS)
102	Telecommunication (T)	Fraction of positive/negative sentiment words in messages (SMS/MMS)

(*continued on next page*)

Table B1 (*continued*)

	Semantic Groups	UGDF variables
103	Telecommunication (T)	Number of positive/negative sentiment word occurrences in messages (SMS/MMS)
104	Telecommunication (T)	Sentiment polarities of messages (SMS/MMS)
105	Telecommunication (T)	Number and fraction of messages (SMS/MMS) whose sentiment polarities are positive/negative
106	Telecommunication (T)	Fraction of messages (SMS/MMS) whose sentiment polarities are positive/negative
107	Silent Metadata (S)	Device brand
108	Silent Metadata (S)	Device type
109	Silent Metadata (S)	Number of devices used to login
110	Silent Metadata (S)	Font installed on the device
111	Silent Metadata (S)	Device battery life
112	Silent Metadata (S)	Time of applying the device updates
113	Silent Metadata (S)	Operating system
114	Silent Metadata (S)	Operating system update status
115	Silent Metadata (S)	WiFi networks
116	Silent Metadata (S)	Do not track setting
117	Silent Metadata (S)	Tracking: Number of locations that individuals frequently access
118	Silent Metadata (S)	Tracking: Type of stores visited
119	Silent Metadata (S)	Tracking: Range of locations
120	Silent Metadata (S)	Tracking: Entropy of locations
121	Silent Metadata (S)	Browser setting
122	Silent Metadata (S)	Browser history
123	Silent Metadata (S)	Filters used for search
124	Silent Metadata (S)	Duration spent browsing the Internet
125	Silent Metadata (S)	Movement on the webpages
126	Silent Metadata (S)	Type of advertisements accessed while browsing on the Internet
127	Silent Metadata (S)	Screen resolution
128	Silent Metadata (S)	Number and proportion of alphabetic characters in the screen name
129	Silent Metadata (S)	Number and proportion of numerical characters in the screen name
130	Silent Metadata (S)	Number and proportion of symbol characters in the screen name
131	Silent Metadata (S)	Length of the screen name
132	Silent Metadata (S)	Email typo
133	Silent Metadata (S)	Email alias: Matching or not with real name
134	Silent Metadata (S)	Email host (ex. Gmail, Outlook, work-mail…etc.)
135	Silent Metadata (S)	Content of the email: Use of numbers/words/characters in email
136	Silent Metadata (S)	Number of times the user changes their password
137	Silent Metadata (S)	Wrong typing of the password
138	Silent Metadata (S)	Password strength
139	Silent Metadata (S)	Number of times the user changes their password
140	Silent Metadata (S)	Wrong typing of the username
141	Silent Metadata (S)	Username alias: Matching or not with real name
142	Silent Metadata (S)	Self-reported address
143	Silent Metadata (S)	Self-reported age
144	Silent Metadata (S)	Self-reported name
145	Silent Metadata (S)	Self-reported occupation
146	Silent Metadata (S)	Time spent before moving an item to the basket
147	Silent Metadata (S)	Time spent before paying the basket
148	Silent Metadata (S)	Pattern of changing the basket
149	Psychometric (P)	Psychometric cognitive test
150	Psychometric (P)	Psychometric speed and attitude toward the tests
151	Psychometric (P)	Psychometric behavioral test
152	Mobile/Web Applications Usage Pattern (M/W)	Type of applications installed
153	Mobile/Web Applications Usage Pattern (M/W)	Entertainment applications installed
154	Mobile/Web Applications Usage Pattern (M/W)	Movement on the applications
155	Mobile/Web Applications Usage Pattern (M/W)	Time spent on applications
156	Mobile/Web Applications Usage Pattern (M/W)	Active level of the user on the applications
157	(M/W) or (SM) or (T)	Channel through which the customer came
158	(M/W) or (SM) or (T)	Application registration time
159	(M/W) or (SM) or (T)	Time spent filling out the application form
160	(M/W) or (SM) or (T)	Application form filling data
161	(M/W) or (SM) or (T)	Writing or copying/pasting the application form data
162	(M/W) or (SM) or (T)	Province where the user lives
163	(M/W) or (SM) or (T)	Time of writing feedbacks
164	(M/W) or (SM) or (T)	Frequency of giving feedbacks
165	(M/W) or (SM) or (T)	Type of feedbacks posted
166	(M/W) or (SM) or (T)	Length of feedbacks posted
167	(M/W) or (SM) or (T)	Language styles of feedbacks posted
168	(M/W) or (SM) or (T)	Spirituality in the feedbacks content
169	(M/W) or (SM) or (T)	Feedbacks that can reveal the user financial situation
170	(M/W) or (SM) or (T)	Usage of emoticons in the user feedback
171	(M/W) or (SM) or (T)	Type of emoticons in the user feedback
172	(M/W) or (SM) or (T)	Number of emoticons in the user feedback
173	(M/W) or (SM) or (T)	Average number of emoticons per feedback
174	(M/W) or (SM) or (T)	Fraction of feedbacks that contain emoticons
175	(M/W) or (SM) or (T)	Standard deviation of number of emoticons in the user feedback
176	(M/W) or (SM) or (T)	Sentiments expressed in the feedback content
177	(M/W) or (SM) or (T)	Sentiment vocabulary (e.g., vulgar language) of feedback
178	(M/W) or (SM) or (T)	Number of positive/negative sentiment words in the user feedback
179	(M/W) or (SM) or (T)	Fraction of positive/negative sentiment words in the user feedback
180	(M/W) or (SM) or (T)	Number of positive/negative sentiment word occurrences in the user feedback
181	(M/W) or (SM) or (T)	Sentiment polarities of feedback
182	(M/W) or (SM) or (T)	Number and fraction of feedback whose sentiment polarities are positive/negative
183	(M/W) or (SM) or (T)	Fraction of feedback whose sentiment polarities are positive/negative
184	(M/W) or (SM) or (T)	Standard deviation of the sentiment polarity values among the feedback's writers

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