Inferring Delay Discounting Factors from Public Observables: Applications in Risk Analysis and the Design of Adaptive Incentives

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Abstract: Decision-makers regularly need to make trade-offs between benefits in the present and the future. Smaller immediate rewards are often preferred over larger delayed rewards. The concept of delay discounting describes how rewards further in the future lose their value in comparison to immediate or more proximal rewards. Empirical evidence shows that people discount future rewards using a hyperbolic function, which gives rise to preference reversals as the delay between a decision and receipt of the reward increases. People show great differences in terms of their tendency to discount future benefits. The extent of discounting is characterized by each individuals' discounting factor k. This study investigates the extent to which the discounting factor k can be inferred from publicly observable pieces of information (i.e. ownership of items, habits) linked to individuals. Data was collected from 331 respondents in an online questionnaire. The analyses show that 37% of the variance can be explained by public observables in the best case, and between 17-33%, when the predictive model is tested on unseen data. The results contribute to the development of a risk analysis method within the domain of information security, which currently lacks the temporal dimension when predicting stakeholder behavior. Furthermore, the results have key implications for the emerging e-health sector, where individuals' immediate incentives need to be aligned with long-term societal benefits.

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1 INTRODUCTION

Information security-related decisions involve trade-offs in the dimension of time. Resources need to be allocated in the present, while their benefits may materialize in the future. In order to enjoy greater benefits in the future, immediate, smaller rewards often must be foregone. For example, a trade-off exists between gaining immediate gratification from various web services (i.e. small immediate reward) and being protected from future privacy breaches (i.e. greater later rewards) (Acquisti and Grossklags, 2003). E-health initiatives aim at reaping the benefits from digitization within the health care sector (Eysenbach, 2001). The health care eco-system is characterized by the interaction of a large number of stakeholder groups (e.g. citizens/patients, healthcare professionals, researchers, data analytic and service providers, etc.), where each group has specific incentives to interact with the system. Future societal benefits (e.g. enhanced drug and treatment research, predictive care, etc.) are fundamentally dependent on the willingness of primary data subjects (i.e. citizens or patients) in the present to share their sensitive health data. The situation requires that all stakeholder groups perceive appropriate incentives to cooperate toward collective goals instead of acting in their individual self-interest which may result in tragedy of the commons (e.g. degradation of common pool information resources by overuse or distrust due to invasion of privacy) (Regan, 2002).

Intertemporal choices are decisions involving trade-offs among costs and benefits at different times. The concept of delay discounting refers to the phenomenon where immediate rewards have a higher value than delayed rewards, giving rise to preferences which are biased toward the present (Acquisti and Grossklags, 2003). Individuals can be characterized by their unique discounting factor k, which governs the rate at which future rewards lose value. Empirical investigations revealed that the discounting factor k shows great inter-individual differences and that such differences are associated with important and varied health-related and economic outcomes (Kirby and Maraković, 1996; Frederick et al., 2002). Therefore, the assessment of a decision-maker's discount-

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ing factor k can have useful implications for several purposes. On one hand it enables the prediction of decisions across time for the purpose of risk analysis; and on the other hand it can enable the design of adaptive incentives which take into account inter-individual differences regarding temporal preferences in an emerging e-health ecosystem.

1.1 Problem Statement and Research Question

This paper aims at contributing to the enhancement of a risk analysis method which is to be applied within the context of a democratic e-health eco-system involving multiple stakeholders with conflicting incentives. To date, the risk analysis method lacks the temporal dimension regarding the stakeholder models, representing a limitation in its behavior prediction capabilities. Thus, the primary objective is to enhance the risk analysis method, while the second objective is to propose a method for incentive design within a e-health context, which takes into consideration stakeholders' individual differences regarding temporal preferences. Temporal preferences need to be assessed unobtrusively based on publicly available pieces of information linked to decision-makers to reach inaccessible or adversarial subjects. Therefore, the main research question is as follows:

Research Question: To what extent is it possible to infer individuals' discounting factor k based on publicly available and observable pieces of information linked to decision-makers?

The paper is organized as follows: Section 2 provides an overview about the theoretical and empirical results related to delay discounting followed by a presentation of the risk analysis method under development. The section concludes with a description of a democratic e-health ecosystem as an application domain for the results. Section 3 describes the instruments used for data collection, procedures and the composition of the sample. Section 4 presents the findings and answers the main research question. Section 5 discusses results and their relevance for risk analysis and the democratic e-health ecosystem. Section 6 concludes the paper.

2 RELATED WORK

2.1 Delay Discounting

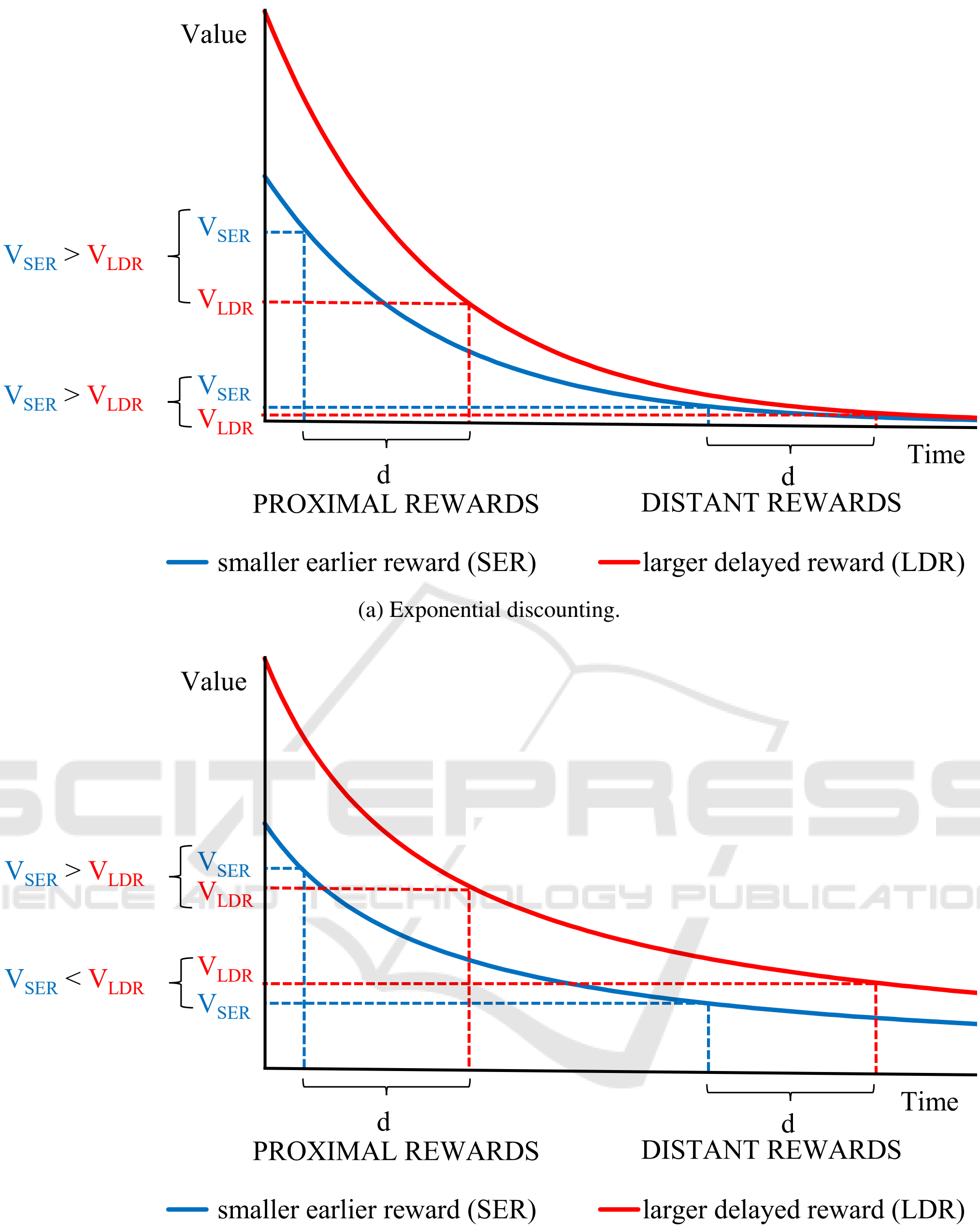
Patience, self-control, willpower are similar concepts describing one's ability to postpone immediate gratification for later, better outcomes. Psychological experiments were conducted about delayed gratification using marshmallows as rewards for preschool children (Mischel et al., 1972). Significant individual differences were found among children in their ability to delay gratification. Follow-up studies with the same subjects revealed that self-control in preschool children was a useful predictor of later outcomes such as scholastic performance, skills to cope with stress, social competences, etc. Willpower has been conceptualized as a cognitive skill which can be enhanced and trained with simple strategies to regulate emotions, overcome temptations and to become more future-oriented (Mischel et al., 1989). The concept has been also incorporated into behavioral economic theories to improve decision-maker models by including the temporal dimension. The concept is known as delay discounting characterizing a decision-maker's impulsivity or present-orientedness. "Delay discounting is a behavioral phenomenon wherein reinforcers become devalued as a function of their delay to receipt" (Kaplan et al., 2016). Two models have been proposed to capture decision-makers' temporal preferences: **exponential discounting** and **hyperbolic discounting**. **Exponential discounting** refers to a constant-rate discounting (constant across delays and reward amounts), described by the following equation:

$$V = Ae^{-kD},$$

where V is the present value of the delayed reward, A is the amount of the delayed reward, k is the discounting rate parameter, and D is the delay (Kirby and Maraković, 1996). In contrast, **hyperbolic discounting** assumes that discounting rates are not constant across delays (higher for small delays and lower for long delays). Empirical investigations showed that real-world decision-makers' behavior is best approximated by a hyperbolic function of the form (Kirby and Maraković, 1996):

$$V = \frac{A}{1+kD}.$$

The key implication of hyperbolic discounting is that it gives rise to temporal preferences for smaller immediate rewards over larger later rewards, but these preferences change as the delay between the choice and receipt of rewards increases. Thus, a **preference reversal** occurs, such that individuals make choices in the present that their future-self would prefer not to have made (Kirby and Maraković, 1996). Figure 1 demonstrates how two rewards (i.e. a Smaller Earlier Reward (SER) and a Larger Delayed Reward (LDR)) are discounted across time according to exponential and hyperbolic functions. Preferences remain stable over time (i.e. SER > LDR for both proximal



(a) Exponential discounting.

(b) Hyperbolic discounting.

Figure 1: Exponential and hyperbolic discounting functions adapted from (Kalenscher and Pennartz, 2008). The delay (d) between options (i.e. SER or LDR), is identical for exponential and hyperbolic functions as well as for proximal and distant rewards. The amounts of reward (A) and discounting factors (k) are identical for both functions.

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and distant rewards) with the exponential function as shown in Figure 1a. With the hyperbolic function (Figure 1b), immediate or proximal rewards get discounted more steeply, compared to distant rewards, resulting in preference for the SER, whereas the LDR is preferred when a significant delay is introduced between the choice and receipt of the reward (i.e. preference reversal occurs: SER > LDR for proximal rewards, but SER < LDR for distant rewards).

Delay discounting shows significant inter-individual differences, and the concept has been used to explain procrastination (Steel and König, 2006), various addictions (e.g. heroin, alcohol, tobacco, gambling) where immediate short-term rewards are chosen at the expense of larger delayed rewards (i.e. better health, longevity) (Kirby et al., 1999). Empirical evidence also shows that people use different discounting rates in different contexts. For example, health-related future benefits are discounted at a higher rate than rewards in the monetary domain (Chapman and Elstein, 1995). Results about the intra-individual stability of the delay discounting construct are mixed. While some data suggests that delay discounting can be assumed as a relatively stable, enduring trait (Odum, 2011), a more recent systematic review (Scholten et al., 2019) identified several studies reporting interventions which successfully decreased discounting rates on the short-term. These results suggest that delay discounting may better be conceptualized as a state variable.

2.2 Conflicting Incentives Risk Analysis

The Conflicting Incentives Risk Analysis (CIRA) was developed within the domain of information security and privacy to simplify the risk analysis procedure by focusing on human stakeholders and their perceived incentives (Rajbhandari and Snekkenes, 2013). Risks within CIRA result from the interdependent relationship between stakeholders, where one person is exposed to the actions or inactions of another person. Two different stakeholder categories are distinguished in the game-theoretic framework: **risk owner** and **strategy owner**. Each stakeholder is modelled by their overall utility using multi-attribute utility theory. Incentives refer to the benefits or losses expected by a stakeholder when interacting with a system and other stakeholders. Incentives may be aligned or misaligned. When incentives are misaligned, there is a risk and every risk is represented by another person's incentive. Risks are subjective to the person (i.e. risk owner) being exposed to the conscious choices of other stakeholders (i.e. strategy owners). Two types of incentive misalignment are possible. **Threat risk** refers to undesirable outcomes for the risk owner and a potential gain for the strategy owner which resembles the traditional notion of risk referring to undesirable consequences. A ransomware attack on patient health records can be considered a threat risk where the patient, or hospital personnel are risk owners, and the hackers motivated by monetary gains are strategy owners. Incentives can also be misaligned in a way that results in **opportunity risk**, where strategy owners lack incentives to act in a desirable way for the risk owner. For example citizens of e-health system may lack incentives to share their data (Spil and Klein, 2014; Sunyaev, 2013), which may result in suboptimal societal outcomes on the long-term (i.e. missed opportunities for better treatments, decreased overall efficiency, etc.). The CIRA method assumes adversarial and inaccessible stakeholders during the risk analysis procedure, therefore the method relies on unobtrusive (i.e. indirect) assessment of personal attributes of stakeholders to decrease the possibility of motivated misrepresentation or cheating by the stakeholders under investigation. Previous work has investigated the extent to which publicly observable features are useful for inferring stakeholder motivational profiles for the purpose of risk analysis (Szekeres and Snekkenes, 2020). Another study demonstrated how unobtrusive psychological profiling can be conducted using publicly available interviews for the improvement of the CIRA method (Szekeres and Snekkenes, 2019).

2.3 Health Democratization

Healthcare is undergoing radical changes due to digitization. The domain is characterized by a large number of stakeholders including patients, healthcare professionals, researchers, industrial players (e.g. pharmaceutical companies, equipment manufacturers), the authorities, national health insurance, etc., each having distinct goals and incentives for interacting with the system (Direktoratet for e-helse, 2018). Incentive conflicts are inherent is such complex systems, therefore it is important to identify and mitigate risks, so that patients get a favourable deal. The Norwegian Health Democratization project aims at reinforcing the health data infrastructure in mobility and assurance through data democratization (N.A., 2019). While democracy is a broad concept and several ideas can be included, a key democratic aspect in the project is that all stakeholders will be represented as equal entities in the protocol, such that their unique distinguishing features (e.g. market influence, administrative power, profitability) are disregarded when parties prove, negotiate and configure their rights w.r.t. health data (N.A., 2019). As the primary data subjects will have increased possibilities to influence outcomes related to how their data is used, their willingness to contribute with sensitive health data is crucial for the expected societal benefits (e.g. cost reduction, improved drug and treatment discoveries, predictive healthcare, etc.). Another important democratic aspect is related to the possibility of choices. The system needs to implement various opportunities to incentivize data trading for benefit or profit depending on several factors (e.g. risks, benefits, temporal preferences, etc.). Democratic e-health initiative's build on citizen's active participation in the decision-making, where patients are treated as partners in health-related decision-making (Aaviksoo, 2015). This approach represents a move away from the traditional paternalistic model of medicine, where specialized service providers assist both doctors and patients in a cooperative decision-making. The envisaged system will utilize autonomous agent-based solutions and smart contracts for data sharing, where agents can represent people, software, or other applications. Various agents (e.g. patient agent, GP agent, ambulance agent) will interact with each other on behalf of their principals. The agents need to be equipped with negotiation mechanisms, rules and protocols, strategies and decision-making models (Boudko and Leister, 2019).

2.4 Summary of Related Work

In a democratic e-health ecosystem patients or citizens considering sharing their data with other entities can be conceptualized both as risk owners and strategy owners in terms of CIRA using a two-step process model. In the first step, a citizen takes the role of the risk owner and conducts an implicit risk assessment considering risks (e.g. data breaches, ransomware attacks, data misuse, etc.) and benefits (e.g. improved treatment, health monitoring, monetary incentives, etc.) associated with sharing sensitive health data. In the second step, citizens take the role of the strategy owner and set sharing options, terms and conditions, rules and access rights, etc. depending on the results of the risk assessment. Such decisions have a high level of complexity and relative rarity; therefore, people are not expected to be skilled in making these decisions. In such situations people can benefit from Nudges or other choice architecture approaches implemented in the system to make socially optimal decisions (Thaler and Sunstein, 2009). On the larger scale the main objective is to mitigate the opportunity risk (i.e. benefits foregone) at the societal level resulting from reluctance of citizens to share their data which may be due to lack of trust, too high risk or a lack of incentives. Future societal benefits can only get realized if decisions in the present are made according to long-term preferences, thus adaptive incentive designs need to be developed to match individual's discounting profiles with a variety of incentives offered.

3 METHODS

This section describes the data collection procedures, the sample and the instruments used for collecting data from participants about personal attributes (i.e. discounting profiles) and public observables (i.e. habits, items owned by respondents).

3.1 Sample and Procedure

As the primary purpose of the study was to assess the usefulness of a large set of publicly observable pieces of information for the construction of stakeholder discounting profiles (i.e. discounting factor k), it was necessary to reach a high number of respondents from the working age population (above 18 years). Therefore, an online survey was selected as the most appropriate data collection method and invitations were distributed on several online channels: first, a pilot study was conducted on Amazon Mechanical Turk (AMT) to test the feasibility of data collection. Based on the results of the pilot study, some modifications were implemented and links to the online survey were distributed on university mailing lists, and key social media platforms (Norwegian Facebook groups, the biggest Norwegian reddit group). The survey was available in English and Norwegian, and the Norwegian version was proof-read by a professional editorial service. The survey was implemented in the open-source Limesurvey tool and was hosted on internal servers provided by the Norwegian University of Science and Technology (NTNU). The questionnaire was completely anonymous, and participants had to read and accept a consent form before the questionnaire started upon visiting the link. The number of fully completed questionnaires is shown in Table 1, organized according to distribution channels.

Table 1: Number of completed surveys by distribution channels. AMT: Amazon Mechanical Turk.

Distribution channel	Number of completed surveys
AMT	9
Social media	25
University e-mail lists	332
Total	**366**

Respondents who completed the survey under 10 minutes (average completion time: 23 minutes) were removed to increase the validity of the dataset. Thus, the final convenience sample consisted of **(n = 331)** respondents (173 males, 153 females, and 5 with unknown sex). The mean age was 40.28 years (SD = 13.27). Most respondents were from Norway (75%), while other countries represented 25% of the sample. Most subjects had a completed Master's degree (53%), followed by a PhD (24%), Bachelor's (16%), and completed secondary education (7%). Most respondents were married or in a long-term relationship (71%), followed by singles (24%) and divorced or separated individuals (5%).

3.2 Measures

The online survey consisted of three main parts following the introduction explaining the purpose of the data collection:

1. Basic demographic information (age, sex, level of education, nationality).
2. Behavioral responses for deriving individuals' delay discounting rates.
3. Publicly observable features linked to the individuals.

3.2.1 Delay Discounting - MCQ-21

The validated 21-item Monetary Choice Questionnaire (MCQ-21) instrument was used for collecting responses from participants to compute each individual's overall discounting factor k. The MCQ-21 is a self-reporting questionnaire comprising of a set of 21 questions requiring participants to make a choice between a smaller, immediate reward (SIR) or a larger, delayed reward (LDR) with monetary values (Kaplan, 2016). The original instructions for the questionnaire: "For each of the next 21 choices, please indicate which reward you would prefer: the smaller reward tonight, or the larger reward in the specified number of days. Although you will not actually receive any of the money, pretend that you will actually be receiving the amount that you indicate. Therefore, please answer each question honestly and as if you will actually receive the amount chosen either tonight or after a specified number of days. To indicate your choice, please clearly circle the amount and time as shown in following example: 0. Would you prefer \$100 tonight, or \$100 in 45 days?" (Kaplan, 2016) were modified so they suit better for the online survey format. For each question two radio buttons were provided to make the choice task clear: e.g. \$30 tonight or \$85 in 14 days.

Discounting metrics were computed for each respondent using the Excel-based automated scoring tool, which facilitates the complex computations to derive the discounting factor k from MCQ-21 (Kaplan et al., 2016). The tool reports summary statistics for the whole sample, checks consistency and outputs several discounting metrics on the individual level: overall k, small k, medium k, large k, geomean k (taking the geometric mean of the small, medium, and large k values), as well as the log and ln for each of the k scores. The following analyses use the "overall k factor" measuring the daily rate at which rewards lose their value. Rearranging the equation of the hyperbolic function gives the formula for the discounting factor k:

$$k = \frac{\frac{A}{V} - 1}{D}$$

where V is the smaller, immediate reward; A is the larger, delayed reward; and D is the delay associated with A. For a more detailed explanation on deriving the overall k factor see: (Kaplan et al., 2016).

3.2.2 Publicly Observable Attributes

This section of the questionnaire aimed at collecting information linked to respondents, which can be easily observed in most public settings (e.g. work) without direct interaction with the stakeholder. Two categories of data can be distinguished: ownership of items and habits. Ownership questions focused on the presence of attributes, while questions related to habits were concerned with the frequency of various actions.

A single choice response format was used to assess the presence of the attributes, and for certain attributes, additional questions were included to obtain a more detailed description. Question categories were as follows: real estate (number, location, size), car (number, brand, model, type, color, energy source, unique license plate), motorcycle (number, brand, type), bicycle (brand, type), boat (brand, type), phone (brand, model, color, cover, cover color), laptop (brand, OS, size, camera cover, decoration), tablet (brand, size), watch (type, brand), headphones (brand), sunglasses (brand), backpack (brand), briefcase (brand), jewellery (type, material), wallet (material), sport equipment (17 items), pets (7 species + other), style description (15 categories), cosmetic surgery, hair dye, hair length, facial hair, dietary lifestyle (7 categories), tattoo (general categories, place of tattoo), social media (existing accounts), preferred browser, preferred search engine.

Questions related to habits asked the frequency of various activities on a 9-point response format where each point had a textual label ranging from *0 - never in the last 12 months* to *8 - every day or nearly every day*. Questions assessed the frequency of: wearing certain clothes (23 items), doing various sports (17 sports), listening to music (14 genres), consuming drinks (11 drink types), consuming other products (6 items), engaging in various other activities (26 activities).

4 RESULTS

The final dataset contained valid responses from a total 331 subjects. The key dependent variable for the analysis was individuals' overall k score. Based on the automated scoring tool for MCQ-21, descriptive statistics were as follows: Mean overall k scores = 0.0115, (SD = 0.0235). Overall consistency of choices was high: 95.6% (SD = 6.21%) showing the dataset had a high validity, while the overall proportion of LDR (larger delayed reward) chosen was 67.33% (SD = 26.34%), indicating a low general tendency to discount future benefits. Overall k scores in the present sample were smaller (i.e. evidence of greater self-control) than the same overall k scores (Mean = 0.0727, SD = 0.0886) found in a similar-sized sample (n = 328) with a gambling disorder diagnosis (Steward et al., 2017). The computed discounting scores were fed back to the master database, and independent categorical (i.e. nominal) variables were dummy coded into indicator variables (where 0 = no/attribute is not present; 1 = yes/attribute is present). This procedure allows categorical variables to be included in regression models. The analyses were performed in SPSS 25 and scikit-learn library for Python.

The forward selection algorithm was used for constructing multiple linear regression models with overall k as the single dependent variable and the set of publicly observable features as predictors in SPSS. The algorithm is a stepwise feature selection procedure which enters variables into the equation based on their strength of correlation with the dependent variable. Criterion for probability of entry was set to: $p \leq 0.05$ and $p \geq 0.1$ for exclusion. The procedure terminated when no more variables met the criterion of entry (IBM, 2016). Model performance was evaluated by two metrics provided by SPSS: R^2 - coefficient of determination or the proportion of the variance in the dependent variable explained by the set of independent variables in the model; and the adjusted R^2 score which penalizes each additional predictor, providing a more conservative estimate about the model's goodness-of-fit. Following the feature selection and model construction procedures the best regression model ($F(21, 309) = 6.125$, $p < 0.00$) with an $R^2 = 0.371$, adjusted $R^2 = 0.311$ was found, as shown in Figure 2. The complete model with the best fit for predicting the overall k score is provided in Table 2. Based on the formula for multiple linear regression, an individual's overall discounting factor k can be predicted by:

$$Y_i = \beta_0 + \beta_1 X_1 + ... + \beta_k X_k + \varepsilon$$

summing the unstandardized $\beta_0 - \beta_k$ coefficients of the predictors multiplied by the unobtrusively assessed raw scores $X_1 - X_k$ (using 0-8 for frequency of habits, and 0-1 for indicator variables) with the relevant ε error terms. All predictors were significant at $p \leq 0.05$. The model can be considered a best-case scenario, since the metrics only provide information about the model's fit, but the error of prediction for unobserved data is not assessed in this step.

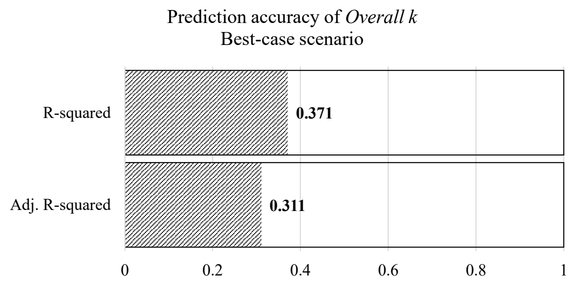

Figure 2: Prediction accuracy for the overall k discounting factor. Goodness-of-fit metrics (R^2 and Adjusted R^2) provide best case scenarios, since error of predicting unobserved data is not assessed. An $R^2 = 1$ would indicate perfect fit of the model.

In order to assess the model's expected performance on unseen data, a 5-fold cross-validation procedure was conducted. Cross-validation makes it possible to quantify how well the model performs on unseen data (i.e. how well the model generalizes beyond the sample used for training the model) (Yarkoni and Westfall, 2017). Due to the relatively small number of subjects, a train-test split was performed where each model was trained on 80% of the original dataset and performance was tested on the remaining 20% of data. The dataset was randomized for each run. The results of the 5-fold cross-validation are presented in Figure 3. Compared to the best-case scenario the expected performance of the model on unseen data reduces to R^2: 0.253 +/- 0.079 (with CI 95%), using the mean of the R^2 scores derived from 5 independent runs.

4.1 Illustrative Scenarios

In order to illustrate the utility of inferring individuals' discounting factor (k) two simple cases relevant to the paper's topic (i.e. prediction of stakeholder behavior for risk analysis and adaptive incentives) are presented. The following examples only focus on differences in sensitivity to delayed rewards, while the security of the e-health system and the risks of data sharing, etc. are not considered. These critical factors need to be addressed carefully during the design and implementation of the system.

In a CIRA-type scenario a CEO of a small or medium-sized enterprise (strategy owner) needs to make a choice between taking out an immediate dividend or investing in security controls with delayed benefits. The discounting factor k of the stakeholder

Table 2: Regression model for predicting the overall k discounting factor. Predictors are sorted in order of importance from most important to least important based on the Standardized β coefficients. Variables assessing frequency of activity are marked with (freq), dummy variables are marked with (y/n).

Predictors	Standardized β Coefficients	t	Unstandardized β Coefficients	Std. Error	Sig.
Constant		5.516	0.032	0.006	0.00
style: wearing tattoo (y/n)	0.264	4.566	0.025	0.005	0.00
gambling (freq)	0.221	4.453	0.004	0.001	0.00
wearing shorts (freq)	-0.220	-4.478	-0.003	0.001	0.00
going to party (freq)	-0.206	-4.052	-0.003	0.001	0.00
style: facial hair (y/n)	0.173	3.57	0.019	0.005	0.00
listening to blues music (freq)	-0.171	-2.894	-0.002	0.001	0.00
listening to jazz music (freq)	0.163	2.992	0.001	0.000	0.00
ownership of SUV (y/n)	0.156	3.176	0.013	0.004	0.00
going fishing (freq)	0.147	3.046	0.002	0.001	0.00
listening to electronic music (freq)	-0.143	-2.777	-0.001	0.000	0.01
drinking coffee (freq)	-0.139	-2.877	-0.001	0.000	0.00
home location: countryside (y/n)	-0.133	-2.781	-0.012	0.004	0.01
wearing baseball cap (freq)	-0.129	-2.654	-0.001	0.001	0.01
ownership of boat (y/n)	0.127	2.668	0.015	0.005	0.01
watch type: digital (y/n)	0.126	2.636	0.010	0.004	0.01
listening to country music (freq)	0.114	2.168	0.001	0.000	0.03
brand of sunglasses: Ray-Ban (y/n)	0.112	2.334	0.006	0.003	0.02
search engine: other than Google (y/n)	-0.112	-2.358	-0.009	0.004	0.02
no account on Instagram (y/n)	0.104	2.088	0.005	0.002	0.04
phone color: white (y/n)	0.103	2.144	0.010	0.004	0.03
playing football (freq)	0.101	2.047	0.002	0.001	0.04

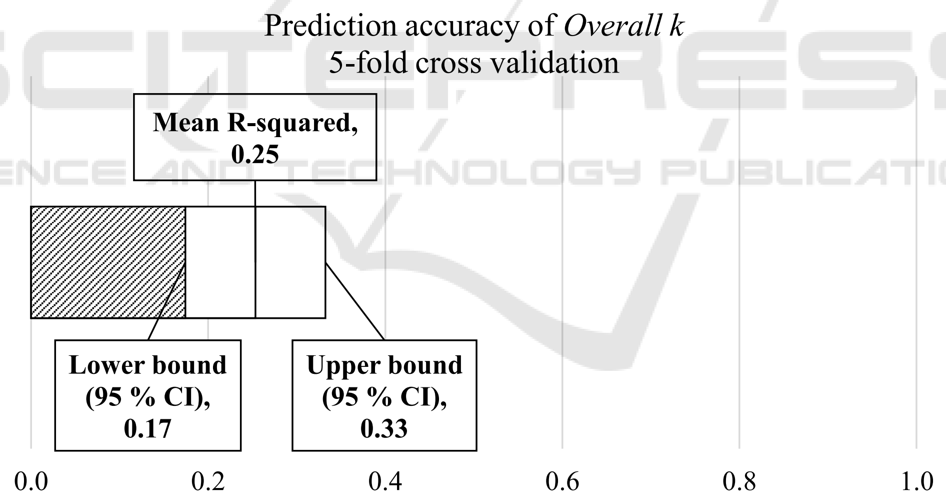

Figure 3: Prediction accuracy of overall k based on 5-fold cross-validation in terms of the mean R^2 metric.

is assessed as 0.01 % /day according to MCQ-21. The bonus (smaller earlier reward - SER) is worth 300k, while the losses avoided by the investment in controls (larger delayed reward - LDR) is worth 500k. Using knowledge about the individual's discounting rate k and the amounts of rewards involved, it is possible to predict the stakeholder's choices in time. In this specific case, when a delay of more than 66 days is present between the SER and the LDR, the person would chose the smaller earlier reward (i.e. bonus) and discount the later benefits of protection, meaning that $U_{SER} > U_{LDR}$. If the same choice was to be made 1 day later with the same amount of delay, the preferences would be reversed so that $U_{SER} < U_{LDR}$, where U refers to the utility of a choice.

Within a democratic e-health system, citizens/patients will exhibit great heterogeneity regarding their delay discounting factors. Based on the assumption, that distant societal benefits fundamentally depend on the population's willingness to share their data in the present, it is reasonable to design **adaptive incentives**, which can be customized based on the needs of different individuals. For example, the willingness to share data with commercial data analytic providers may be increased by matching incentives based on each individual's discounting factor. A citizen with a high overall discounting factor k of 0.2 is more likely to share data in exchange for smaller immediate rewards (e.g. immediate social approval), while a patient with a low overall discounting factor k of 0.01, is more likely to wait for a greater later reward (e.g. a valuable travel voucher). Thus, a democratic health ecosystem system can be designed which enables people to exercise freedom of choice with respect to various incentives / business models matching their preferences.

5 DISCUSSION AND FURTHER WORK

The purpose of this study was to investigate the extent to which individual's discounting factor k can be inferred from publicly observable pieces of information. The discounting concept has been shown to play a significant role in various socially important behaviors (e.g. substance use disorders, obesity, environmental concerns, sexual risks, technology dependence, etc.) (Kaplan et al., 2016). To the authors' knowledge this is the first study to investigate the extent of predictability of the discounting factor k from publicly observable pieces of information.

This online survey-based study collected data about a broad range of items possessed by subjects and about their habits. The survey utilized the validated instrument MCQ-21 and the accompanying automated scoring tool which facilitates the computation of several discounting metrics (Kaplan et al., 2016). The results indicate that the best model is capable of explaining around 31-37% of the variance in the overall k scores, and between 17-33% when a 5-fold cross-validation technique is used to assess how well the model generalizes beyond the training set.

The results can be applicable in two domains for different purposes. The primary use of the results is within the CIRA method, which can be enhanced with the temporal dimension to predict stakeholder behavior. Inferring the discounting factor of inaccessible and/or adversarial stakeholders from publicly observable pieces of information can increase the analyst's capability to assess the action-desirability as perceived by the stakeholder allowing the prediction of behavior in the temporal dimension. However, there is a need to decrease uncertainties in the prediction accuracy which may be achieved by increasing the number of respondents in subsequent studies and by including other sets of publicly available pieces of information.

The other domain where the results are to be utilized is within the Health Democratization project, where the existence of the right incentives for data subjects (i.e. citizens, patients) in the present, is crucial for generating desirable societal outcomes in the future. People face different risks based on their needs, expectations and health conditions. In a democratic healthcare ecosystem where patients are both risk owners (i.e. facing the risk of data breaches) and strategy owners (i.e. able to influence outcomes and make informed decisions), it is important to match incentives for data sharing with various personal preferences (e.g. temporal, risk tolerance, etc.). Health data is being generated by more and more devices and organizations (e.g. fitness devices and apps, medical devices in outpatient care settings). Currently the key incentives for citizens is to access health-related information generated by wearable devices; receive services (e.g. data analytics, health-related recommendations) or get improved care in case of medical monitoring sensors (Baig et al., 2017). The willingness of data subjects to share or trade health data for other purposes (e.g. research, profit) needs to be explored and various incentive mechanisms may be necessary to facilitate data portability beyond current possibilities. Trust in organizations which generate and collect personal health data is necessary which can be established by making organizational practices transparent and easy to understand. Allowing people to make informed choices and opting out of undesirable data processing activities (e.g. local storage of data) without negative consequences is important to give people control over their data and facilitate portability (Garmin, 2021). In order to avoid a tragedy of the commons scenario regarding privacy (Regan, 2002) in the e-health sector, incentives for all stakeholder groups (e.g. citizens, commercial actors, regulators) should be designed so that self-interests are aligned with societal interests. Future work also needs to investigate how negotiation agents (Boudko and Leister, 2019) can be enhanced with information about the principal's temporal preferences and other characteristics to mitigate risks. Future work will also investigate how various health conditions can be used to augment risk owner profiles using international classifications such as the International Statistical Classification of Diseases and Related Health Problems (ICD) (WHO, 2021).

It is important to mention that the study is not without limitations. The sample was a convenience sample, therefore probabilistic sampling methods with more subjects would be desirable for future studies to increase generalizability. It should be noted that the instrument (MCQ-21) used for collecting discounting scores is restricted to monetary rewards. As evidence shows, people tend to use different discounting rates for different contexts (Chapman and Elstein, 1995), thus the utility of the derived discounting rates outside of the monetary domain is questionable. Additionally, the MCQ-21 uses relatively small hypothetical rewards (highest reward is $85), therefore the validity of the discounting scores for much larger rewards needs careful considerations. Other instruments focusing on rewards in different domains and with higher reward values can be used in future studies as well. Considering that emotions and moral concerns play a key role in human decision-making, it is also important to investigate how non-monetary incentives (e.g. emotional, moral, social) are discounted, and which non-monetary incentives are applicable in the e-health domain. These questions are especially relevant since the commercial exploitation of human biological materials and personal health data is often seen as morally problematic. However, the promotion of communal benefit sharing and the establishment of appropriate regulations (which hinder the commodification of the human body) could render the commercial use of biobanks and health data more acceptable (Steinsbekk et al., 2013).

Finally, certain principles and ethical standards need to be considered for incentive-designers. The potential to abuse information gained from unobtrusive measures needs careful attention (e.g. unfair incentive schemes). Vulnerable groups (e.g. high discounters) may get offered lower pay-outs and false incentives if unethical actors infer discounting scores. Regulations need to be designed with the expectation that certain actors will try to maximize their benefits at the expense of other stakeholders in an unfair manner.

6 CONCLUSIONS

Despite increasing levels of digitization in several domains of life, people are fundamentally responsible and accountable for the decisions which affect themselves and others. E-health represents an emerging domain where incentive conflicts will be highly prevalent due to the large number of stakeholder groups in an interdependent relationship. Understanding how people overvalue the present at the expense of the future has key implications for behavior prediction within risk analysis using the CIRA method, and for designing incentives based on individual differences in a democratic e-health system, where individual's will be active participants with a desire to make informed decisions related to how their data is used. Aligning incentives in the present so that people make decisions which will generate beneficial outcomes in the future is key to a successful democratic health eco-system.

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REFERENCES

Aaviksoo, A. (2015). E-Health Brings Democracy to Healthcare. [Online; accessed 26. May 2021].

Acquisti, A. and Grossklags, J. (2003). Losses, gains, and hyperbolic discounting: An experimental approach to information security attitudes and behavior. In *2nd Annual Workshop on Economics and Information Security-WEIS*, volume 3, pages 1–27. Citeseer.

Baig, M. M., GholamHosseini, H., Moqeem, A. A., Mirza, F., and Lindén, M. (2017). A systematic review of wearable patient monitoring systems–current challenges and opportunities for clinical adoption. *Journal of medical systems*, 41(7):1–9.

Boudko, S. and Leister, W. (2019). Building blocks of negotiating agents for healthcare data. In *Proceedings of the 21st International Conference on Information Integration and Web-based Applications & Services*, pages 635–639.

Chapman, G. B. and Elstein, A. S. (1995). Valuing the future: Temporal discounting of health and money. *Medical decision making*, 15(4):373–386.

Direktoratet for e-helse (2018). Konseptvalgutredning for helseanalyseplattformen. [Online; accessed 2. Jun. 2021].

Eysenbach, G. (2001). What is e-health? *Journal of medical Internet research*, 3(2):e20.

Frederick, S., Loewenstein, G., and O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, 40(2):351–401.

Garmin (2021). Privacy policy for Garmin Connect, Garmin Sports and compatible Garmin devices. [Online; accessed 16. Jun. 2021].

IBM (2016). Linear Regression Variable Selection Methods. [Online; accessed 4. Jun. 2021].

Kalenscher, T. and Pennartz, C. M. (2008). Is a bird in the hand worth two in the future? the neuroeconomics of intertemporal decision-making. *Progress in neurobiology*, 84(3):284–315.

Kaplan, B. (2016). 21-item-mcq.pdf. [Online; accessed 2. Jun. 2021].

Kaplan, B. A., Amlung, M., Reed, D. D., Jarmolowicz, D. P., McKerchar, T. L., and Lemley, S. M. (2016). Automating scoring of delay discounting for the 21- and 27-item monetary choice questionnaires. *The Behavior Analyst*, 39(2):293–304.

Kirby, K. N. and Maraković, N. N. (1996). Delay-discounting probabilistic rewards: Rates decrease as amounts increase. *Psychonomic bulletin & review*, 3(1):100–104.

Kirby, K. N., Petry, N. M., and Bickel, W. K. (1999). Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. *Journal of Experimental psychology: general*, 128(1):78.

Mischel, W., Ebbesen, E. B., and Raskoff Zeiss, A. (1972). Cognitive and attentional mechanisms in delay of gratification. *Journal of personality and social psychology*, 21(2):204.

Mischel, W., Shoda, Y., and Rodriguez, M. I. (1989). Delay of gratification in children. *Science*, 244(4907):933–938.

N.A. (2019). Health Democratization – IKTPLUSS NFR project - NTNU. [Online; accessed 2. Jun. 2021].

Odum, A. L. (2011). Delay discounting: trait variable? *Behavioural processes*, 87(1):1–9.

Rajbhandari, L. and Snekkenes, E. (2013). Using the conflicting incentives risk analysis method. In *IFIP International Information Security Conference*, pages 315–329. Springer.

Regan, P. M. (2002). Privacy as a common good in the digital world. *Information, Communication & Society*, 5(3):382–405.

Scholten, H., Scheres, A., De Water, E., Graf, U., Granic, I., and Luijten, M. (2019). Behavioral trainings and manipulations to reduce delay discounting: A systematic review. *Psychonomic bulletin & review*, 26(6):1803–1849.

Spil, T. and Klein, R. (2014). Personal health records success: why google health failed and what does that mean for microsoft healthvault? In *2014 47th Hawaii International Conference on System Sciences*, pages 2818–2827. IEEE.

Steel, P. and König, C. J. (2006). Integrating theories of motivation. *Academy of management review*, 31(4):889–913.

Steinsbekk, K. S., Ursin, L. Ø., Skolbekken, J.-A., and Solberg, B. (2013). We're not in it for the money—lay people's moral intuitions on commercial use of 'their' biobank. *Medicine, Health Care and Philosophy*, 16(2):151–162.

Steward, T., Mestre-Bach, G., Fernández-Aranda, F., Granero, R., Perales, J. C., Navas, J. F., Soriano-Mas, C., Baño, M., Fernández-Formoso, J. A., Martín-Romera, V., et al. (2017). Delay discounting and impulsivity traits in young and older gambling disorder patients. *Addictive Behaviors*, 71:96–103.

Sunyaev, A. (2013). Evaluation of microsoft healthvault and google health personal health records. *Health and Technology*, 3(1):3–10.

Szekeres, A. and Snekkenes, E. A. (2019). Predicting ceo misbehavior from observables: Comparative evaluation of two major personality models. In *E-Business and Telecommunications. ICETE 2018. Communications in Computer and Information Science*, volume 1118, pages 135–158. Springer, Cham.

Szekeres, A. and Snekkenes, E. A. (2020). Construction of human motivational profiles by observation for risk analysis. *IEEE Access*, 8:45096–45107.

Thaler, R. H. and Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness*. Penguin.

WHO (2021). International Statistical Classification of Diseases and Related Health Problems (ICD). [Online; accessed 4. Jun. 2021].

Yarkoni, T. and Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, 12(6):1100–1122.

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