Incentivizing User Input for Data Enrichment

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Abstract:

Companies increasingly rely on individual-level data to make decisions. To collect such data, they often ask users to manually enrich existing data sources. This paper studies how such manual data enrichment can best be incentivized. Across two field experiments, we differentiate incentives that benefit participants themselves and incentives that benefit others and measure their effect on (i) participation in manual data enrichment and (ii) the quality of information shared. The studies are conducted in a restaurant where guests have the chance to scan an NFC-enabled drinking glass (Smartglass) using their smartphones and can subsequently provide information through a mobile-optimized survey in return for an incentive. Our results suggest that the effect of incentive amount on the quality of information follows a U-shaped pattern, while participation is rather inelastic to different incentives. We explain our findings based on the theory of self-concept maintenance.

Keywords: Internet of Things, incentives, manual data enrichment

Track: Innovation Management & New Product Development

1. Introduction

Individual-level data are becoming increasingly important to identify behavioral patterns, understand consumption preferences, or optimize existing offerings. Therefore, companies and other organizations invest substantial effort into collecting such data. For example, in Germany, the Robert-Koch-Institute launched the Corona data donation app to better understand the spread of COVID-19. The app automatically collects behavioral and health data from consenting users' smartwatches, but also asks users to manually share additional information like their gender, age, weight, and height. Similarly, the annual census initiative in Germany uses individual-level data to learn about citizens' living and working conditions. To this end, it automatically collects data from municipalities' population registers but also requires selected citizens to indicate additional information manually. Also, in many commercial settings, companies need to entice their customers to provide information to enrich existing data manually.

For manually collecting data, companies must overcome two major hurdles: Customers must (i) be willing to participate in manual data enrichment (*participation*) and (ii) provide correct information in the process (*quality of information shared*). Unlike governmental organizations (e.g., census), which can make information sharing mandatory through the threat of fines, companies can only entice their customers to share information by offering incentives. Therefore, the present paper explores the effect of different incentives on participation and the quality of information shared. We follow conventions from extant literature on incentivization (e.g., Deutskens, de Ruyter, Wetzels, & Oosterveld, 2004; Furse & Stewart, 1982) and distinguish the effects of self- (Inc_{self}, i.e., those which benefit customers themselves) and other-oriented incentives (Inc_{other}, i.e., those which benefit others, most prominently in the form of a donation to charity). Following standard utility theory (e.g., Jensen, 1967), we hypothesize that the offered incentive amount (Inc_{self} or Inc_{other}) positively relates to participation in manual data enrichment. Drawing on the theory of self-concept maintenance (Mazar, Amir, & Ariely, 2008), we hypothesize that the effect of incentive amount (Inc_{self} or Inc_{other}) on the quality of information follows a U-shaped pattern.

Our study differs from extant research in that it takes place in a real-world setting: We gather responses from actual customers rather than online survey participants or subjects in a lab environment. We test our hypotheses in two field experiments, during which customers of a restaurant could interact with a novel Internet of Things (IoT) device, namely a Near Field Communication (NFC)-enabled drinking glass (Smartglass). Customers could scan the glass with their smartphones and were then asked to respond to a mobile-optimized survey in return for different incentives. We experimentally varied the type and amount of incentives over time and measured their effect on participation in manual data enrichment and the quality of information shared.

2. Literature Review

We review the extant literature on the effect of self- and other-oriented incentives on our two outcomes of interest, namely (i) participation and (ii) the quality of information shared.

2.1 Participation

Overall, extant literature presents somewhat conflicting findings regarding the effect of incentives on participation. Early evidence from mail surveys suggests that participation increases if participants directly benefit from the incentives (e.g., Furse & Stewart, 1982; Gendall & Healey, 2010; Robertson & Bellenger, 1978). Similarly, several studies on participation in online surveys also identify a positive effect of incentives on participation (e.g., Conn, Mo, & Sellers, 2019; Deutskens et al., 2004). However, other studies contradict these findings and report no significant effects of incentives on participation (e.g., Porter & Whitcomb, 2003).

The lack of consensus in the literature may imply that the effects could be context specific to some extent. For example, the theory of prosocial behavior suggests that participants may react negatively to monetary incentives if they are already intrinsically motivated. The additional incentives may then deprive them of the opportunity to participate for intrinsic reasons (e.g., Bénabou & Tirole, 2006; Gneezy, Meier, & Rey-Biel, 2011). Similarly, relational incentives theory states that incentives are only beneficial if they align with the type of relationship between the incentivizing and incentivized party (Gallus, Reiff, Kamenica, & Fiske, 2022). For example, incentives tend to be beneficial in market pricing relations but backfire in communal sharing relationships (Gallus et al., 2022).

2.2 Quality of information

The quality of information is influenced by two different factors. On the one hand, it depends on respondents’ diligence: Respondents may not pay sufficient attention and, as a side effect of this laziness, provide non-truthful information. On the other hand, it depends on their honesty: Respondents may consciously provide non-truthful information.

Extant research suggests incentives have little to no impact on diligence in information sharing. Past studies have measured diligence using different operationalizations including item non-response (e.g., Furse & Stewart, 1982; Hubbard & Little, 1988), number of "don't know" answers (Deutskens et al., 2004), straight lining (Göritz, 2004), correct answers to attention checks (Conn et al., 2019), and length of responses to open-ended questions (Hansen, 1980). Independent of how diligence is measured, most studies find no significant effect of incentives on diligence. An exception is Hansen (1980), who finds that offering monetary and non-monetary incentives results in decreased diligence relative to offering no incentive.

The effect of incentives on honesty is understood chiefly from a theoretical view, with little empirical evidence. Specifically, extant theory suggests that low incentive amounts may increase dishonest behavior, while high incentive amounts may curb dishonesty. Mazar, Amir, and Ariely (2008) advance in their theory of self-concept maintenance that most individuals behave dishonestly only to a limited extent: They aim to benefit from dishonest behavior, but only to a point where they can still see themselves in a positive light, i.e., maintain a positive self-concept. Individuals do so by using certain neutralization techniques that allow them to mentally categorize or re-interpret their dishonest behavior in a self-concept-compatible way (e.g., Barkan, Ayal, Gino, & Ariely, 2012; Hochman, Peleg, Ariely, & Ayal, 2021; Mazar et al., 2008; Sykes & Matza, 1957). If an individual can re-interpret a dishonest behavior without much difficulty, the behavior is said to have high *categorization malleability*. In contrast, it is said to have low categorization malleability if such a re-interpretation is rather difficult or even impossible (Mazar et al., 2008). According to Jones (1991), a behavior's categorization malleability depends, among others, on the magnitude of consequences, defined as "the sum of the harms (or benefits) done to victims (or beneficiaries) of the moral act in question" (Jones, 1991, p. 374). Applied to our context, the magnitude of consequences is given by the incentive amount offered in return for information shared. Accordingly, we expect situations which offer a rather low incentive amount to have a high categorization malleability and be more prone to inviting dishonest behavior, while we expect the opposite to hold for situations with a rather high incentive amount.

3. Hypotheses

According to standard utility theory (e.g., Jensen, 1967), individuals should prefer to receive a higher incentive over a lower one to maximize their own utility. We, therefore, expect that participation will increase along with the incentive amount for both Inc_{self} and Inc_{other}:

H1a: The amount of Inc_{self} and respondents’ participation in manual data enrichment are positively related.

H1b: The amount of Inc_{other} and respondents’ participation in manual data enrichment are positively related.

Regarding the quality of information shared, we need to differentiate the effects of incentives on (i) diligence and (ii) honesty. In line with extant literature, we do not foresee that incentives should bear a significant effect on diligence. However, we anticipate that incentive amount and honesty are related through a U shape, following the theory of self-concept maintenance (Mazar et al., 2008). We argue that incentives, and their specific amounts, can alter a behavior’s categorization malleability: If only a relatively small incentive amount is offered, respondents may decide to reap a benefit without sharing honest information in return. The situation’s categorization malleability is relatively high and allows respondents to do so without feeling the necessity to re-evaluate their self-view. As a result, we expect honesty to decrease for small incentives. As the incentive amount increases further, however, the stakes for the defrauded party become higher, and it becomes harder to categorize a dishonest act as aligned with the self-view. Hence, honesty is set to increase.

Taken together, we hypothesize a U-shaped relation between incentive amount and the quality of information shared:

H2a: The effect of an incentive amount on respondents’ quality of information shared in manual data enrichment follows a U-shaped pattern for Inc_{self}.

H2b: The effect of an incentive amount on respondents’ quality of information shared in manual data enrichment follows a U-shaped pattern for Inc_{other}.

4. Empirical Studies

4.1 Experimental design and sample

We conducted two field experiments in a large-scale German restaurant, one four-week experiment in 2020 and one eight-week experiment in 2021, with stable COVID regulations. In both experiments, customers had the opportunity to interact with an NFC-enabled drinking glass (Smartglass) during their visit. The restaurant’s management introduced the technology to explore how it could be used to collect information about customers it would otherwise not obtain. It also wanted to see which incentives would be most effective in motivating customers to share such information. The restaurant placed a flyer on each table with information about the NFC compatibility of the glass and instructions on how to scan it using a smartphone. If a customer decided to scan a glass, they were asked to provide answers to a mobile-optimized survey and, in return, could reap certain benefits. Hereafter, we describe the underlying process (see Figure 1).

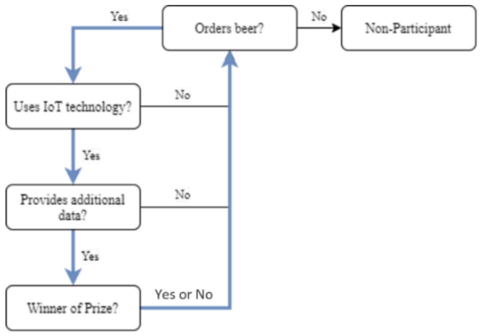

Figure 1. Experimental Framework

In the first step, a customer could decide to use the device, i.e., scan a Smartglass with their NFC-enabled smartphone. Each use of the device automatically triggered a data entry in the Cloud, including information such as the ID of the scanned glass, time of the scan, size of the glass, and customer's device type. At this stage, customers were not yet aware of any incentives.

After a customer scanned a glass, a survey would open on their smartphone, prompting them to provide certain information. Among others, the survey asked customers two identification questions: they had to indicate the first four letters of their street name and their day of birth. Jointly, the two answers served as an anonymized, unique customer identifier, which was used to track repeated usage behavior and to gauge the quality of information shared (see Section 4.3). We informed customers on the first page of the survey as to how their efforts would be rewarded and experimentally varied the incentives over time. Incentives that benefitted participants themselves (Inc_{self}) consisted of lottery prizes that customers could redeem immediately at the restaurant if they were among the lucky finders of a winning glass. Their total value varied every week. Incentives that benefitted others (Inc_{other}) consisted of donating to a local charity for every completed survey. We varied the donation amount per completed survey daily on a systematic basis.

To encourage customers to answer all survey questions, we informed them only on the last page of the survey whether their glass was a winner and enabled them to redeem a prize. Customers could then decide to order another drink, scan the corresponding Smartglass, provide data in the survey, and see if they found one of the winning glasses.

In total, the restaurant served 20,821 drinks in a Smartglass, of which 18.24% were scanned (3,798 scans). 84.62% of scans resulted in a complete survey response (3,214 survey responses), 5.69% of which contained non-truthful data (183 surveys). Out of the 2,002 distinct guests taking the survey, 31.67% engaged in several scans (634 customers).

4.2 Experimental manipulations

In Study 1, Inc_{self} existed in two amounts, a high (20 sample beers per week, equivalent to a daily prize amount of €18.80) and a low quantity (10 sample beers per week, equivalent to a daily prize amount of €9.40). Since the restaurant was wary of asking its guests to provide information without any reward, our experimental design did not contain a condition without Inc_{self}. Inc_{other} was either present (€0.10 donation to a local charity per completed survey) or absent. In Study 2, Inc_{self} also existed in two amounts, a high (40 sample beers per week, equivalent to a daily prize amount of €37.60) and a low quantity (5 sample beers per week, equivalent to a daily prize amount of €4.70). Inc_{other} was either high (€0.50 donation to a local charity), low (€0.10 donation to a local charity), or absent.

4.3 Operationalization of outcome variables

We operationalize participation as the percentage of Smartglass scans that resulted in a complete survey response. Here, the number of scans, rather than the number of customers, serves as the baseline for the participation rate because (i) it is less affected by daily fluctuations in customer numbers and (ii) customers learned about the offered incentives on the first page of the survey, i.e., only after scanning.

To operationalize the quality of information, we test whether the information from the two identification questions is incorrect according to objective standards. A response is deemed incorrect if the provided street name initials do not match those of any of the street names in a comprehensive street list of Germany and/or if the customer indicated a nonsensical number as their day of birth. We do not differentiate whether a response was incorrect due to dishonest behavior or a lack of diligence but instead focus on their joint influence. We also acknowledge that this measure likely underestimates the number of incorrect entries since an answer can be incorrect in other ways. Still, it should serve well as a floor estimate of incorrect responses.

5. Results

We regress our experimental conditions on (i) participation in manual data enrichment and (ii) the quality of information shared. Given the field study character of our experiment, we additionally account for several control variables. Regarding participation, we can control only for information collected outside of the survey, such as the size of the Smartglass, the device type used for scanning, the timing of the scan (hour of the day and weekend vs. weekday), and weather-related factors, e.g., rain and temperature, as they may affect consumption and consequentially IoT usage behavior. Regarding the quality of information, we additionally control for information collected or inferred from the survey (gender, age, prior NFC experience, fulness of glass, scan motivation, repeat scans).

4.1 Participation

We summarize our regression results with participation as the dependent variable in Table 1. We do not observe a significant effect of the low-$\text{Inc}_{\text{other}}$ condition on participation relative to the no-$\text{Inc}_{\text{other}}$ condition in either study ($p_{1,2} > .1$). However, there is a significantly negative effect of the high-$\text{Inc}_{\text{other}}$ condition on participation relative to the low-$\text{Inc}_{\text{other}}$ condition ($p_2 < .05$) and also relative to the no-$\text{Inc}_{\text{other}}$ condition ($p_2 < .1$) in Study 2. We see a negative effect of the high-Inc_{self} condition on participation relative to the low-Inc_{self} condition, which reaches significance in Study 2 ($p_2 < .05$). Overall, our results do not support H1a and H1b.

DV: Participation	Study 1		Study 2	
Independent variables	β	*p*	β	*p*
Intercept	2.29	*	1.72	***
Experimental manipulations:				
Inc_{self} (high vs. low)	-0.14	n.s.	-0.29	**
$\text{Inc}_{\text{other}}$ (low vs. none)	-0.22	n.s.	0.12	n.s.
$\text{Inc}_{\text{other}}$ (high vs. low)			-0.41	**
$\text{Inc}_{\text{other}}$ (high vs. none)			-0.30	*
Scan-level control variables:				
Glass size (large vs. small)	-0.38	**	-0.06	n.s.
Device type (Android vs. other)	0.01	n.s.	0.04	n.s.
Hour of the day	0.01	n.s.	0.01	n.s.
Weekend (vs. weekday)	0.18	n.s.	-0.05	n.s.
Rain	-5.38	n.s.	50.72	*
Temperature	-0.01	n.s.	-0.01	n.s.

p<.001 ****; *p*<.01 ***; *p*<.05 **; *p*<.10 *; *p*>.10 n.s.

Table 1. Logistic Regression of Incentive Conditions on Participation

4.2 Quality of information

We observe a significantly negative effect of the low-$\text{Inc}_{\text{other}}$ condition on the quality of information relative to the no-$\text{Inc}_{\text{other}}$ condition ($p_{1,2} < .05$; controlling for survey responses: $p_1 < .1$, $p_2 < .01$). Furthermore, results from Study 2 show a significantly positive effect of the high-$\text{Inc}_{\text{other}}$ condition on the quality of information relative to the low-$\text{Inc}_{\text{other}}$ condition ($p_2 < .05$; controlling for survey responses: $p_2 < .01$), however, only a non-significant effect relative to the no-$\text{Inc}_{\text{other}}$ condition ($p_2 > .1$). Finally, we detect a significantly positive effect of the high-Inc_{self} condition on the quality of information relative to the low-Inc_{self} condition ($p_1 < .05$, $p_2 < .001$; controlling for survey responses: $p_1 < .01$, $p_2 < .001$) in both studies (Table 2).

These results support H2a and H2b (although we cannot test for all hypothesized relationships).

DV: Quality of Information	Study 1				Study 2			
Independent variables	β	*p*	β	*p*	β	*p*	β	*p*
Intercept	1.52	n.s.	-1.38	n.s.	-0.42	n.s.	-2.87	**
Experimental manipulations:								
Inc_{self} (high vs. low)	0.72	**	0.98	***	0.74	****	0.83	****
Inc_{other} (low vs. none)	-0.53	**	-0.49	*	-0.48	**	-0.63	***
Inc_{other} (high vs. low)					0.66	**	0.81	***
Inc_{other} (high vs. none)					0.18	n.s.	0.18	n.s.
Scan-level control variables:								
Glass size (large vs. small)	0.07	n.s.	0.08	n.s.	-0.39	*	-0.43	*
Device type (Android vs. other)	0.14	n.s.	0.29	n.s.	-0.30	n.s.	-0.20	n.s.
Hour of the day	-0.01	n.s.	-0.02	n.s.	0.14	***	0.12	**
Weekend (vs. weekday)	0.64	**	0.48	n.s.	0.26	n.s.	0.29	n.s.
Rain	120.3	**	117.7	**	19.75	n.s.	8.36	n.s.
Temperature	0.09	*	0.13	**	0.09	***	0.10	***
Survey-level control variables:								
Gender (female vs. other)			0.26	n.s.			0.03	n.s.
Year of birth (1950s vs. <1950s)			-0.35	n.s.			1.85	**
Year of birth (1960s vs. <1950s)			0.70	n.s.			1.58	**
Year of birth (1970s vs. <1950s)			0.13	n.s.			1.31	**
Year of birth (1980s vs. <1950s)			0.75	n.s.			1.77	***
Year of birth (1990s vs. <1950s)			0.87	n.s.			1.82	***
Year of birth (2000s vs. <1950s)			0.45	n.s.			2.08	***
NFC experience (yes vs. no)			-0.78	***			0.09	n.s.
Fulness of glass (full vs. empty)			0.86	*			0.26	n.s.
Fulness of glass (>1/2 vs. empty)			0.14	n.s.			0.56	*
Fulness of glass (<1/2 vs. empty)			0.10	n.s.			0.51	*
Motivation (curiosity vs. other)			0.97	**			0.25	n.s.
Motivation (raffle vs. other)			1.18	**			0.15	n.s.
Motivation (hint before visit vs. other)			0.18	n.s.			-1.31	*
Motivation (hint by other guests vs. other)			0.56	n.s.			-0.11	n.s.
Motivation (observing other guests vs. other)			0.41	n.s.			-0.17	n.s.
Motivation (scan in front of friends vs. other)			0.02	n.s.			-0.48	n.s.
Number of scans (multiple vs. single)			1.55	****			1.04	***
Scan number (subsequent vs. first scan)			0.23	n.s.			0.04	n.s.

p<.001 ****; *p*<.01 ***; *p*<.05 **; *p*<.10 *; *p*>.10 n.s.

Table 2. Logistic Regression of Incentive Conditions on Quality of Information

6. Conclusion

Our evidence from two field experiments suggests that incentives can have a positive effect on the quality of information, however, only if they are large enough. In other words, introducing a small incentive amount leads to a decrease in the quality of information, but a further increase in the incentive amount again yields a higher quality. Thereby, we show that the theory of self-concept maintenance is transferable to the setting of IoT-mediated information sharing. On the other hand, participation in manual data enrichment seems not to require any incentivization. Arguably, guests' curiosity about the technology and their intrinsic motivation is already sufficient to drive participation.

Future research could replicate our experiments in other contexts to learn how our findings generalize to other applications of manual data enrichment. It could also explore alternative ways to measure the quality of information. Finally, we encourage future research to study settings where a condition without any incentive is feasible.

7. Literature

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