# The Impact of Attitudinal and Behavioral Customer Characteristics on the Adoption of Behavior Tracking-based Services

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# The Impact of Attitudinal and Behavioral Customer Characteristics on the Adoption of Behavior Tracking-based Services

**Abstract**

Despite their widespread adoption in private contexts, knowledge of consumers' acceptance of behavior tracking-based services (BTS) in business contexts is sparse. In this study, BTS are defined as services that require detailed tracking of individual user behavior as a prerequisite to their value proposition of providing economic benefits to customers whose behavior aligns with the service provider's objectives. The goal of this study is to investigate the determinants of BTS adoption, particularly the influence of attitudinal and behavioral customer characteristics. The results suggest that behavioral constraint expectations have negative impact, while willingness to change behavior, perceived goal congruence, and GPS-enabled application usage are positively related to BTS adoption. Moreover, the presence of interaction effects of customer characteristics with perceived benefits and risks is confirmed. These findings contribute to existing research on the antecedents of BTS adoption.

*Keywords: behavior tracking-based services, pay-as-you-live, pay-as-you-drive*

*Conference Track: Services Marketing*

## 1. Introduction and background

Driven by the advancements in information technologies, behavior tracking-based services (BTS) gain in relevance. BTS are most popular in private contexts (e.g., self-tracking apps for personal sports activities) but increasingly become more relevant in business contexts such as healthcare and financial services. For example, Discovery Bank calls itself the first behavioral bank (Forbes, 2020) as it segments and serves customers based not only on their income, but also on more general behaviors and therefore represents “the bank that watches your every move” (Browdie, 2019, p. 1). To reduce their cost or business-related risk, BTS providers incentivize their customers to adopt certain behaviors. Carsharing customers are rewarded with credit if they fill up the tank after the trip, bank customers will have waived their account fees if they make certain transaction volumes and insurance customers pay reduced premiums when they engage in low-risk behavior. The prerequisite to provide such economic benefits is the constant monitoring of customer behavior. Research has developed a considerable body of studies investigating factors that affect the acceptance of general data-intensive services, such as smart home (e.g., Hong, Nam, & Kim, 2020) mobile (e.g., Shareef, Baabdullah, Dutta, Kumar, & Dwivedi, 2018) location-based (e.g., Min, So, & Jeong, 2019), and cloud-based services (e.g., Lee & Brink, 2020). However, little research has been carried out to specifically examine BTS and scholars recently called for more work on their adoption (Soleymanian, Weinberg, & Zhu, 2019). In this study, BTS are defined as a type of service that requires continuous tracking of individual user behavior as a prerequisite to its value proposition of offering economic benefits to customers when individual behavior is in line with the goals of the service provider. Thus, acceptance of BTS may be more contingent on existing habits and related attitudes than other technology-mediated smart services because service outcomes are dependent on individual user behavior by definition. As such, the goal of this research is to study both the direct and indirect effects of attitudinal and behavioral customer characteristics on BTS adoption.

## 2. Conceptual model and hypotheses

The extant literature on smart service adoption mainly draws on the technology acceptance model (TAM) and the value-based adoption model (VAM) and generalized findings are that perceived value (or benefits) are weighed against the perceived costs (or risks) of adoption. Figure 1 presents the conceptual model of BTS adoption guiding this study. It reflects previous research by including perceived benefits and perceived risks as key determinants and expands the current state of research by adding attitudinal and behavioral customer characteristics as major influencing factors of BTS adoption.

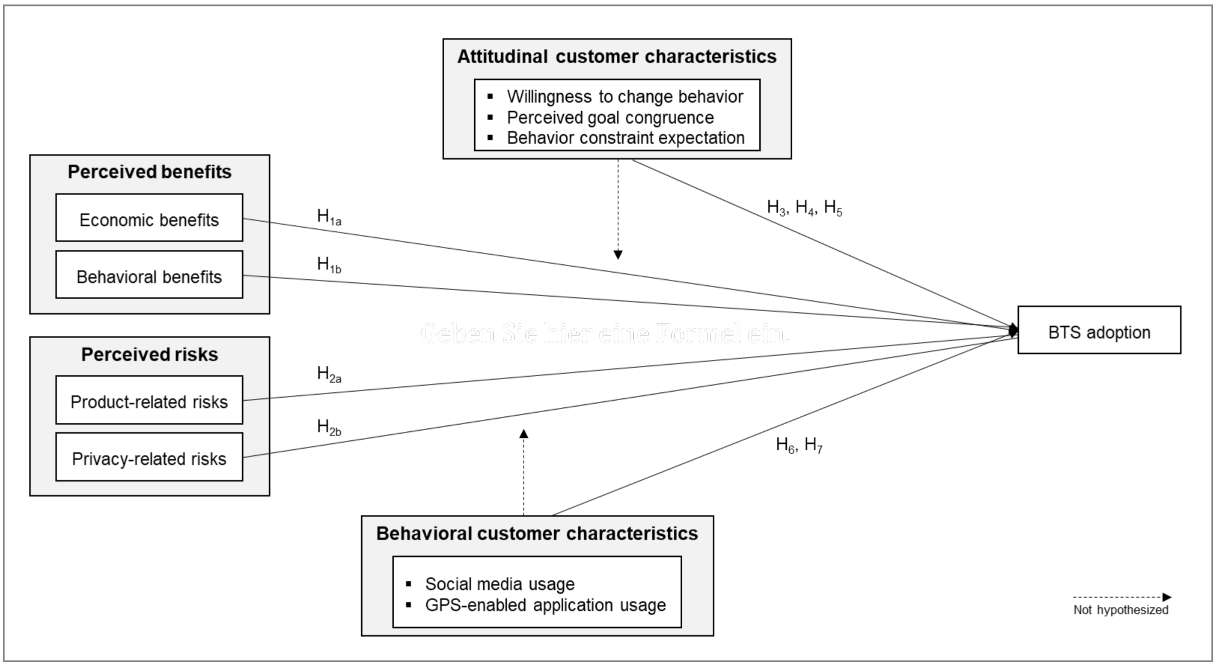


Figure 1: Conceptual model of BTS adoption

Overall, nine hypotheses are put forward. For reasons of parsimony, the following section only briefly outlines the hypotheses development to provide an overview of the basic theoretical rationale. In addition, as the first four proposed relationships have already been established by previous research on BTS adoption, $H_{1a}$ through $H_{2b}$ are not elaborated below.

**$H_{1a}$:** Perceived economic benefits are positively associated with BTS adoption.

(Gerpott & Berg, 2013, personal benefits)

**$H_{1b}$:** Perceived behavioral benefits are positively associated with BTS adoption.

(Gerpott & Berg, 2013; Wiegard & Breitner, 2019, perceived benefits)

**$H_{2a}$:** Perceived product-related risks are negatively associated with BTS adoption.
(Gerpott & Berg, 2013; importance of technical system quality)

**$H_{2b}$:** Perceived privacy-related risks are negatively associated with BTS adoption.

(Gerpott & Berg, 2013; Wiegard & Breitner, 2019, privacy concerns)

Regarding attitudinal characteristics, three psychological states are proposed to influence BTS adoption: First, *willingness to change behavior* is considered a key determinant as BTS reward certain customer behaviors and thus demand behavior change from its users for them to receive favorable service outcomes. Prior to adoption of the new service, it may not be entirely recognizable for customers what the exact goals and ideal behaviors will be, what effort it takes and how much individuals need to adopt to reach the requirements in order to benefit from the reward. Therefore, individuals must demonstrate a basic willingness to change behaviors to increase their chances to receive favorable service outcomes from BTS.

**H$_3$**: Willingness to change behavior is positively associated with BTS adoption.

Depending on an individual's personal goals, there might be a better or worse match of BTS goals and customer goals. If a potential customer enjoys behaviors opposite to what BTS envision, there is a lack of *goal congruence*. Conversely, in case an individual already approves and pursues behaviors that BTS reward anyway, a higher level of *goal congruence* is present and adoption of BTS will become more likely.

**H$_4$**: Perceived goal congruence is positively associated with BTS adoption.

In a similar vein, if pre-adoption behaviors are very dissimilar to the behavioral goals defined by BTS, larger *behavioral constraints expectations* may arise for individuals as they adopt BTS. If potential users expect to be too restricted in their routines, or if they fear losing their freedom to live a carefree life, adoption of BTS becomes more unlikely.

**H$_5$**: Behavioral constraint expectation is negatively associated with BTS adoption.

Regarding behavioral characteristics, two BTS-related behaviors are proposed to influence BTS adoption: *social media usage* and *GPS-enabled application usage*. BTS demand a high level of trust and consent from their users in terms of data privacy. As BTS collect and store sensitive personal information, users might be concerned about data misuse, data breach and other consequences that could lead to major disadvantages for customers. Users of social media and GPS-enables applications demonstrate that they do not reject the conditions of services, that collect a lot of sensitive personal data points. Although the types of data shared in social media differ to location sharing in GPS-enabled apps, both represent rather intimate kinds of information, similar to the types of data that BTS typically demand. Thus, if a customer already utilizes such services, BTS adoption becomes more likely.

**H$_6$**: Social media usage is positively associated with BTS adoption.

**H$_7$**: GPS-enabled application usage is positively associated with BTS adoption.

## 3. Empirical study

### *3.1 Data collection and sample*

To test the hypotheses, the context of usage-based insurance (UBI) was selected.[1] UBI is a recent innovation in car insurance that allows insurers to collect individual-level driving data, provide feedback on driving behavior and offer tailored discounts depending on each customer's driving behavior (Soleymanian et al., 2019). UBI typically uses onboard sensors in connection with mobile apps to collect sensor- and satellite-based GPS location, driving behavior and context data. On this basis, users receive individualized premiums that are lower (or potentially higher) depending on their individual driving style and accident risk.

A scenario-based online survey was conducted with a random sample of insurance customers of a Swiss insurance company. The company did not yet introduce UBI offerings but was considering the implementation of such tariffs in the future. In the survey, the mechanism of a new UBI-offering was clearly described to participants at the beginning followed by questions regarding their overall perception and judgement of it. This resulted in 1.202 completed responses. Table 1 depicts the sample characteristics.

**Table1: Sample description**

| Variable | Category | Frequency | % |
|---|---|---|---|
| Gender | Male | 747 | 62.1 |
| | Female | 455 | 37.9 |
| Age | 18 - 25 | 167 | 13.9 |
| | 26 - 35 | 264 | 22.0 |
| | 36 - 45 | 244 | 20.3 |
| | 46 - 55 | 247 | 20.5 |
| | 56 or above | 280 | 23.3 |
| Income | Less than CHF 4.000 | 213 | 17.7 |
| | CHF 4.001 – CHF 6.000 | 323 | 26.9 |
| | CHF 6.001 – CHF 8.000 | 234 | 19.5 |
| | CHF 8.001 – CHF 10.000 | 132 | 11.0 |
| | More than CHF 10.000 | 140 | 11.6 |
| | N/A | 160 | 13.3 |

Note: Sample size n = 1.202

### *3.2 Measures*

Survey measures for the questionnaires were developed building on prior research. The constructs of the study were operationalized each with three to five items adapted from the

[1] In extant literature, UBI is also referred to as pay-as-you-drive (PAYD), which represents a similar concept.

literature. For example, economic and behavioral benefits each were measured with three items adapted from Gerpott and Berg (2013). All requirements for psychometric properties were met. For reasons of parsimony in the company-led survey, variables on customer characteristics needed to be operationalized as single-item measures (Bergkvist & Rossiter, 2007). Also, the dependent variable BTS adoption "Would you enroll in a usage-based insurance policy?" was operationalized as single-item with a 3-point ordinal scale labeled with (1) "no", (2) "undecided", and (3) "yes". In the proposed model, multicollinearity seems not to be an issue because the maximum variance inflation factor was well below the threshold of 10 (VIF = 2.02; Hair, Black, Babin, & Anderson, 2013).

*3.3 Results*

To test the hypotheses, an ordinal logistic regression using a complementary log-log link function was estimated because the dependent variable was found to be left skewed, i.e., higher categories are more probable.[2] Table 2 details the analysis results of two models: Model 1 includes the control variables and Model 2 contains the main effects.[3] The results confirm that perceived benefits (economic benefits $\beta = .519$, SE = .082, $p < .0001$; behavioral benefits $\beta = .178$, SE = .058, $p < .01$) have a positive effect and perceived risks (product-related risks $\beta = -.130$, SE = .053, $p < .05$; privacy-related risks $\beta = -.368$, SE = .053, $p < .0001$) have a negative significant influence on BTS adoption. Moreover, attitudinal customer characteristics affect BTS adoption as predicted: Both willingness to change behavior ($\beta = .133$, SE = .036, $p < .001$) as well as perceived goal congruence ($\beta = .201$, SE = .051, $p < .0001$) positively affect BTS adoption while behavior constraint expectation ($\beta = -.148$, SE = .027, $p < .0001$) is negatively related. Regarding behavioral customer characteristics, GPS-enabled application usage has a significant positive influence on BTS adoption ($\beta = .213$, SE = .072, $p < .01$). In contrast, the relation of social media usage with BTS adoption ($\beta = -.016$, SE = .070, $p > .05$) is not significant. The effect sizes in the form of hazard ratios (HR), suggest that for every one-unit increase in, for example, economic benefits (HR = 1.68), the odds of being more likely to adopt BTS is multiplied by 1.68 times (i.e., increases 68%), holding constant all other variables. In absolute terms, the descending order of effect sizes is economic benefits (+68%), privacy-related risks (-31%), GPS-enabled application usage (+24%), perceived goal congruence (+22%), behavior constraint expectation (-14%), willingness to change behavior (+14%), and product-related risks (-12%).

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[2] Robustness checks with alternative regression model estimations such as logit and OLS lead to concurring results in terms of significance, direction and magnitude of effects.

[3] Due to space constraints, the moderated regression model is not included in the table. Instead, the results of additional significant interaction terms are reported within section 3.4.

**Table 2: Ordinal Regression Estimates of BTS Adoption**

| Variable | *β* | SE | *p* | HR | *β* | SE | *p* | HR |
|---|---|---|---|---|---|---|---|---|
| **Main Effects** | | | | | | | | |
| Economic benefits | | | | | .519 | .082 | <.0001 | 1.68 |
| Behavioral benefits | | | | | .178 | .058 | .002 | 1.19 |
| Product-related risks | | | | | -.130 | .053 | .013 | 0.88 |
| Privacy-related risks | | | | | -.368 | .053 | <.0001 | 0.69 |
| Willingness to change behavior | | | | | .133 | .036 | .000 | 1.14 |
| Perceived goal congruence | | | | | .201 | .051 | <.0001 | 1.22 |
| Behavior constraint expectation | | | | | -.148 | .027 | <.0001 | 0.86 |
| Social media usage | | | | | -.016 | .070 | .822 | 0.98 |
| GPS-enabled app usage | | | | | .213 | .072 | .003 | 1.24 |
| **Controls** | | | | | | | | |
| Gender (ref. cat. male) | .024 | .085 | .778 | 1.02 | -.217 | .096 | .023 | 0.80 |
| Age (ref. cat. '18-25') | | | | | | | | |
| 26 - 35 | .123 | .127 | .332 | 1.13 | .116 | .145 | .423 | 1.12 |
| 36 - 45 | .193 | .135 | .152 | 1.21 | .225 | .152 | .139 | 1.25 |
| 46 - 55 | .361 | .138 | .009 | 1.44 | .321 | .161 | .046 | 1.38 |
| 56 or above | .599 | .138 | <.0001 | 1.82 | .292 | .164 | .076 | 1.34 |
| Income (ref. cat. '< CHF 4.000') | | | | | | | | |
| CHF 4.001 – CHF 6.000 | .037 | .113 | .746 | 1.04 | -.027 | .123 | .827 | 0.97 |
| CHF 6.001 – CHF 8.000 | .214 | .135 | .113 | 1.24 | .258 | .148 | .083 | 1.29 |
| CHF 8.001 – CHF 10.000 | .177 | .162 | .274 | 1.19 | .174 | .177 | .325 | 1.19 |
| More than CHF 10.000 | .121 | .163 | .455 | 1.13 | .140 | .180 | .440 | 1.15 |
| N/A | -.275 | .140 | .049 | 0.76 | -.165 | .158 | .299 | 0.85 |
| Thresholds | | | | | | | | |
| No \| Undecided | -.975 | .130 | <.0001 | 0.38 | -.256 | .331 | .440 | 0.77 |
| Undecided \| Yes | .279 | .123 | .024 | 1.32 | 1.609 | .332 | <.0001 | 4.99 |
| *n* | | 1202 | | | | 1195 | | |
| Residual Deviance | | 2548.05 | | | | 1778.25 | | |
| AIC | | 2572.05 | | | | 1820.25 | | |
| $R^2$ (Nagelkerke) | | .04 | | | | .56 | | |

*3.4 Further exploratory analysis of interaction effects*

Besides hypotheses testing, additional analyses are carried out to investigate whether there are moderating effects of attitudinal and behavioral characteristics with perceived risks or benefits that influence BTS adoption. Table 3 exhibits the interactions terms that have a significant moderating impact, the remainder of interactions is insignificant.

**Table 3: Significant interactions with BTS Adoption**

| Interaction term | $\beta$ | SE | $p$ | HR |
|---|---|---|---|---|
| Economic benefits x behavior constraint expectation | -.057 | .029 | .049 | 0.94 |
| Behavioral benefits x perceived goal congruence | .137 | .061 | .024 | 1.15 |
| Product-related risks x willingness to change behavior | -.108 | .053 | .019 | 0.90 |

## 4. Discussion

The focus of the study was to investigate factors that affect the adoption of BTS services. As BTS demand detailed customer behavior to be tracked continuously on an individual level as a requirement for its key value proposition and value creation, the intent of this research was to examine the role of behavior-related attitudinal and behavioral customer characteristics on BTS adoption. In addition, established effects of perceived benefits and risks were validated to be in line with the results of prior research. This confirms the basic notion that consumers balance the risks (e.g., privacy risk) against benefits (e.g., economic benefits) in the process of deciding whether or not to adopt BTS.

The study findings contribute to the literature by demonstrating that four out of five hypothesized customer characteristics significantly affect BTS adoption. In addition, interaction effects that moderate established relationships of benefits and risks with BTS adoption were identified. While previous research has focused on many other determinants of BTS adoption (see Gerpott & Berg, 2013; Wiegard & Breitner, 2019) and considers main effects at large, this study expands current knowledge by showing that both attitudinal traits and behavioral characteristics exhibit both direct and indirect effects, and as such, are new antecedents to BTS adoption.

Regarding attitudinal customer characteristics, the finding that perceived goal congruence impacts the likelihood of service adoption suggests that customers judge BTS depending on how well they fit with their personal convictions and usual behaviors. In addition, the negative effect of behavioral constraint expectations suggests that customers are less likely to adopt BTS when they would need to cope with bigger behavioral changes and restrictions. This is the case if pre-adoption behavioral goals of individuals are not already well-aligned to BTS-specific goals, or, in conjunction with that, the willingness to change behavior is rather limited. This variable comes into play as a further determinant that was found to be positively related to BTS adoption, which may be a more foundational prerequisite of BTS acceptance. Overall, the results also point to potential interaction effects among attitudinal customer characteristics which could be a worthwhile topic for future research.

Regarding behavioral customer characteristics, a positive relation of GPS-enabled application usage was confirmed while the hypothesized effect of social media usage was not supported. These results may trace back to the specific study context of UBI which in comparison to social media is much more similar in terms of the data type that the service requires.

In light of this, service providers may promote BTS adoption by segmenting customers and tailoring their offerings according to the identified customer characteristics. For example, companies that provide mobile apps for users to handle their customer accounts may be able to determine which individuals already use GPS-enabled applications. Because BTS require behavioral sacrifices and a great deal of discipline from their clients, they can be more of a deterrent. For this reason, it is particularly important for BTS providers not only to create a purely functional service, but also to highlight (non-monetary) behavioral benefits such as improved health or higher road safety.

Finally, as companies likely will collect more and more behavioral customer data in the future, it can be expected that over the next few years an increasing number of BTS-offerings will hit the market. Against this, future research may consider BTS as worthwhile research theme for further investigation. For example, it may study in more depth the spheres of value creation and co-creation in the context of BTS (Grönroos & Voima, 2013). In this regard, it may be of interest to better understand the mechanisms of continuously providing personalized behavioral feedback interventions for customers when using BTS as a potential source for additional value creation.

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