THE EFFECTS OF A FLEET-MANAGEMENT APP ON DRIVER BEHAVIOR

Research in Progress

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Abstract

Whereas implementing a mobile application (app) in support of organizational processes is quite common in contemporary organizations, only few empirical studies have investigated the effects of app implementation on employee behavior. This study aims at exploring the effects of a fleet-management app on the behavior of drivers, in particular the extent to which they are involved in risky behavior. We hypothesize that use of the app before driving reduces such behavior, and that this effect is mitigated by the existence of notifications while driving. These hypotheses are tested with data about 11,805 trips by 109 drivers employed in a large-scale organization. The preliminary results support the research hypotheses and confirm that the implementation of a fleet-management app has an organizational impact via an app-induced change in driver behavior.

Keywords: Mobile App, Fleet Management, Driving Incidents, Driver Behavior.

1 Introduction

As smartphone penetration is expected to reach 99% in North America and 92% in Western Europe until 2021 (Cisco Mobile VNI, 2017), it seems that the potential effects of mobile apps in an organizational context, by influencing employee behavior, have been largely neglected. Given that apps help users to share and collaborate, they have the potential to impact all organizational aspects (Torres et al., 2013). Despite this potential, only few studies so far have investigated the organizational impacts of apps (Knoesen and Seymour, 2016; Sørensen and Landau, 2015). Against this background, this study aims at contributing to existing knowledge about the organizational implications of app implementation by empirically investigating the behavioral effects of implementing a fleet-management app. Specifically, this study focuses on the following research question: Can a fleet-management app positively affect the behavior of employee drivers?

Risky driving behavior refers to hard braking, accelerating, speeding, and turning (Castignani et al., 2015; Musicant et al., 2010). Two technologies that can record and enable access to data about risky driving behavior are In-Vehicle Data Recorders (IVDRs) and apps. Unlike IVDRs, which improve driving only through real-time notifications and periodic reports, apps also allow pre-driving app use for training, feedback, learning, and analysis of previous trips anytime and anywhere. This study empirically explores how mobile apps influence driver behavior, by shifting the focus from notifications while driving to pre-driving app use, a capability that exists in apps but not in IVDRs.

Toward exploring the effects of a fleet-management app in the present study, a large-scale organization provided data collected from 109 employed drivers who performed 11,805 trips. The fleet-management app provides the studied organization with two main capabilities related to the risky behavior of its drivers: (1) real-time notifications to drivers while driving about their risky behaviors, and (2) the ability to explore driving behavior while the driver is not engaged in driving. Given these capabilities of the studied app, the data gathered facilitated the exploration of how risky behavior is affected by pre-driving app use and real-time notifications.

To set the background for the study, the next section briefly summarizes the literature pertaining to the impact of apps, focusing on fleet-management and on driver behavior. Section 3 is devoted to model and hypothesis development, while Section 4 details the preliminary empirical analysis employed and its results. Finally, Section 5 concludes with a discussion of the key findings, limitations, and avenues for further research.

2 Background

A number of studies in the past decade have collected evidence about the organizational impacts of apps. Rossi et al. (2007), based on a case study at the Finnish Amer Tobacco Company in Estonia, demonstrated improved efficiency and better customer service through simplified processes, transparent sales information, improved document handling, and reduced typing errors by using mobile technology. Doolin and Ali (2008), in an exploratory cross-case analysis of app adoption in the supply chain of three organizations in New Zealand, showed that app adoption by one of the organizations expedited business processes and enabled improved information flow, remote download of up-to-date information on products, customers, sales, stock levels, and delivery dates, and remote order entry. According to Giessmann et al. (2012), the main organizational contribution of apps is in supporting field workers in sales, maintenance, and services.

Apps facilitate personalization, instant services, multitasking (Byrne and Heavey, 2006), as well as availability and ubiquity in real-time . By using apps, field workers can access data and information in real-time (Gabler et al., 2013). Employees harness apps to improve productivity by using data on pricing, sales options, configurations, financial terms, and other information regarding services or products, resulting in a positive influence on employee performance and business processes (Knoesen and Seymour, 2016). In cloud-based environments especially, performance and productivity may increase through better tracking of organizational resources and raw material (Gelogo and Kim, 2014). The supply-chain impacts of apps pertain to pickups, deliveries, packaging, and scheduling, leading to changes in operational logistics, such as purchasing, manufacturing, warehousing, and distribution (Hu et al., 2015).

Fleet-management information systems, such as IVDRs, first appeared in the trucking industry in the early 1980s, but were limited to routing and tracking (Toledo et al., 2007). The role of information systems in monitoring and transporting people and goods increased during the 1990s (Stojanović et al., 2009), and IVDRs began to collect more detailed data, providing essential tracking capabilities to fleet organizations. Reporting and analysis capabilities, however, were periodic and not in real time. The fleet-management industry is engaged in studying driver behavior for several reasons: reducing insurance costs, monitoring vehicles, optimizing fuel consumption, and identifying idle vehicles (Kargupta et al., 2010). By 2022, this industry is presumed to reach $34 billion and include heavy and light commercial vehicles, aircrafts, railways, and ships (Sonawane, 2017).

Although effective and efficient fleet management is essential for gaining organizational competitive advantage (Hu et al., 2015), the literature about the impact of apps on fleet management is sparse, probably because organizations are reluctant to share data (Zhang et al., 2016). IVDRs aim at encouraging drivers to avoid undesirable incidents (Musicant et al., 2010). Found to enable the study of driver behavior (Musicant et al., 2007; Toledo et al., 2008), IVDRs were also shown to reduce risky behavior by individual drivers (Albert et al., 2011; Arroyo et al., 2016; Musicant et al., 2014; Toledo and Shiftan, 2016). Toledo and Shiftan (2016) conducted a three-stage IVDR experiment with 155 vehicles and 350 drivers. Quayle and Forder (2012) explored driver behavior at T-Mobile following the implementation of a website that allowed employees working in a high-risk area to learn each week about their incidents. While these studies provide evidence that IVDRs improve driver performance, they shed no light on the impact of new technologies, in particular mobile apps, on driver behavior. The next section is devoted to the development of a research model and to the formulation of hypotheses that address this gap in the literature.

3 Research model

"Risky driving refers to behaviors that do not intend to cause harm to others but potentially have negative outcomes because precautions are not taken. Such behaviors may be socially unacceptable or socially acceptable but dangerous" (Ge et al., 2015, p.76) Within the context of a fleet-management app, the research model in Figure 1 describes how risky driving behavior (operationally defined as a count of risky driving incidents in a single trip) is affected by two explanatory variables of pre-driving app use and app notifications, as well as by three control variables (trip duration and identifiers for the car and the driver). Given the scarcity of studies about the effects of apps on driver behavior, hypothesis development relies mostly on the literature about the effects of IVDR.

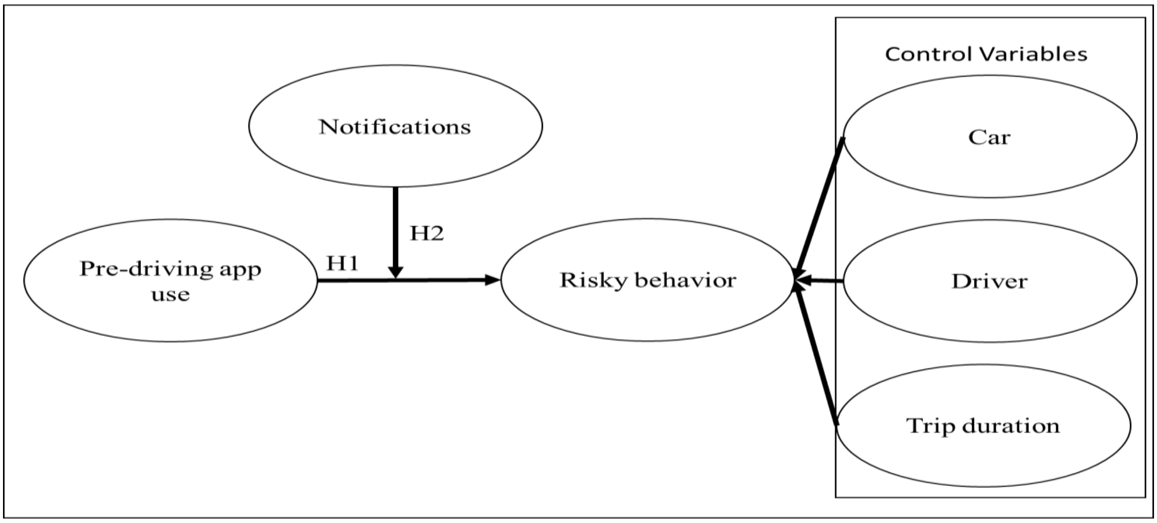

Figure 1. Research model.

The first hypothesis refers to the negative effect of pre-driving app use on risky driving behavior. Real-time notifications from IVDR and apps are received mainly via dashboard display or sound, while periodical reports on driver performance are received electronically or via hard copy. Both features of IVDRs have the potential to reduce risky behavior (Quayle and Forder, 2012; Toledo and Shiftan, 2016). Unlike IVDRs, however, apps also make possible pre-driving app use for training, feedback, learning, and analysis of previous trips. To our knowledge, no study has explored this app feature, in general, and whether it may help reduce risky behavior, in particular.

Past studies have demonstrated a reduction in the risky behavior of employees exposed to a weekly report containing verbal and graphic feedback (Grindle et al., 2000; Sulzer-Azaroff and Austin, 2000). According to Shimshoni et al. (2015), IVDR notifications, parental training, and additional feedback may reduce risky behavior of novice drivers. T-Mobile effectively encourages its drivers to read analysis reports of their risky behavior every week (Quayle and Forder, 2012). Toledo and Shiftan (2016) assert that post-hoc feedback can reduce unsafe incidents and that the main improvement can be a result of personal verbal feedback.

Fleet-management apps, aiming at the reduction of risky behavior in following trips, expose drivers to personal safety analysis of trips, including incident rate, driving routes, and simulations of how and when risky behavior occurred. App capabilities can therefore be a substitute for periodic electronic reports and for personal feedback from a fleet manager. Thus, we propose the following hypothesis:

H1: Pre-driving app use reduces risky driving behavior.

The second hypothesis refers to the moderating effect of app notifications on the relationship, described in H1, between pre-driving app use and risky behavior. Research has already shown that notifications-while-driving improve eco-driving behavior (Boriboonsomsin et al., 2010) and reduce risky behavior. The existence of a notification system that alerts the driver in real-time about her unsafe driving should reduce her motivation to voluntarily use the app to gain knowledge about her driving behavior. Put differently, knowledge about risky behavior can be acquired voluntarily, by using the app not while driving, and involuntarily, by being exposed to notifications. As the two knowledge sources are more substitutive than complementary, because both refer to knowledge about incidents of unsafe driving, the existence of notifications is expected to substitute for the effect of pre-driving app use on driving behavior. If the driver acquires the knowledge about her driving behavior in real-time, she has less knowledge to acquire by using the app before driving. In contrast, a driver without the ability to acquire knowledge in real-time through a notification system has more knowledge to gain by using the app before driving. Thus, we propose the following hypothesis:

H2: The existence of notifications while driving weakens the negative effect of pre-driving app use on risky behavior.

4 Methodology

4.1 Data collection

A large organization in the engineering industry with over 2,000 employees implemented a fleet-management app to manage over 500 cars, driven by employed professional drivers in trips to customers. This organization provided the app data records for this study. Drivers, using various cars from nine manufacturers (e.g., Ford, Chevrolet, Acura, and GMC) according to availability, were expected to enter their username and password and start running the app installed on their mobile devices before commencing each trip. Data records collected from the app databases in the UK and the US over a period of five months in early 2016 included a count of risky behaviors like speeding, braking, turning, and accelerating for a single trip (Ehsani et al., 2014; Simons-Morton et al., 2011). For each trip, data were collected on its date, start time, end time, distance, risky behavior count (the number of such incidents), and identification codes of the driver and the car. Data on other driver characteristics, such as age, gender, and rank, were not available to us, as those were not recorded in the app databases.

For the purposes of this study, we sampled 16,443 trips by 109 drivers, who drove 28 cars. Outliers in terms of trip distance or duration were excluded from the sample, yielding a total of 11,805 trips by the same number of drivers for data analysis. Specifically, 3,526 trips were excluded for distances shorter than 100 meters or longer than 250 kilometers (Figure 2), and 2,189 trips were excluded for lasting less than 0.2 minutes or over 150 minutes (Figure 3).

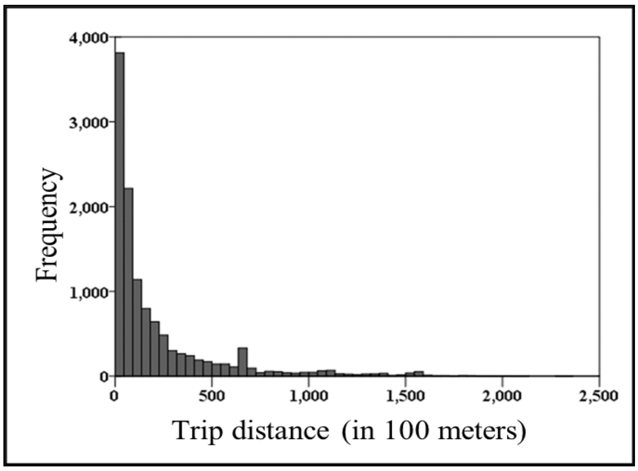

Figure 2. Distance frequency distribution

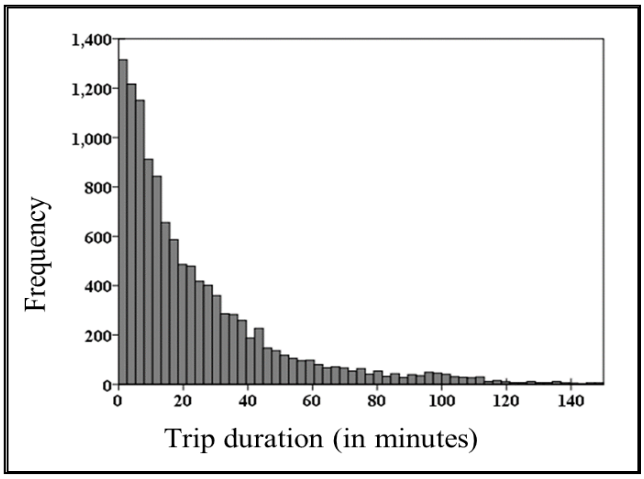

Figure 3. Duration frequency distribution

Previous driving-behavior studies suggested using a driving period without notifications as a baseline for driving behavior with notifications (Musicant et al., 2014; Toledo and Shiftan, 2016). Among the 109 drivers sampled for this study, 32 drivers in one of the sites received no notifications from the app during the first two weeks of driving with the app (the app did work in the background). The other 77 drivers received notifications throughout the period in which they drove with the app.

The two explanatory variables in this study were measured as follows. Pre-driving app use was measured as the number of times the driver used the app in the week preceding the specific trip. For instance, if there were two trips within one week, the pre-driving app use value was the same for these two trips. Notifications were measured as a binary variable, indicating whether the driver received notifications while driving (‘1’) or not (‘0’). Risky driving behavior was measured as a count of speeding, braking, turning, and accelerating incidents in a single trip, which is an accepted measure of risky driving behavior in the transportation and safety literature (Bell et al., 2017; Ehsani et al., 2014; Musicant et al., 2010; Musicant et al., 2014; Simons-Morton et al., 2011). Descriptive statistics for the variables included in data analysis are presented in Table 1.

Variable	Description	Mean	Standard deviation	Min	Max
Pre-driving app use	The number of logins by driver recorded in the week preceding the trip, at the driver level.	0.4	1.1	0	16
Notifications	A binary variable indicating whether ('1') or not ('0') the driver received notifications during the trip	0.9	0.2	0	1
Risky behavior	Total count of risky behavior incidents during a single trip	1.2	4.6	0	373
Trip duration (control)	Duration of trip in minutes	22.6	25.0	0.2	150
Car (control)	Car ID	Categorical			
Driver (control)	Driver ID	Categorical			

Table 1. Descriptive statistics (N=11,805)

In assessing collinearity levels, no collinearity was found as all variance inflation factors (VIF) were below 3.3 (Petter et al., 2007). The distance of each trip, initially considered as another control variable, was excluded from data analysis because of a bivariate correlation of 0.880 ($p<0.001$) with the variable of trip duration.

4.2 Data analysis

To test the two hypotheses, mixed-effects Poisson regression models were used with pre-driving app use, notifications, and trip duration as fixed effects, car ID and driver ID as random effects, and risky behavior as the explained variable. We used Poisson regressions because the explained variable was measured as a count of incidents. The results of model estimation are presented in Table 2. Models 1-3 aimed at explaining risky behavior, with only the three control variables entered in Model 1, the two explanatory variables added in Model 2, and the interaction term to test for H2 (moderating effect of notifications) added in Model 3.

Variable	Risky behavior		
	(1)	(2)	(3)
Intercept	-0.892*** (0.000)	-0.699*** (0.171)	-0.618*** (0.171)
Car	+	+	+
Driver	+	+	+
Trip duration	0.025*** (0.000)	0.025*** (0.000)	0.025*** (0.000)
Pre-driving app use		-0.036** (0.012)	-0.438*** (0.095)
Notifications ('1').		-0.198** (0.083)	-0.273*** (0.084)
Pre-driving app use × notifications			0.407*** (0.095)

Notes. Unstandardized coefficients are presented, with standard errors in parentheses;
** p<0.05; ** p<0.01; *** p<0.001; + The variable was included in the model as a random effect;*
AIC values for all models are between 65,723.6 and 65,726.4.

Table 2. Summary of regression results

Consistent with the literature and our reasoning, pre-driving app use and notifications were found to have significant negative effects on risky driving behavior in both Models 2 and 3, providing support for H1 (pre-driving app use reduces risky behavior). When the complete model, with the interaction term, was estimated (Model 3), the coefficient for the interaction of pre-driving app use with notifications was positive and statistically significant, thus providing support for H2 that notifications weaken the negative effect of pre-driving app use on risky behavior.

To better understand the nature of this significant interaction, we used the graphing procedure described by Aiken et al. (1991) and the process procedure described by Hayes (2012) to test for moderation effects. The process procedure explores the nature of the moderation using the 'pick-a-point' approach by analyzing the interactions at several values (Breitborde et al., 2010). Upon graphing the interactions, values at plus and minus one standard deviation from the mean were taken into consideration.

Figure 4 presents the results of using these procedures to graphically describe the moderating effect of notifications on the relationship between pre-driving app use on the X-axis and risky behavior on the Y-axis. The figure shows that notifications positively moderated the effect of pre-driving app use on risky behavior because the regression slope with notifications is less negative than that without notifications. The results of t-tests indicated that both slopes for trips with notifications (slope = -0.098, t = -4.633, $p < 0.001$) and for trips without notifications (slope = -0.306, t = -3.456, $p < 0.001$) were significantly different from zero. The interaction results, depicted in Figure 4, are supportive of H2 about the moderating effect of notifications on the relationship between pre-driving app use and risky behavior. Because the moderating variable was categorical, it was not possible to use the technique by Johnson and Neyman (1936) to depict the regions of significance, which specify the levels of a variable at which the mean differences are significant.

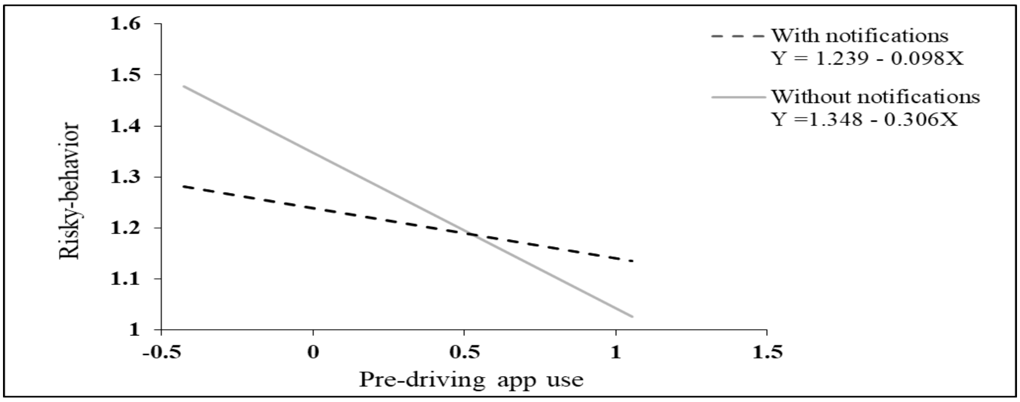

Figure 4. Moderating effect of notifications

5 Preliminary Findings, Implications, Limitations, and Future Research

The two hypotheses are supported by our empirical analysis. Our preliminary findings, at the current stage of the study, show that the more drivers use the app prior to driving, the less they are likely to be involved in driving incidents. It is important to note here that this finding is correlational rather than causal. Although we used a time lag to ensure that use precedes driving (i.e., that measurement of the explanatory variable precedes measurement of the explained variable) and although we included the driver as a random effect in the regression analyses, we are unable, given the data available to us, to completely rule out the potential confounding effects of situational variables. Nonetheless, this finding is indicative of the ability of app use to change driver behavior. Furthermore, the results show that the availability of notifications about driving behavior in real time mitigates the behavioral effect of app use before driving. To the best of our knowledge, such evidence about the behavioral consequences of app use in an organizational context have yet to be reported in the literature.

The main implication of this study for research is in going beyond past IVDR studies (Albert et al., 2011; Musicant et al., 2014; Toledo and Shiftan, 2016) and empirically exploring the impact of apps on driver behavior. The present study shows that by harnessing a fleet-management app, driver behavior can change via two capabilities – pre-driving app use and notifications while driving – that largely substitute each other.

The first limitation of this study concerns the sample. The company whose fleet-management app was studied shared data about employee behavior on a large scale over an extended period. Yet, in the absence of full control over sampling by the researchers, the sample may not adequately represent the relevant population. The second limitation concerns the absence of a control group of drivers equipped with a fleet-management app who did not receive notifications. To mitigate this limitation, we obtained data about drivers who received no notifications while driving in the first two weeks of using the app. Nonetheless, given obvious selection problems (the drivers that drove without notifications were not randomly selected), we are unable to rule out selection as a potential threat to the internal validity of the findings concerning the effects of notifications. The third limitation reflects doubts about whether the data sampled were inclusive of all trips actually made in the relevant period. The fleet-management app, unlike IVDRs, requires drivers to login upon starting their trip by entering their username and password. Hence, it is reasonable to assume that not all trips were recorded in the sample since, for instance, drivers who were late may have driven faster and did not record such trips for lack of time or even to hide unsafe driving behavior. Notwithstanding this issue, it is reasonable to assume that 11,805 recorded trips are a sufficient sample to validly test the research hypotheses. The fourth limitation refers to the deduction of implications at the organizational level from changes in behavior at the employee level – the analysis confirms only the effects of the fleet-management app on driver behavior.

This study is currently in progress. In the following stages of data analysis, we plan to investigate adoption of the app over time and its behavioral consequences by drawing on conceptualizations of learning. We also plan to move beyond a total count of driving incidents as the explained variable to models that seek to explain the effects of app use on different types of driving incidents. Data analysis suggests that better understanding of how to improve driver behavior with the support of fleet-management apps requires better understanding of the differences among incident types.

In summary, this study provides evidence about the ability of a mobile app to change behavior in an organizational context. In the face of sparse literature about the organizational impacts of apps and about their capacity to bring about organizational changes, this work moves forward the discussion on effective app implementation in organizations. Against the background of numerous studies about the ability of apps to change consumer behavior in the context of electronic commerce, the present work is among the few quantitative studies about the impact of apps on employee behavior and about the manner in which apps may help organizations achieve their business objectives.

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