

**PLANNING FOR NEW FARE PAYMENT SYSTEMS:
AN EQUITY ANALYSIS OF SMARTPHONE, CREDIT CARD, AND POTENTIAL
MOBILE TICKETING ADOPTION BY BUS RIDERS IN NASSAU COUNTY**

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1 ABSTRACT

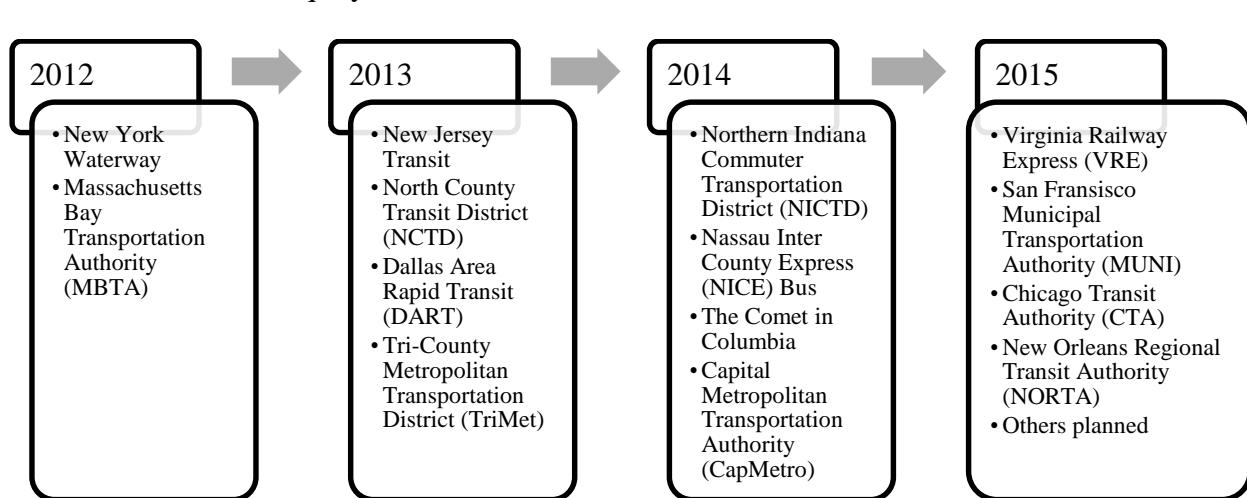
2 Transit agencies are rapidly deploying new fare payment systems, and many of these systems
3 rely on passenger-provided technologies, such as mobile phones. Mobile ticketing systems
4 typically utilize tickets that are purchased and validated on smartphones; however, not all transit
5 riders have smartphones or other electronic payment media needed to make a mobile payment.
6 Subsequently, transit agencies want to understand rider adoption of smartphones, credit/debit
7 cards, and other electronic payment media when planning for deployment of mobile ticketing
8 systems. Therefore, the objective of this research is to assess access to mobile payments across
9 different socioeconomic groups. The methodology is a case study of Nassau Inter-County
10 Express (NICE) bus system, where two passenger surveys about smartphone, credit card, and
11 potential mobile ticketing adoption were conducted. Binary logit was used to analyze
12 smartphone, credit/debit card and potential mobile ticketing adoption across different
13 socioeconomic groups using the survey data. The model results suggest that younger riders are
14 more likely to have smartphones, while older, more affluent riders are more likely to have
15 credit/debit cards. Based on a stated survey question about potential mobile ticketing use, early
16 adopters of mobile payments are likely to be younger riders. These findings may help inform
17 other transit agencies on the suitability of mobile ticketing in their markets and influence
18 stakeholders prepared to make large capital investments in new fare collection systems.

1 INTRODUCTION

2 In the last few years, there has been a push toward utilizing new fare payment technologies in the
 3 transit industry, particularly mobile ticketing systems in which riders pay their transit fare
 4 directly on their smartphones using a credit card, debit card, or other electronic payment (1, 2).
 5 Since 2012, numerous transit providers in the United States have deployed mobile ticketing
 6 systems, and many other agencies are in various stages of planning and procurement. As shown
 7 in Figure 1, the New York Waterway first launched a mobile ticketing application in early 2012,
 8 and this was followed by Boston's commuter rail later that year (1). In 2013, New Jersey Transit,
 9 DART in Dallas, NCTD in San Diego, and TriMet in Portland deployed mobile ticketing
 10 applications (1, 3). The next year (2014) included mobile ticketing launches at CapMetro in
 11 Austin, NICTD in Indiana, NICE Bus in Nassau County, NY, and the Comet Bus in Columbia,
 12 South Carolina (1, 4). Since the beginning of 2015, numerous additional transit providers (VRE,
 13 MUNI, CTA and NORTA) have already launched mobile ticketing (1, 5).

14 This movement toward mobile ticketing is occurring for many reasons. Mobile payments
 15 linked to credit/debit cards can reduce the number of cash transactions at ticket windows and
 16 onboard trains or buses, which can potentially reduce operational costs and simplify the fare
 17 collection process for transit providers. They also provide transit agencies with valuable planning
 18 data that are currently not available in cash-based systems (i.e., disaggregate origin and
 19 destination information). Furthermore, mobile payments can improve the rider experience by
 20 replacing prepayment at ticket windows or vending machines, which typically require some
 21 amount of waiting in line, thereby saving passengers travel time. In addition, smartphone
 22 applications can provide transit customers with a comprehensive payment and information
 23 platform, including account management capabilities, transit service alerts, and real-time vehicle
 24 location/arrival information.

25 Many of the aforementioned benefits of mobile ticketing rely on the fact that transit riders
 26 utilize their personal devices (namely smartphones) to purchase tickets. However, public
 27 transportation providers have diverse rider constituencies, and subsequently, not all transit riders
 28 have smartphones. Therefore, it is critical for transit agencies who are planning or deploying
 29 mobile ticketing systems to understand passenger adoption of smartphones and the other
 30 electronic payment media (such as credit/debit cards) that are needed to make purchase mobile
 31 tickets for reasons of equity.



33
 34
 35 **FIGURE 1 Timeline of Mobile Ticketing Launch in American Transit Systems.**

1 OBJECTIVE

2 The objective of this research is to assess socioeconomic trends of bus riders who are capable of
3 and interested in using mobile ticketing through a case study of the Nassau Inter-County Express
4 (NICE) bus system on Long Island, New York, which is the first bus-only transit system to
5 deploy mobile ticketing in the United States. This study focuses on smartphone and credit/debit
6 card adoption rates, as well as potential interest in mobile ticketing. System-wide onboard survey
7 data and a small, targeted web-based survey were used in a discrete choice modeling framework
8 to assess equity in socioeconomic trends.

9 PRIOR RESEARCH

10 Given that mobile ticketing is a recent innovation in transit fare collection, there is limited
11 literature available concerning this new payment medium. One noteworthy study of transit
12 mobile ticketing examined potential adoption of mobile payments by commuter rail riders prior
13 to the launch on the Massachusetts Bay Transportation Authority (MBTA)'s commuter rail
14 system in 2012. Researchers conducted an onboard paper survey of more than 900 riders on two
15 commuter rail lines in Boston, and the survey questionnaire included questions about smartphone
16 adoption (76% of survey respondents used smartphones). After briefly explaining how mobile
17 ticketing would work on the commuter rail in the future, survey respondents were asked how
18 likely they were to utilize mobile ticketing if it were available. This stated preference survey
19 question was used to create a statistical model to forecast future demand system-wide, and the
20 model revealed that approximately 26% of riders were very likely to adopt mobile ticketing on
21 Boston's commuter rail. The research also showed that commuter rail riders in the Boston area
22 were predominately white, high-income, and employed (6).

23 Another relevant prior study investigated smartphone adoption rates in the context of
24 providing real-time information with the St. Louis Metro bus and light rail system (7). The goal
25 was to determine whether real-time information delivered through smartphone applications
26 ("apps") would be accessible to all demographic groups. Based on survey data collected in 2012,
27 the researchers found that about 70% of St. Louis Metro bus and light rail riders had
28 smartphones, which was higher than the national average at the time. They also discovered that
29 certain socioeconomic groups were less likely to own smartphones, such as riders over 40 years
30 old.

31 While the prior research informed this study, neither paper is fully applicable. In the case
32 of Boston, the commuter rail demographics are quite different than those of the riders of NICE
33 and other typical American bus systems. Regarding the study of St. Louis, the research did not
34 investigate mobile ticketing, but instead focused on real-time information and smartphone
35 adoption. Therefore, further research pertaining to adoption to smartphones and payment
36 technologies is deemed necessary to inform the fare collection planning process currently
37 happening at many American transit agencies, and the following study of NICE bus aims to fill
38 this gap in the literature.

39 BACKGROUND ON NASSAU INTER-COUNTY EXPRESS (NICE) BUS

40 This study analyzes the potential for a mobile ticketing program at NICE, the bus transit system
41 in Nassau County, New York. Nassau County is a suburban county on Long Island, located
42 immediately east of New York City, with a population of over 1.3 million people. It is among the
43 wealthiest counties in the United States with over 48% of households having an annual income
44 of over \$100,000. It is a predominately white county with about 75% of Nassau County residents

1 identifying as white. In contrast, NICE bus riders tend to have lower household income levels
2 and are more likely to identify as African American or Latino. Only 3% of NICE bus riders have
3 an annual income of over \$100,000 and close to 70% have an annual income of under \$35,000.
4 About 75% of riders identify as African American or Latino (8).

5 NICE is a public-private operating partnership between Nassau County and Veolia
6 Transportation. Veolia manages all aspects of the transit system under contract to the county.
7 NICE serves about 100,000 riders daily in Queens, Nassau and Suffolk counties. NICE operates
8 52 fixed routes with a fleet of 300 buses (9).

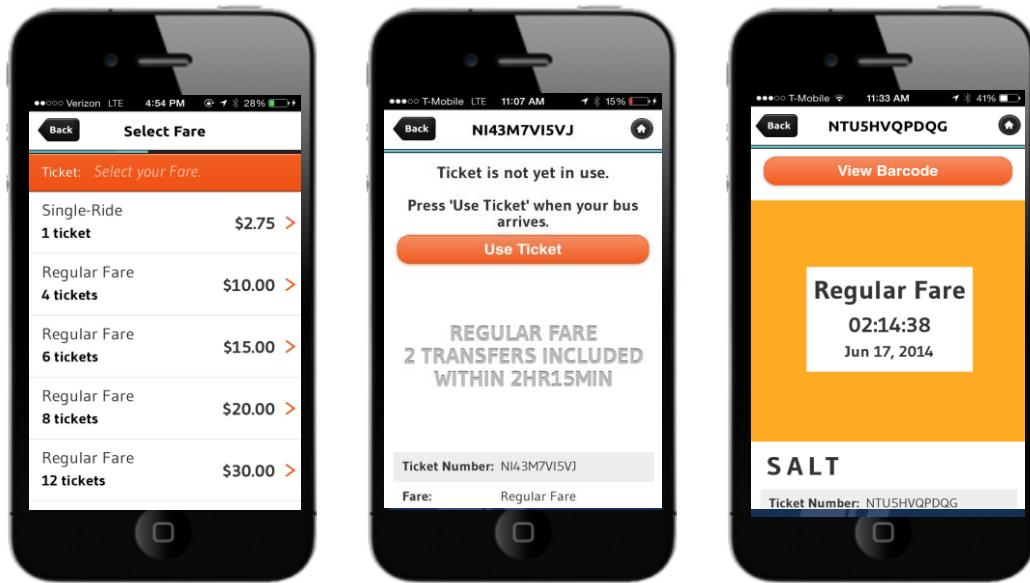
9 NICE uses a farebox-validated payment scheme. Riders can prepay using their
10 MetroCard, a magnetic stripe card from New York City's Metropolitan Transportation Authority
11 (MTA), or pay using exact change on board. Fare media is solely issued by the MTA, so NICE is
12 unable to make significant changes to the payment network and had limited ability to
13 independently set fare policy. For example, there are limited points of sale for the MetroCard in
14 Nassau County, and NICE is unable to deploy additional units. Despite its shortcomings, NICE
15 must continue to support the MetroCard as close to 25% of NICE riders transfer into the MTA
16 system daily, and the MetroCard is the only feasible way to ensure free inter-system transfers.
17 While the MTA has announced plans to deploy a new fare system, current plans suggest the
18 MetroCard may be in place until 2020 (10). Considering the issues noted above, as well as old
19 magnetic stripe fareboxes approaching the end of their useful life, NICE sought to offer
20 passengers an alternative.

21 In early 2014, NICE decided to pilot a visual mobile ticketing program as a potential
22 stopgap measure until stakeholders felt confident investing in a more robust deployment. The
23 program had minimal up-front costs as it did not required onboard hardware, and the vendor
24 would be paid through a small percentage of mobile ticketing transactions. Implementation took
25 less than six months from contract signing to deployment, with beta testing beginning in late
26 April 2014, and full rollout occurring in early June 2014. This initial deployment used visual
27 mobile tickets, where bus drivers visually inspect a smartphone screen and then click the farebox
28 to record the boarding. Passengers could still pay with existing fare media, including the MTA's
29 MetroCard and cash.

30 In the current mobile ticketing program, riders prepay for mobile tickets, which can be
31 used immediately or stored for later use. Currently, only pay-per-ride tickets are available,
32 although they can be purchased in bundles of 1, 4, 6, 8, 12 and 20 tickets (see left screenshot in
33 Figure 1). Given equity and Title VI concerns involved with a smartphone payment solution,
34 mobile tickets were priced to match existing MetroCard fares. NICE also chose not to eliminate
35 any existing payment choices or offer special pricing that would only be available to smartphone
36 owners. Similarly, riders who purchase a bundle of 20 mobile tickets receive 1 free ticket to
37 match the 5% bonus MetroCard riders are awarded when they add money to their fare cards.

38 To use a mobile ticket, a rider pushes 'use ticket' just prior to boarding (see middle
39 screenshot in Figure 1). This activation starts a countdown clock on the screen and also displays
40 a secure, flashing visual element in the form of a color and word of the day (see right screenshot
41 in Figure 1). Prior to departing on their daily run, drivers check the color and word of the day at a
42 monitor by the dispatch window. When a passenger boards with a mobile ticket, the driver
43 pushes a mobile boarding button on the farebox to capture data within the legacy fare collection
44 software. Passengers have two hours and fifteen minutes from the moment of activation to ride
45 and transfer within the NICE bus system.

1 While NICE has experienced no major issues since deployment and required no new
2 onboard infrastructure, the mobile ticketing program is heavily reliant on drivers properly
3 inspecting tickets. NICE is looking to improve the system by deploying innovative multi-format
4 readers, and NICE has already installed a test unit on one vehicle. These readers are format
5 agnostic; they are capable of accepting barcodes, contactless bank cards, proximity smartcards
6 (e.g., student or employer ID cards), and emerging payment technologies such as Bluetooth Low
7 Energy.



25
26 **FIGURE 2 Demonstration Screenshots of NICE Mobile Ticketing Application.**
27

28 **DATA COLLECTION**

29 In order to prepare for the mobile ticketing program, survey data were collected to understand
30 the potential adoption and equity of mobile ticketing. Two separate surveys were conducted prior
31 to the initial pilot program of mobile ticketing that began in June 2014. The first was a system-
32 wide paper survey conducted onboard buses in the fall of 2013, which was intended for general
33 planning purposes, but specifically included a question about smartphone adoption levels. The
34 second survey was a smaller-sized web-based survey conducted in February 2014 that focused
35 primarily on fare payment and mobile ticketing. The following paragraphs delineate the methods
36 used to collect the responses to these two surveys.

37 **Survey 1: Onboard System-wide Survey**

38 A third party firm collected the data through an onboard survey. Surveys were collected on all
39 NICE bus routes during a two week period from October 19, 2013 until October 30, 2013. The
40 firm used a stratified random sampling methodology to collect data that accurately represented
41 NICE ridership. Prior to data collection, a sampling target was calculated for each route
42 reflective of average daily ridership provide by NICE. The third party firm then created response
43 targets for each route to ensure a confidence level of 95 percent and a +/- 10 percent margin of
44 error (based on daily average ridership by route).

1 Survey Content and Sample Size

2 The onboard survey was designed to capture travel patterns and behavior, including where
3 people are traveling to and from; how they access transit service; when they travel, how they
4 travel to their final destination; frequency of use; trip purpose; trip length; and other travel modes
5 they use. These questions were used for standard planning purposes. In preparation for the
6 upcoming mobile ticketing program, the survey included a question on smartphone adoption.
7 Last, the survey also captured rider demographics, including race, gender, ethnicity, income, and
8 employment and student status.

9 All customers boarding the surveyed routes were given the opportunity to take the
10 survey, and a total of 9,430 responses were received. Of these 9,430 respondents, 7,951
11 answered the smartphone adoption question.

12 Survey 2: Web-based Mobile Ticketing Survey

13 In mid-February 2014, NICE conducted a web-based survey that was designed by the authors of
14 this paper. The goal of this survey was to understand the fare payment and technology habits of
15 riders, as well as the likelihood that they would adopt mobile ticketing. Survey responses were
16 collected from February 11, 2014 through March 3, 2014. The survey was posted on the
17 homepage of the NICE website, advertised regularly through NICE social media accounts, and
18 emailed to a list serve of over 2,000 riders accessed through the NICE customer service database.
19 Riders were incentivized to take the survey; ten respondents were randomly chosen to win 30-
20 day MetroCards valued at \$112.

21 Survey Content and Sample Size

22 The web-based survey was designed to capture technology adoption and fare payments habits
23 that would inform the upcoming mobile ticketing program. The survey asked about current fare
24 payment choices, smartphone and bankcard adoption, frequency of mobile payment use at
25 merchants (e.g. Starbucks), desire to use mobile ticketing for NICE buses, and demographics.

26 Potential respondents clicked on the survey link approximately 1,900 times. NICE
27 collected a total of 978 responses, of which 942 were considered valid. Respondents were
28 required to respond to the smartphone and mobile ticketing questions in order to submit the
29 survey.

30 ANALYSIS

31 The following analysis is divided into two sections. The first section presents results from the
32 system-wide survey to assess adoption of smartphones by NICE bus riders and identify trends
33 between different socioeconomic groups. The second section assesses the small-scale web-based
34 survey of NICE bus riders aimed at understanding the adoption potential of mobile ticketing.

35 Analysis of the System-wide Survey

36 This section presents an analysis of the system-wide survey of NICE bus riders, in which all
37 respondents were asked if they have a smartphone. A cross-tabulation of this question was done
38 to show differences in the socioeconomic status as they relate to smartphone ownership, and the
39 results are shown in Table 1 for the 7,951 respondents who answered this question.

1 TABLE 1 Smartphone Cross-tab from the NICE Bus System-wide Survey Data

| | | Yes Smartphone | | No Smartphone | | All Riders | |
|-------------------------|------------------------|----------------|-------|---------------|-------|------------|----------|
| | | Count | % Row | Count | % Row | Count | % Column |
| All Respondents | | 5,337 | 67% | 2,613 | 33% | 7,950 | 100% |
| Age | Under 16 | 35 | 71% | 14 | 29% | 49 | 1% |
| | Age 16-18 | 429 | 79% | 112 | 21% | 541 | 7% |
| | Age 19-24 | 1,537 | 85% | 261 | 15% | 1,798 | 23% |
| | Age 25-44 | 1,998 | 73% | 755 | 27% | 2,753 | 35% |
| | Age 45-64 | 1,036 | 49% | 1,072 | 51% | 2,108 | 27% |
| | Age 65+ | 116 | 33% | 234 | 67% | 350 | 4% |
| | N/A | 186 | 53% | 165 | 47% | 351 | 4% |
| Employment Status | Full-time | 2,497 | 70% | 1,094 | 30% | 3,591 | 45% |
| | Part-time | 1,756 | 72% | 669 | 28% | 2,425 | 31% |
| | Retired | 130 | 42% | 180 | 58% | 310 | 4% |
| | Not employed | 794 | 62% | 493 | 38% | 1,287 | 16% |
| | N/A | 160 | 47% | 177 | 53% | 337 | 4% |
| Gender | Male | 2,082 | 72% | 807 | 28% | 2,889 | 36% |
| | Female | 2,731 | 65% | 1,455 | 35% | 4,186 | 53% |
| | N/A | 524 | 60% | 351 | 40% | 875 | 11% |
| Ethnicity* | Hispanic/Latino | 1,404 | 70% | 605 | 30% | 2,009 | 25% |
| | White | 504 | 56% | 392 | 44% | 896 | 11% |
| | Asian | 362 | 66% | 184 | 34% | 546 | 7% |
| | Black/African American | 2,307 | 70% | 1,001 | 30% | 3,308 | 42% |
| | Indian/Alaskan | 45 | 48% | 48 | 52% | 93 | 1% |
| | Hawaiian/Pacific | 35 | 69% | 16 | 31% | 51 | 1% |
| | Other / Multiple races | 287 | 79% | 75 | 21% | 362 | 5% |
| | N/A | 393 | 57% | 292 | 43% | 685 | 9% |
| | Less than \$15,000 | 1,578 | 63% | 924 | 37% | 2,502 | 31% |
| Annual Household Income | \$15,000 to \$24,999 | 488 | 71% | 203 | 29% | 691 | 9% |
| | \$25,000 to \$34,999 | 972 | 71% | 403 | 29% | 1,375 | 17% |
| | \$35,000 to \$49,999 | 483 | 74% | 173 | 26% | 656 | 8% |
| | \$50,000 to \$74,999 | 627 | 74% | 218 | 26% | 845 | 11% |
| | \$75,000 to \$99,999 | 250 | 76% | 77 | 24% | 327 | 4% |
| | \$100,000 or more | 179 | 84% | 33 | 16% | 212 | 3% |
| | N/A | 760 | 57% | 582 | 43% | 1,342 | 17% |
| | Full-time | 1,434 | 84% | 268 | 16% | 1,702 | 21% |
| Student | Part-time | 728 | 78% | 210 | 22% | 938 | 12% |
| | Not a student | 2,759 | 62% | 1,713 | 38% | 4,472 | 56% |
| | N/A | 416 | 50% | 422 | 50% | 838 | 11% |

Note: All numbers and percentages rounded to the nearest whole number.

*Riders could select all that apply.

1 *Binary Logit Model of Smartphone Adoption*

2 Next, the system-wide survey data were used in a discrete choice model to determine the extent
3 to which different socioeconomic characteristics, such as age, annual income, and ethnicity,
4 related to the use of smartphones. A binary logit model was specified for riders having a
5 smartphone versus not having a smartphone, and it was estimated using the open source
6 statistical program R (11). All of the independent variables in the logit model were binary and set
7 equal to one if the respondent fell into that category. For each category, a reference variable was
8 defined, and the coefficients were interpreted relative to that reference category. Respondents
9 who refused to answer a question were excluded, which reduced the total sample size to 5,345
10 participants. The results of the binary logit models are shown in Table 2 and discussed in the
11 following paragraph.

12 The alternative specific constant in the model for smartphone use has a positive,
13 significant coefficient of 0.97, which indicates that, all else being equal, NICE bus riders choose
14 to have a smartphone. Each variable in the first category, annual household income, is positive
15 and significant. This suggests that bus riders with higher incomes are more likely to have
16 smartphones than those with lower incomes (less than \$25,000 per year). The ethnicity category
17 was evaluated with a reference variable of white; since all of the other categories are positive and
18 significant, it can be concluded that minority groups may be more likely to have a smartphone
19 than whites. The positive, significant coefficient of the male variable implies that male bus riders
20 may be more likely than females to have smartphones. For the age category, the negative
21 coefficients of those ages 25 to 44 and age 45 and older suggest that they are less likely to have
22 smartphones than riders under 25 years old. In the employment category, being retired was
23 weakly significant ($p<0.1$) and the category for unemployed was very significant; both had
24 negative coefficients, which implies that retired and unemployed riders are less likely to have a
25 smartphone than riders who are employed full-time. The student variable had a positive
26 significant coefficient, so students may be more likely to have a smartphone than those who are
27 not students. Last, the overall goodness of fit was good, as is indicated by a pseudo R-squared of
28 0.44.

29

1 **TABLE 2 Smartphone Binary Logit Model from the NICE Bus System-wide Survey Data**

| | Independent Variable | Coefficient | (Standard Error) |
|-------------------------|----------------------------------|--------------------|-------------------------|
| | Alternative Specific Constant | 0.97*** | (0.14) |
| Annual Household Income | Less than \$25,000 | | (reference) |
| | \$25,000 to \$49,999 | 0.35*** | -0.08 |
| | \$50,000 to \$74,999 | 0.30*** | (0.11) |
| | \$75,000 or more | 0.66*** | (0.14) |
| Ethnicity | White | | (reference) |
| | Hispanic/Latino | 0.39*** | (0.11) |
| | Black/African American | 0.55*** | (0.10) |
| | All Other (including multiple) | 0.29** | (0.12) |
| Gender | Female | | (reference) |
| | Male | 0.32*** | (0.07) |
| Age | Age 24 and under | | (reference) |
| | Age 25-44 | -0.53*** | (0.10) |
| | Age 45 and over | -1.66*** | (0.10) |
| Employment Status | Full-time | | (reference) |
| | Part-time | -0.09 | (0.08) |
| | Retired | -0.31* | (0.17) |
| | Not employed | -0.62*** | (0.10) |
| Student | Not a student | | (reference) |
| | Student (full or part-time) | 0.50*** | (0.09) |
| Summary Statistics | AIC | 5635.84 | |
| | BIC | 5728.02 | |
| | Log Likelihood | -2803.92 | |
| | Deviance | 5607.84 | |
| | McFadden's Pseudo R ² | 0.4432 | |
| | Number of Observations | 5345 | |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2

3 **Analysis of the Mobile Ticketing Survey**

4 This section presents an evaluation of the mobile ticketing survey responses. First, the survey
 5 data were analyzed by cross-tabulation to provide description statistics. Table 3 shows the results
 6 of the cross-tabulation for NICE bus riders who have smartphones (first set of columns) and for
 7 those who have credit or debit cards (second set of columns). The third set of columns show
 8 participants' responses to a stated preference question asking if they would like to use mobile
 9 ticketing once it becomes available (yes/no). It is important to note that this survey was not
 10 collected via probability sampling, and therefore, the descriptive statistics are not be
 11 generalizable to all NICE bus riders.

12 Next, the mobile ticketing survey data were used in a discrete choice modeling
 13 framework to determine the extent to which different socioeconomic characteristics, such as age,
 14 annual income, and ethnicity, related to the use of smartphones, credit/debit cards, and potential
 15 use of mobile ticketing. Three binary logit models were specified, and all models were estimated
 16 using the open source statistical program R (11). The first model was for riders having a
 17 smartphone versus not having a smartphone, and the second was for NICE bus riders having a

1 credit/debit card versus not having one. The third model is for those who would like to use
2 mobile ticketing versus those riders who stated that they do not want to use mobile ticketing.

3 All of the independent variables in the logit models were binary and set equal to one if
4 the respondent fell into that category. For each category, a reference variable was defined, and
5 the coefficients were interpreted relative to that reference category. Respondents who refused to
6 answer a question were excluded, which reduced the total sample size to 851 participants. The
7 results of the binary logit models are shown in Table 4 and discussed in the following
8 paragraphs.

9

10 *Model 1: Smartphones*

11 The alternative specific constant in the first model for smartphone use had a positive, significant
12 coefficient of 1.97, which indicates that, all else being equal, NICE bus riders choose to have a
13 smartphone. The first set of categorical variables, annual household income, only had one
14 moderately significant variable ($p<0.1$), which suggests that respondents in households with the
15 highest income levels (\$75,000 or more) may be more likely to have a smartphone. The ethnicity
16 variable was evaluated with a reference group of white individuals, and the positive, significant
17 coefficients of African Americans and Hispanics suggest that those groups may be more likely to
18 have smartphones than Caucasian bus riders. For the age category, the only statistically
19 significant variable was for respondents age 45 and older; the negative coefficient suggests that
20 older bus riders are less likely have a smartphone. Similarly, the employment category had
21 negative, significant coefficients for individuals who were retired or not employed, which can be
22 interpreted as those individuals being less likely to have smartphones than bus riders who are
23 employed full-time. The variable for students had a positive, significant coefficient, which
24 suggests that they are more likely to have smartphones than those who are not students. Last, the
25 gender variables were not significant, and the overall goodness of fit was moderate, as is
26 indicated by a pseudo R-squared of 0.28.

27

28 *Model 2: Credit/Debit Cards*

29 In the binary logit model for use of credit/debit cards, the alternative specific constant had a
30 positive, significant coefficient of 1.85; this suggests that NICE bus riders choose to have
31 credit/debit cards when holding all else equal. All variables in the first category, annual
32 household income, were positive and significant. Therefore, riders in households with higher
33 income levels may be more likely to have credit or debit cards than those in household with
34 income levels less than \$25,000 per year. Both age variables were positive and significant,
35 suggesting that bus riders over age 25 are more likely to have credit or debit cards than those
36 under 25 years of age. In the employment category, the coefficient for those who were not
37 employed had a negative, significant coefficient, which can be interpreted as those without jobs
38 being less likely to have a credit or debit card compared to those who are employed full-time.
39 Additionally, the student variable had a positive significant coefficient, which was surprising
40 since younger respondents appeared less likely to have credit/debit cards those older
41 respondents. Last, the ethnicity and gender variables were not significant, and the overall
42 goodness of fit was moderate (pseudo R-squared of 0.31).

43

44 *Model 3: Stated Use of Mobile Ticketing*

45 The third binary logit model was for the stated use of mobile ticketing. The alternative specific
46 constant was weakly significant ($p<0.1$), and the positive value suggests that, holding all else

1 equal, survey respondents would like to use mobile ticketing. The coefficient for the gender
2 variable representing men was positive and significant, which suggests that men may be more
3 likely to use mobile ticketing than women. For the age category, the variable for those age 45
4 and older had a negative coefficient that was significant, indicating that older bus riders may be
5 less likely to adopt mobile ticketing. Similarly, in the employment status category, the variable
6 for retired respondents had a negative coefficient, indicating that retirees may therefore be less
7 likely to use mobile ticketing than those who are employed full-time. The variable for students
8 had a positive, significant coefficient; students may be somewhat more likely to adopt mobile
9 ticketing than non-students. None of the variables in the income or ethnicity categories were
10 statistically significant in this model. Last, the overall goodness of fit was somewhat low (pseudo
11 R-squared of 0.16) compared to the other two models.

1
2
TABLE 3 Socioeconomic Status of Smartphone, Credit/Debit Card and Mobile Ticketing

| Mobile Ticketing Survey | | Do you have a smartphone? | | | | Do you have a credit/debit card? | | | | Do you want to use mobile ticketing? | | | | All Respondents | |
|-------------------------|------------------------|---------------------------|-------|-------|-------|----------------------------------|-------|-------|-------|--------------------------------------|-------|-------|-------|-----------------|----------|
| Category* | Independent Variable | Yes | | No | | Yes | | No | | Yes | | No | | | |
| | | Count | % Row | Count | % Row | Count | % Row | Count | % Row | Count | % Row | Count | % Row | Count | % Column |
| | All Respondents | 808 | 86% | 134 | 14% | 871 | 92% | 71 | 8% | 608 | 65% | 334 | 35% | 942 | 100% |
| Age | Age 24 and under | 239 | 94% | 15 | 6% | 219 | 86% | 35 | 14% | 191 | 75% | 63 | 25% | 254 | 27% |
| | Age 25-44 | 398 | 91% | 38 | 9% | 411 | 94% | 25 | 6% | 302 | 69% | 134 | 31% | 436 | 46% |
| | Age 45-64 | 157 | 69% | 71 | 31% | 218 | 96% | 10 | 4% | 106 | 46% | 122 | 54% | 228 | 24% |
| | Age 65+ | 8 | 47% | 9 | 53% | 17 | 100% | 0 | 0% | 6 | 35% | 11 | 65% | 17 | 2% |
| | No Answer | 6 | 86% | 1 | 14% | 6 | 86% | 1 | 14% | 3 | 43% | 4 | 57% | 7 | 1% |
| Employment Status | Full-time | 449 | 87% | 65 | 13% | 497 | 97% | 17 | 3% | 326 | 63% | 188 | 37% | 514 | 55% |
| | Part-time | 232 | 91% | 24 | 9% | 241 | 94% | 15 | 6% | 186 | 73% | 70 | 27% | 256 | 27% |
| | Retired | 12 | 48% | 13 | 52% | 25 | 100% | 0 | 0% | 10 | 40% | 15 | 60% | 25 | 3% |
| | Not employed | 105 | 78% | 30 | 22% | 97 | 72% | 38 | 28% | 81 | 60% | 54 | 40% | 135 | 14% |
| | No Answer | 10 | 83% | 2 | 17% | 11 | 92% | 1 | 8% | 5 | 42% | 7 | 58% | 12 | 1% |
| Gender | Male | 404 | 85% | 69 | 15% | 433 | 92% | 40 | 8% | 320 | 68% | 153 | 32% | 473 | 50% |
| | Female | 397 | 86% | 64 | 14% | 430 | 93% | 31 | 7% | 284 | 62% | 177 | 38% | 461 | 49% |
| | No Answer | 7 | 88% | 1 | 13% | 8 | 100% | 0 | 0% | 4 | 50% | 4 | 50% | 8 | 1% |
| Ethnicity** | Hispanic/Latino | 122 | 92% | 11 | 8% | 121 | 91% | 12 | 9% | 95 | 71% | 38 | 29% | 133 | 14% |
| | Black/African American | 239 | 94% | 16 | 6% | 236 | 93% | 19 | 7% | 176 | 69% | 79 | 31% | 255 | 27% |
| | White | 249 | 76% | 78 | 24% | 302 | 92% | 25 | 8% | 192 | 59% | 135 | 41% | 327 | 35% |
| | All Other (with mixed) | 159 | 88% | 21 | 12% | 167 | 93% | 13 | 7% | 117 | 65% | 63 | 35% | 180 | 19% |
| | No Answer | 39 | 83% | 8 | 17% | 45 | 96% | 2 | 4% | 28 | 60% | 19 | 40% | 47 | 5% |
| Annual Household Income | Less than \$25,000 | 300 | 85% | 54 | 15% | 308 | 87% | 46 | 13% | 236 | 67% | 118 | 33% | 354 | 38% |
| | \$25,000 to \$49,999 | 226 | 87% | 33 | 13% | 248 | 96% | 11 | 4% | 180 | 69% | 79 | 31% | 259 | 27% |
| | \$50,000 to \$74,999 | 109 | 87% | 16 | 13% | 124 | 99% | 1 | 1% | 76 | 61% | 49 | 39% | 125 | 13% |
| | \$75,000 or more | 132 | 88% | 18 | 12% | 144 | 96% | 6 | 4% | 97 | 65% | 53 | 35% | 150 | 16% |
| | No Answer | 41 | 76% | 13 | 24% | 47 | 87% | 7 | 13% | 19 | 35% | 35 | 65% | 54 | 6% |
| Student | Full-time | 183 | 96% | 8 | 4% | 169 | 88% | 22 | 12% | 151 | 79% | 40 | 21% | 191 | 20% |
| | Part-time | 79 | 94% | 5 | 6% | 80 | 95% | 4 | 5% | 58 | 69% | 26 | 31% | 84 | 9% |
| | Not a student | 535 | 82% | 117 | 18% | 608 | 93% | 44 | 7% | 395 | 61% | 257 | 39% | 652 | 69% |
| | No Answer | 11 | 73% | 4 | 27% | 14 | 93% | 1 | 7% | 4 | 27% | 11 | 73% | 15 | 2% |

*Riders could select all that apply. Multiple selections combined with Other.

**All numbers and percentages rounded to the nearest whole number.

1

TABLE 4 Binary Logit Models from the Mobile Ticketing Survey

| Category | Independent Variable | Model 1: Smartphone | Model 2: Credit Card Credit/Debit Card | Model 3: Mobile Ticketing |
|---------------------------|----------------------------------|------------------------|---|------------------------------|
| | Alternative Specific Constant | 1.97*** (0.46) | 1.85*** (0.51) | 0.58* (0.30) |
| Annual Household Income | Less than \$25,000 | (reference) | (reference) | (reference) |
| | \$25,000 to \$49,999 | 0.14 (0.29) | 1.08*** (0.39) | 0.24 (0.20) |
| | \$50,000 to \$74,999 | 0.37 (0.37) | 2.46** (1.04) | -0.09 (0.25) |
| | \$75,000 or more | 0.60* (0.36) | 0.82* (0.49) | 0.06 (0.23) |
| Ethnicity | White | (reference) | (reference) | (reference) |
| | Hispanic/Latino | 0.71* (0.37) | -0.32 (0.42) | 0.16 (0.24) |
| | Black/African American | 0.98*** (0.31) | 0.36 (0.40) | 0.13 (0.20) |
| | All Other (including multiple) | 0.51 (0.31) | 0.2 (0.41) | -0.03 (0.21) |
| Gender | Female | (reference) | (reference) | (reference) |
| | Male | 0.13 (0.22) | -0.23 (0.30) | 0.39** (0.15) |
| Age | Age 24 and under | (reference) | (reference) | (reference) |
| | Age 25-44 | -0.28 (0.39) | 0.72** (0.36) | -0.07 (0.22) |
| | Age 45 and over | -1.59*** (0.39) | 1.36*** (0.50) | -0.92*** (0.25) |
| Employ- ment Status | Full-time | (reference) | (reference) | (reference) |
| | Part-time | -0.13 (0.33) | -0.07 (0.44) | 0.18 (0.22) |
| | Retired | -0.90* (0.53) | 14.11 (880.32) | -0.44 (0.50) |
| | Not employed | -1.07*** (0.34) | -2.09*** (0.39) | -0.43* (0.25) |
| Student | Not a student | (reference) | (reference) | (reference) |
| | Student (full or part-time) | 1.09*** (0.39) | 0.83** (0.38) | 0.40* (0.22) |
| Summary Statistics | AIC | 582.82 | 373.22 | 1051.37 |
| | BIC | 649.27 | 439.67 | 1117.82 |
| | Log Likelihood | -277.41 | -172.61 | -511.68 |
| | Deviance | 554.82 | 345.22 | 1023.37 |
| | McFadden's Pseudo R ² | 0.2849 | 0.3146 | 0.1649 |
| | Number of Observations | 851 | 851 | 851 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard errors shown in parentheses.

2

1 **COMPARISON**

2 The following is a brief comparison of the insights gathered from the NICE bus system-wide
3 survey, the mobile ticketing-specific web-based survey, and other related research.

4 First, the smartphone adoption rates and regression results can be directly compared
5 between the two surveys of NICE bus riders. In the system-wide survey, overall smartphone
6 adoption levels were approximately 67%, while in the web-based survey adoption levels were
7 approximately 86%. The web-based survey likely reported a much higher adoption rate because
8 it was conducted using non-probability sampling and was not representative of all bus riders;
9 therefore, the system-wide survey smartphone adoption numbers are relied on to draw
10 conclusions using summary statistics and cross-tabs. 67% is similar to recent research conducted
11 on St. Louis Metro, where approximately 70% of riders had smartphones (7). The NICE
12 smartphone adoption results also compared favorably to nationwide smartphone adoption, which
13 was approximately 58% in 2014 when the survey was conducted (12).

14 Second, in both smartphone binary logit models, older riders were less likely to have
15 smartphones than younger riders, while Hispanics/Latinos and African Americans are more
16 likely than white riders to have smartphones. These data are relevant to transit agencies that must
17 ensure certain socioeconomic groups are not disproportionately disadvantaged by a new fare
18 collection program. While certain minority groups are more likely to own smartphones than
19 white riders, which aligns with prior research at St. Louis Metro, higher income riders are still
20 slightly more likely to own smartphones. Nevertheless, as prices of smartphones and data plans
21 drop, there may be a flattening of adoption levels among all income groups. This trend may
22 already have begun; among NICE riders ages 19-24, there is virtually no difference in
23 smartphone adoption levels between various income groups using data from both NICE rider
24 surveys.

25 Third, in the regression model for credit/debit card adoption, income appears to be the
26 most important indicator. In contrast to smartphone adoption, older people are also more likely to
27 have credit cards or debit cards than younger riders. As a result, transit agencies may want to
28 investigate alternative billing methods for younger riders that do not require credit or debit cards.

29 Last, about 65% of survey respondents in the small-scale web-based survey indicated that
30 they want to use mobile ticketing, with younger riders showing more interest. It is worth re-
31 mentioning that close to 25% of NICE riders transfer between NICE and the MTA; over 40% of
32 respondents that did not want to use mobile ticketing indicated retaining the free transfer to the
33 MTA was the main reason. Therefore, regional integration could be an important determinant in
34 future fare media choices of passengers.

35 **CONCLUSIONS AND FUTURE RESEARCH**

36 This research demonstrates significant potential for adoption of mobile ticketing at NICE bus,
37 considering the smartphone and credit/debit card adoption rates of riders. In particular, the
38 system-wide onboard survey data revealed that approximately 67% of riders use smartphones,
39 with even higher adoption rates among younger riders. The web-based survey revealed that older
40 riders were more likely to have credit/debit cards, and that younger riders were more interested
41 in using mobile ticketing. Based on comments from the mobile ticketing survey, many NICE bus
42 riders view the new technology positively. For example, one rider stated the following in the
43 comment box at the end of the web-based survey: *"This is a fantastic plan, it will be very
44 convenient and an easy alternative to carrying change-which can be a hassle to get in the first
45 place. Additionally, metro cards are seldom sold in the stores within our communities, I usually*

1 *have to wait until I travel into the city to buy a metro card. I love this app idea, thanks so*
2 *much!!!”*

3 Last, there are many avenues for future research that emerged from this analysis. First,
4 because the mobile ticketing program has recently launched on NICE buses, an interesting topic
5 for future research would be to study overall adoption levels and trends in socioeconomic status
6 of the earliest adopters. Second, the mobile ticketing application collects data about where and
7 when NICE bus riders pay their fares, which could be an excellent new data source for future
8 research. Third, it may be interesting to study the impact of mobile ticketing on vehicle dwell
9 times, in a similar fashion to existing research with other fare collection methods (13). In
10 summary, there are likely to be many new and interesting areas for future research pertaining to
11 mobile ticketing as this new fare payment technology becomes increasingly common in the
12 transit industry.

13

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