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Global financial services and its related technology usage

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Abstract: A major global study was undertaken that included 20 markets and over 22,000 online interviews. The survey results were initially reported in percentages, which were used as a basis for analysis. The basic finding was that on average 1 in 3 digitally active consumers use two or more FinTech services. That is significant enough to suggest that such technology has reached early mass adoption. A common assumption is that FinTech firms struggle to translate innovation and great customer experience into meaningful numbers. The initial findings reflect considerable consumer appetite for new and innovative financial service products that take advantage of new consumer technologies, such as mobile and cloud.

Keywords: developing economies; emerging financial markets; EY FinTech adoption index, 2017; financial inclusion; financial technology and usage; FinTech; technology adoption.

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1 Introduction

There can be little doubt that there are massive investments in digital transformation that are fuelling a global growth in financial technology and usage (FinTech) as many business and governments are racing to take advantage of these technologies to reach more customers/citizens and give them access to improving their standards of living through commercialism and publicly funded services. Improving accessibility to FinTech is typically referred to as financial inclusion (Dev, 2006; Turvey and Xueping, 2017). For purposes of the present study on FinTech will be defined as "access to and the use of formal financial products and services by low-income earners, poor households, smallholder farmers, small enterprises, and firms which hitherto were either under-served (under-banked) or unserved (unbanked)" [Ababio, et al., (2021), 42]. Thus, it is about encouraging all individuals, households, and firms to have access to the full benefits and use of mainstream financial products and services (Allen et al., 2011; Beck et al., 2006, 2008, 2007). Examples of these technological innovations include blockchain in supply chain and cryptocurrency, fueled by major advances in artificial intelligence (AI) that will continue to accelerate and frequently disrupt the financial services industry. As more individuals begin shifting to digital channels, digital-only players will pose more and more challenges to the FinTech industry.

Online lending technology and streamlined lending processes will continue to made room for alternative lenders. New definitions of what are the major tenants of FinTech will be gained, as more meaning from larger and larger volumes of regulatory data and analytics are made available. As suggested by Beck et al. (2008), there are numerous barriers for access to FinTech, such as requiring minimum account and loan balances, handling fees associated with account, documentation. These barriers directly result in poor levels public banking reach. Each country has certain characteristics that enhances FinTech and its ability to serve the populace (e.g., creditor rights and enforcement, credit information infrastructures, reduced restrictions, sound financial disclosure practices, transportation infrastructures, internet service, and freedom of speech). Hence, the opposite of these factors greatly increases the barrier of entry and accessibility of these greatly needed financial services. Interesting, Beck, et al. also indicated that based on their research on 209 banks in 22 countries, financial service providers (banking institutions) are significantly higher government-owned banking systems are the major provider, but these barriers are lower in stances of a strong foreign bank presence. Hence, FinTech as a discipline and an infrastructure are rapidly becoming important players in the 'customer's journey.' Ultimately, big data is getting bigger and more influential in defining what are the roles that FinTech needs to play in the developed and developing world.

1.2 Purpose and research questions

Emerging economies and global financial markets are rapidly capturing the headlines of financial firms as companies are seeking to expand into underserved markets. Of course, the initial push is that these companies seek a change for relatively quick profits and possibly exploiting these underserved populations. However, the emerging economies have many untapped resources and populations that are eager to have access to financial resources in order to improve their lives. Meeting these pent up demands create new opportunities for these nations to grow and prosper as well as meet the needs of their populace. This is certainly a win-win situation for all stakeholders involved. The database collected for the large study serves, as the context to perform a detailed extension is to perform an analytical study, via R-language, to answer the following research questions:

Research question 1 (RQ1)	Choose three important metrics that could be used to assess financial technology usage.
Research question 2 (RQ2)	Are there some interesting correlations between financial technology usage metrics and other factors? What do they mean for policy and practice?
Research question 3 (RQ3)	Are there differences in financial technology usage across countries or regions?
Research question 4 (RQ4)	What are some of the factors that may drive financial technology usage around the globe not covered in the EY FinTech Adoption Index, 2017? How could these factors be assessed. What are some of the preferred choices or techniques. What are some major interesting results from this managerial practical analytical study?

2 Background

2.1 Factors associated with global determiners of FinTech

Reviewing the business and financial literature, there were five major determiners for the acceptance of global FinTech that were related to the variables that were collected in the EY FinTech Adoption Index 2017. The factors that were chosen to highlight were adoption of mobile phones, presence of nontraditional financial institutions, employment rate, account accessibility/convenience, and desire to access the global marketplace. There has been much mistrust by the general public on the goals and practices of the financial leading institutions (Kumar, 2013; Sarma and Pais, 2011) since the global recession of 2008 (Turvey et al., 2012), especially in light of large salaries and bonuses of its executives, scandals, and large-scale governmental bailouts at taxpayers' expense. Hence, the exponential rise of FinTech since this financial crisis as many seek an alternative solution. From the published EY Global FinTech Adoption Index, the use of alternatives to big banking or FinTech alternatives, the adoption rates from 2015 (16%), 2017 (33%), to 2019 (64%) in 2019 (Agarwal and Zhang, 2020). This shadow or hidden industry had created much opportunity for nontraditional banking that have been around for decades, such as peer-to-peer lending (P2P lending) (Smith, 2004; Rupp and Smith, 2004) or crowdfunding (Cockrell et al., 2016) as a common source for loans that many financial institutions would typically ignore.

3 Methodology

3.1 Statistical approaches

The use of R-language and R-Markdown options, especially the linear model (lm) package was essential in performing the statistical analysis, especially associated with RQ1, via multiple linear regression (MLR). The basic steps included converting the response statistics in terms of percentages, not actual number of users. This step was employed, since sampling numbers among countries can highly vary. The output statistics are screen captures from R-script and results. . In defining the various steps to develop model predicting the selected FinTech usage metrics (formally defined in the next section), the first task was to test models with the candidate dependent variables. By comparing adjusted R-squared values of candidate models to determine the maximum variability explained for a specific dependent variable by the selected independent variables, a selection is possible that has the most important independent variables. The results of this procedure would allow the ability to create a new model using only those selected variables and observe the decrease in variability. Ultimately, if these decreases were acceptable, the final phase would be to create a new model using these selected independent variables with the minimal of variables in the model to achieve maximum predictive capture of explained variation, allowing the exploration of related demographic granularities.

As for the sample, the EY FinTech Adoption Index, 2017 was used as the source of data to be analysed (EY FinTech Adoption Index 2017 …, 2017). It is a recent and remarkably detailed global survey of approximately 22,000 individuals that are relatively versed in digital access consumers. Originally started in 2015, it showcases the exponential growth in applications of FinTech within the established 20 different economically developed and developing/emerging global markets. The original data format is recorded as portions, which multiplied by 100%, would give the percentage of survey responses that could be grouped in each category. The data were group by regions, markets, countries, which aggregate values that were further divided into 10 or more subcategories based on demographics (e.g., age levels, gender, income levels, currently in or out of employment, etc.). Based on the finished summary report, the major trends that were highlighted were strong probabilities for growth through the globe for increased development and use of FinTech. Other discernable insights able global FinTech included a very quickly evolving evolution of new technologies and accessibility, and exponential adoption and marketing acceptance, especially from more traditional banking institutions to smaller, more tailored cash/credit needs,

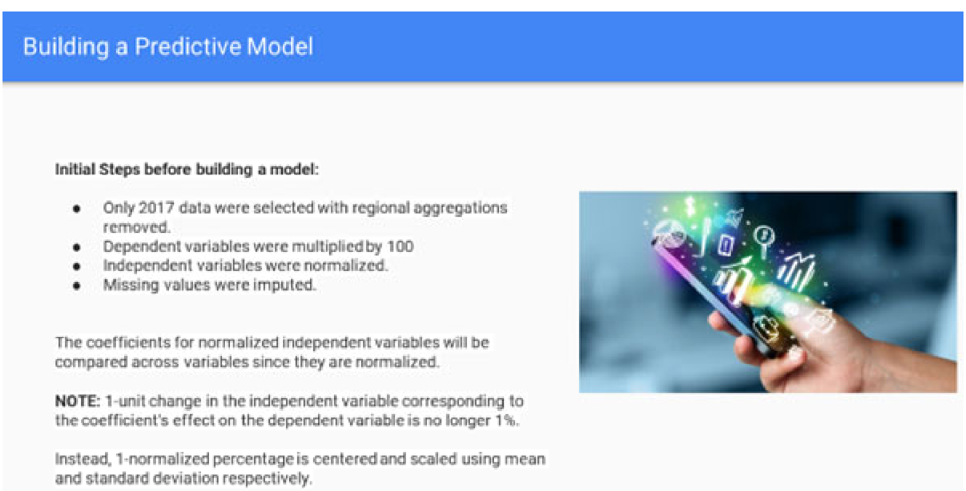
4 Results

(RQ1) Choose three important metrics that could be used to assess financial technology (FinTech) usage.

Scanning the enormous database, three important metrics (among many as the refinement of the detail collected can actually obscure the main research threads) became rather obvious among the many nations. A major and common barrier to developing countries that have relative poor FinTech infrastructures was access to communicate technologies to take advantage of financial services that they need, thus increasing levels of poverty (Greenwood and Jovanovic, 1990; Jalilian and Kirkpatrick, 2002). Therefore, it was decided to use the continuous variable, number of times an individual respondent cited that they used a mobile phone or the internet-linked device to check account balance in the past year (mobile balance). As this variable seemed very important, it was deemed that the number of times an individual used a mobile phone or the internet to access an account in the past year (mobile account) was an important measure for FinTech usage. Lastly, the number of times a user access the internet to buy something online in the past year (B2C) was chosen as a direct measure of comfortability to engage in e-commerce (Turvey and Xueping, 2017), regardless of cultural and geographical differences. These factors have been consistently found to be useful in related financial studies of accessibility and online shopping behaviours (Smith, 2011; Smith and Flanegin, 2006; Smith et al., 2019).

RQ2 Are there some interesting correlations between financial technology usage metrics and other factors? What do they mean for policy and practice?

Figure 1 Model interpretations and assumption of the EY FinTech Adoption Index, 2017 for significant factors associated with mobile and internet-based FinTech (see online version for colours)



During the attempt to identify the three financial technology usage metrics, there were several other several potential candidates and other metrics that were identified that may serve to indicate economic strength and conversely the need for economic development.

It was by comparing all of the correlations that the three metrics discovered in database. These correlations are based on data from all three years included in the dataset. The metric indicating having borrowed for a business or farm was weakly correlated with other positive non-technology usage metrics. Therefore, it was decided to look at correlations for each year separately. This resulted in no usable data for 2011 and approximately half the amount of correlations produced for 2014 compared to our aggregate correlation results. Fortunately, 2017 yielded data very similar to the aggregate. Figure 3 illustrates the basic model assumptions before a detailed correlative analysis of continuous variables were performed.

As evident from Figure 3, only 2017 data with regional aggregations removed as the whole nation's economy was to be analysed. To better discriminate the dependent variables chosen, they were multiplied by 100 and the many selected independent variables were nominalised and imputed. The purpose of this step is to ensure that the normalised independent variables could be compared and correlations could be computed as the magnitudes were quite different in many cases. By normalising these variables, magnitudes and their differences would not interfere in comparing these. Of course, this means that that a 1-unit change variable corresponding to the coefficients' effect on the dependent variable would no longer be of the same magnitude of 1%. The 1-unit change percent would be centred on the mean and scaled on the distribution's standard deviation (standard score of z-values). These preliminary calculations allow for the determination of the correlation matrix.

It was hoped that by computing the correlations of the three dependent variables with selected independent variables, the ability to test models of candidate dependent variables would be enhanced. The next step beyond the correlations would be to compare adjusted R-squared values of candidate models to determine the maximum variability explained for a specific dependent variable by the selected independent variables. Ultimately, it would the ability to select the most important independent variables and create a new model using only those selected variables and observe the decrease in overall variability. It can be assumed that if this decrease is acceptable, then it would the creation of a new model using these selected independent variables; hence allowing further exploration of the demographic granularities. As graphically illustrated in Figure 2, the positive correlation group associated with FinTech adoption included the following: account ownership; mobile or internet checking account balance; mobile or internet accessing an account; internet paying bills or buy an item online; internet buying an item online; internet paying bills; paid utility bills using an account; received wages into an account; received government payments into account; used debit card to make purchase; used credit card; ability to produce emergency fund; outstanding housing loan; borrowed for business venture; and saving for old age. As shown in Figure 2, the negative correlation group associated with FinTech adoption included the following: insufficient funds; banking services too expensive; institutions are too far away; lack of necessary documentation; and borrowed for medical expense.

The next step is to take these multiple correlations that are apparent to the three dependent variables [i.e., used a mobile phone or the internet to check account balance in the past year mobile balance), used a mobile phone or the internet to access an account in the past year (mobile account), and used the internet to buy something online in the past year (B2C)].

Figure 2 Colour-coded correlational matrix of major factors associated with FinTech adoption previous outlined in Section 2.0 (see online version for colours)

Interestingly enough, the 2014-year study showed that the variable ‘having borrowed for entrepreneurial reasons’ was negatively correlated with some of the other positive metrics and positively correlated with the strongest negative metric, having borrowed for medical expenses. However, 2017 data shows the exact opposite correlation pattern of being strongly correlated with the other positive metrics and strongly negatively correlated with other negative metrics. Additionally, the positive metrics of mobile/internet access to an account, credit card usage and ability produce emergency funds all exhibit a weaker correlation with the barrier metrics when compared to the other positive metrics indicating a lesser sensitivity to these barriers. Lastly, the strongest indicator of the need for economic improvement is percentage having borrowed for medical expenses which exhibits the strongest negative correlation to the positive metrics and a positive but less strong correlation to the other negative metrics.

As illustrated in Figure 4 is the ANOVA and Figure 5 is the MLR results associated with the testing of independent variables that showed promise and related to building a global FinTech network with the first dependent variable, using mobile device or internet to check account balance (mobile balance). As evident from the statistical results found in the table, the overall relationship was found to be highly significant ($F = 176.5$, $p < .001$) and with an adjusted variance explained of 95.78%. Specifically, the independent variables that were found to be significant and positively related to the number of times an individual used mobile account checking included: access ($t = 3.356$, $p < 0.001$), internet purchases ($t = 3.356$, $p = 0.034$); using the internet to pay bills ($t = 3.746$, $p < 0.001$), using debt cards to purchase items ($t = 2.547$, $p = 0.012$), and using finance to home loans ($t = 2.867$, $p < 0.001$). The only variable negatively associated to predicting mobile balance was saving for retirement ($t = –3.262$, $p < 0.001$).

Figure 3 MLR results with dependent variable mobile balance using 2017 data via the lm function in R script

```
Call:
lm(formula = check_bal ~ ., data = gf2017)

Residuals:
     Min       1Q   Median       3Q      Max
-12.6259  -3.2360   0.0399   2.1071  17.3492

Coefficients: (1 not defined because of singularities)
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           25.5242     0.7119  35.853  < 2e-16 ***
own                    2.9037     1.8033   1.610 0.109955
access                 4.4742     1.3333   3.356 0.001058 **
int_purch_or_bill_pay -5.2388     4.7948  -1.093 0.276741
int_purch              6.0257     2.8053   2.148 0.033711 *
bill_pay              12.0204     3.2092   3.746 0.000277 ***
acc_util              -2.5725     1.4814  -1.737 0.085020 .
acc_wages              2.1612     1.4386   1.502 0.135620
acc_gov_pay            0.1195     0.9118   0.131 0.895979
debit_purch            3.9580     1.5540   2.547 0.012120 *
cc                     1.0852     0.9295   1.168 0.245282
prod_funds            -0.6947     0.6492  -1.070 0.286750
nsf                   -1.7968     1.3472  -1.334 0.184813
too_exp               -0.6044     0.8070  -0.749 0.455360
dist                   1.9867     1.0710   1.855 0.066028 .
lack_doc               0.1852     0.8786   0.211 0.833414
medical_debt          -0.9576     0.6487  -1.476 0.142507
home_loan              2.7584     0.9620   2.867 0.004885 **
business_debt              NA         NA      NA       NA
save_ret              -3.2182     0.9865  -3.262 0.001437 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.92 on 121 degrees of freedom
  (4 observations deleted due to missingness)
Multiple R-squared:  0.9633,    Adjusted R-squared:  0.9578
F-statistic: 176.4 on 18 and 121 DF,  p-value: < 2.2e-16
```

Notes: NS denotes not significant at the .01 level for a 2-tailed test, S denotes significant at the 0.05 level for a 2-tailed test, MS denotes marginally significant at the 0.05 level for a 2-tailed test, HS denotes highly significant at the 0.01 level for a 2-tailed test.

In summary, the positive relationships include access (HS), purchases (HS), bill paying (HS), debit purchases (S), home loans (HS), long distances (MS), while the negative relationships include saving for retirement (HS). Some of the insights from that can be derived from an inspection of Figures 4 and 5 are that there should be greater emphasis placed on routine/short-term purchases and home loans geared for home ownership protection. There might be less emphasis on long-term planning and retirement (if an initiative, much re-education to do), as especially in economically depressed regions, the emphasis is no providing a suitable standard of living now, not years off in the future. Of course, long-term planning and retirement savings are a luxury for most people receiving insufficient wages and income streams. Kenya has been an unusual success story in terms of FinTech and its positive impacts on the general populace (Nasr, 2017; Shee et al. 2015). There are success stories as 93% of Kenyans have used mobile sources of money, with 70% send cash to family and friends or others, followed by 43.3% used to pay bills. Most use mobile money weekly (40.8%) or monthly (37.5%) (Why does Kenya …, 2015).

Figure 4 ANOVA results with dependent variable mobile balance using 2017 data via the lm function in R script

```
Analysis of Variance Table

Response: check_bal
                       Df Sum Sq Mean Sq   F value    Pr(>F)    
own                     1  59788   59788 2469.5544 < 2.2e-16 ***
access                  1   9193    9193  379.7084 < 2.2e-16 ***
int_purch_or_bill_pay   1   5873    5873  242.5897 < 2.2e-16 ***
int_purch               1      2       2    0.0831  0.773623    
bill_pay                1   1132    1132   46.7690 3.482e-10 ***
acc_util                1     18      18    0.7361  0.392619    
acc_wages               1    169     169    6.9815  0.009324 ** 
acc_gov_pay             1      1       1    0.0320  0.858252    
debit_purch             1    174     174    7.1878  0.008364 ** 
cc                      1      7       7    0.2858  0.593938    
prod_funds              1     25      25    1.0530  0.306870    
nsf                     1     25      25    1.0421  0.309367    
too_exp                 1      1       1    0.0234  0.878767    
dist                    1     14      14    0.5896  0.444075    
lack_doc                1      0       0    0.0016  0.967783    
medical_debt            1     10      10    0.4132  0.521582    
home_loan               1    160     160    6.6250  0.011262 *  
save_ret                1    258     258   10.6412  0.001437 ** 
Residuals             121   2929      24                        
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Notes: NS denotes not significant at the 0.01 level for a 2-tailed test, S denotes significant at the 0.05 level for a 2-tailed test, MS denotes marginally significant at the 0.05 level for a 2-tailed test, HS denotes highly significant at the 0.01 level for a 2-tailed test.

Figures 6 and 7 present the MLR and ANOVA results, respectively using the dependent variable using a mobile phone or the internet to access an account in the past year (mobile access). As evident from the statistical results found in the tables, the overall relationship was found to be highly significant ($F = 71.75$ $p < 0.001$) and with an adjusted variance explained of 89.8%. Specifically, the independent variables that were found to be significant and positively related to the number of times an individual mobile phone or the internet to access an account in the past year included: own ($t = 7.436$, $p < 0.001$), checking balance ($t = 3{,}447$, $p < 0.001$), bill baying ($t = 4.792$, $p < 0.001$), account for utilities ($t = 3.133$, $p = 0.002$), and protecting against NSF ($t = 7.252$, $p < 0.001$). The only variable negatively associated to predicting mobile balance was using a debit card for purchases ($t = –3.920$, $p < 0.001$). Overall, it can summarised from the analysis presented in Figures 6 and 7 that the positive relationships include own (HS), check balances (HS), bill pay (HS), account utilities (HS), debit purchases (HS), NSF (HS), while the negative relationships include debt purchases (HS); while too expensive and using account to pay governmental taxes and fees were marginally significant, but traditionally important.

Figure 5 MLR results with dependent variable mobile access using 2017 data via the lm function in R script

```
Call:
lm(formula = access ~ ., data = gf2017a)

Residuals:
     Min       1Q   Median       3Q      Max
-16.6139  -4.5793  -0.9327   4.5501  16.8060

Coefficients: (1 not defined because of singularities)
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)              27.5724     0.9542  28.895  < 2e-16 ***
own                      14.9340     2.0082   7.436 1.44e-11 ***
check_bal                 9.6599     2.8024   3.447 0.000773 ***
int_purch_or_bill_pay   -12.1362     6.6592  -1.822 0.070772 .
int_purch                -0.5825     3.9976  -0.146 0.884381
bill_pay                 20.6170     4.3024   4.792 4.60e-06 ***
acc_util                  6.2963     2.0094   3.133 0.002153 **
acc_wages                 2.1440     2.0148   1.064 0.289322
acc_gov_pay              -2.2595     1.2408  -1.821 0.070998 .
debit_purch              -8.2158     2.0957  -3.920 0.000145 ***
cc                       -1.2229     1.2981  -0.942 0.347990
prod_funds               -0.5844     0.8919  -0.655 0.513546
nsf                      11.3583     1.5662   7.252 3.77e-11 ***
too_exp                  -2.0448     1.1129  -1.837 0.068529 .
dist                     -0.2684     1.4785  -0.182 0.856251
lack_doc                  1.7418     1.2006   1.451 0.149336
medical_debt              0.5792     0.8921   0.649 0.517376
home_loan                -1.2044     1.3738  -0.877 0.382328
business_debt                 NA         NA      NA       NA
save_ret                  2.0861     1.4103   1.479 0.141611
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.889 on 125 degrees of freedom
Multiple R-squared:  0.9118,    Adjusted R-squared:  0.899
F-statistic: 71.75 on 18 and 125 DF,  p-value: < 2.2e-16
```

Notes: NS denotes not significant at the 0.01 level for a 2-tailed test, S denotes significant at the 0.05 level for a 2-tailed test, MS denotes marginally significant at the 0.05 level for a 2-tailed test, HS denotes highly significant at the 0.01 level for a 2-tailed test.

The next step in the model-build process, after testing the two models with the candidate dependent variables (mobile checking account balance and mobile access). By comparing adjusted R-squared values of candidate models to determine the maximum variability explained for a specific dependent variable by the selected independent variables, Figure 8 displays the results of this selection process. Checking account balance has the largest adjusted R-square value, so it was chosen as the dependent variable in the next phase of the model-building process. This procedure, which is reflected in Figure 8, allowed the creation of a new model using only those selected variables (check balance = loans for home ownership, access, and bill paying) for the 2017 dataset. The resulting model was highly significant ($F = 868.2$, $p < 0.001$) with an adjusted R-square of 94.93%. The next and final phase of model creation would be to create a new model using these selected independent variables (Figures 8–9), followed by exploring the demographic granularities.

Figure 6 ANOVA results with dependent variable mobile balance using 2017 data via the lm function in R script

```
Analysis of Variance Table

Response: access
                      Df Sum Sq Mean Sq  F value    Pr(>F)    
own                    1  40053   40053 843.9251 < 2.2e-16 ***
check_bal              1  12586   12586 265.1910 < 2.2e-16 ***
int_purch_or_bill_pay  1     19      19   0.4041 0.5261590    
int_purch              1    362     362   7.6207 0.0066394 ** 
bill_pay               1   1667    1667  35.1310 2.804e-08 ***
acc_util               1    790     790  16.6517 7.949e-05 ***
acc_wages              1    460     460   9.7023 0.0022827 ** 
acc_gov_pay            1    720     720  15.1808 0.0001583 ***
debit_purch            1    669     669  14.0967 0.0002648 ***
cc                     1     22      22   0.4641 0.4969604    
prod_funds             1    125     125   2.6409 0.1066650    
nsf                    1   3361    3361  70.8191 7.648e-14 ***
too_exp                1    142     142   3.0010 0.0856778 .  
dist                   1     61      61   1.2878 0.2586268    
lack_doc               1    124     124   2.6070 0.1089147    
medical_debt           1      5       5   0.1125 0.7378711    
home_loan              1     21      21   0.4424 0.5072060    
save_ret               1    104     104   2.1879 0.1416107    
Residuals            125   5933      47                       
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Notes: NS denotes not significant at the 0.01 level for a 2-tailed test, S denotes significant at the 0.05 level for a 2-tailed test, MS denotes marginally significant at the 0.05 level for a 2-tailed test, HS denotes highly significant at the 0.01 level for a 2-tailed test.

As evident from a comparison of the tables, the model with the dependent variable, checking an account balance remotely, accounted for 95.78% of explained variance. The model with using accessing a financial account (access) was significantly reduced to 89.90% 0f explained variance, while is an indicator of extremely high model performance. The next stage was testing a model with checking an account balance remotely (Check_bal) as the dependent variable with home ownership (own), access, and paying bills only (bill_pay) accounted for a very high model performance (adjusted R-square of 94.93% of explained common variance in the dependent variable). Hence, the elimination of 16 independent variables resulted in less than 1% decreased in adjusted R-square in the quest for the best and simplest model possible. The next step is to eliminate these 16 independent variables in the final model and explore all home ownership loans/accounts in its various levels of demographic separation as reported in the EY FinTech Adoption Index, 2017 dataset.

The final model includes all subsets of home loans (own), access, and bill pay [Check_bal ~ own (all subsets) + access + bill pay], with model and performance statistics described in Figures 8–9). As outlined in the methodology section the goal is to pick the best predictive model with the fewest independent variables, but retain a large and significant amount of explained variance. It deleting independent variables, although they may account for a statistically significant as evident in the MLR and ANOVA coefficients, it their removing results in a relatively small decrease in overall model performance as measured by R-square, and they should be removed. In summary, using checking account balances as the dependent variable (Check_bal), there were 20 independent variables used in the model creation (adjusted R-squared = 0.9578). In the reduced model at the next stage (Check_bal ~ own + access + bill_pay), the resulting model's performance was only slightly reduced (adjusted R-squared = 0.9493). The next stage included all the subsets recorded in the EY FinTech Adoption Index, 2017 database that were separated by various demographic segments, such as age, gender, to name a few). The final model [Check_bal ~ own (all subsets) + access + bill_pay], the adjusted R-squared = 0.9475. Hence, the introduction of all demographic subsets of account ownership resulted in a 0.0018 reduction to adjusted R-squared. However, the p-values for almost all of the coefficients for the demographic subsets of account ownership (greater than 0.05) and not considered statistically significant). These relatively high and insignificant p-values would imply the corresponding MLR standardised-coefficients should be very close to zero (e.g., contributing very little to the predictive power of this model). Since, the step took one significant variable (home ownership) and decomposed it into 10 variables of the same variable, but into the subsets of the same variable based on demographic slices, this outcome was consider to be plausible. If the number of samples were increased, it is likely that a portion of these variables would become significant.

A more detailed analysis of the final model analysis derived from Figures 8–9 suggest some very specific trends in the model. For example, the percentage reporting using mobile/internet to check an account balance is marginally more sensitive to male account ownership (acct_male). Perhaps, this was a direct result of fewer female account holders (acc_female) in global dataset. Obviously, the more refined or sliced the variables in the dataset become, the subset sample size drops accordingly). Interestingly, similar predictive results were found for in (acc_labour_in) and out (acc_labour_out) of the labour force and richest income (acc_inc_richest_60) 60% poorest 40% (acc_inc_poorest_40) in terms of checking an account balance online.

In terms of age, the percentage reporting using mobile/internet to check an account balance is significantly more sensitive to account ownership of adults age 25+. Perhaps, as to be discussed in more detail in later sections of the present research effort, be the result of barriers facing young adult financial technology accessibility due to lack of mobile devices and essentially no credit histories. The sensitivity to education level is almost exactly the same impact in the model, but affects balance checking in opposite directions, as expected as lower educational levels reflected more impoverish conditions. Rural account owners result in a lesser percentage reporting using mobile/internet to check an account balance, reflecting a less developed communications and FinTech infrastructure.

RQ3 Are there differences in financial technology usage across countries or regions?

It was decided to divide countries into four income levels (i.e., high, upper middle, lower middle, and low) with three selected representative countries for each level from the research database. In general, as the number of accounts established, the three metrics (i.e., mobile balance, mobile account, B2C) also increased. The higher the countries' wealth, so does the number of financial or banking account established. These countries exemplify those trends with the chosen metrics. Table 1 illustrates the four-levels or tiers of income that directly corresponds to the number of accounts. There were a few exceptions, such as Kenya and Zimbabwe. For example, over 17 million Kenyans now use Kenya's world-leading mobile-money system (M-PESA, which was established in 2007). This is equivalent to more than 67% of the adult population and about 25% of the GDP flows through it (Why does Kenya lead …, 2015).

Figure 7 MLR and ANOVA results with dependent variable mobile check balance with the best predictive variables (loans for home ownership, access, and bill paying) found in the discovery process from the previous analysis using 2017 data via the lm function in R script

A. MLR results.

```
Call:
lm(formula = check_bal ~ own + access + bill_pay, data = gf2017)

Residuals:
     Min       1Q   Median       3Q      Max
-13.1110  -3.3508  -0.0363   2.7587  19.0788

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  24.7148     0.4568  54.107  < 2e-16 ***
own           5.4423     0.8313   6.547 1.11e-09 ***
access        2.4574     0.9820   2.503   0.0135 *
bill_pay     16.5486     1.0796  15.329  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.395 on 136 degrees of freedom
  (4 observations deleted due to missingness)
Multiple R-squared:  0.9504,	Adjusted R-squared:  0.9493
F-statistic: 868.2 on 3 and 136 DF,  p-value: < 2.2e-16
```

B. ANOVA results.

```
Analysis of Variance Table

Response: check_bal
           Df Sum Sq Mean Sq F value    Pr(>F)
own         1  59788   59788 2053.85 < 2.2e-16 ***
access      1   9193    9193  315.79 < 2.2e-16 ***
bill_pay    1   6840    6840  234.97 < 2.2e-16 ***
Residuals 136   3959      29
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Notes: NS denotes not significant at the 0.01 level for a 2-tailed test, S denotes significant at the 0.05 level for a 2-tailed test, MS denotes marginally significant at the .05 level for a 2-tailed test, HS denotes highly significant at the 0.01 level for a 2-tailed test.

Figure 8 MLR result with dependent variable mobile check balance with the best predictive variables (loans for home ownership, access, and bill paying) found in the discovery process from the previous analysis using 2017 data via the lm function in R script

```
Call:
lm(formula = check_bal ~ ., data = gf2017b)

Residuals:
     Min       1Q   Median       3Q      Max 
-12.6844  -3.3251  -0.2087   2.5715  18.6038 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)         24.6746     0.4668  52.863   <2e-16 ***
acc_male            -9.8008    15.9965  -0.613   0.5412    
acc_in_labor        -2.3556     4.1713  -0.565   0.5733    
acc_out_labor       -1.0930     3.6471  -0.300   0.7649    
acc_fem             -8.5474    16.9640  -0.504   0.6152    
acc_young_adult      3.4710     3.0258   1.147   0.2535    
acc_older_adult     18.2119    12.0019   1.517   0.1317    
acc_ed_below_hs      0.5553     1.9534   0.284   0.7767    
acc_ed_hs_or_above  -0.5808     2.1905  -0.265   0.7913    
acc_inc_poorest_40   5.2585    14.0030   0.376   0.7079    
acc_inc_richest_60   4.9514    18.4369   0.269   0.7887    
acc_rural           -4.3566     4.7174  -0.924   0.3575    
access               2.1219     1.2361   1.717   0.0885 .  
bill_pay            16.7333     1.2830  13.042   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.488 on 126 degrees of freedom
  (4 observations deleted due to missingness)
Multiple R-squared:  0.9524,    Adjusted R-squared:  0.9475 
F-statistic:   194 on 13 and 126 DF,  p-value: < 2.2e-16
```

Notes: NS denotes not significant at the 0.01 level for a 2-tailed test, S denotes significant at the 0.05 level for a 2-tailed test, MS denotes marginally significant at the 0.05 level for a 2-tailed test, HS denotes highly significant at the 0.01 level for a 2-tailed test.

RQ4 What are some of the factors that may drive financial technology usage around the globe? How would you assess them? Explain your choice of technique and be explain five interesting results from the initial practical analytical use?

Based on the initial model build exercise captured in RQ2, Figures 3–9 and Table 1, accessibility to FinTech, as measured by the ability to check account balances in order to own one’s home, pay bills online, and participate in the global economy via e-commerce (Turvey and Xueping, 2017), there were five major factors that were derived from the analysis and the collaborating literature. These five factors included the following: adoption of mobile phones; presence of non-traditional financial institutions; local employment rates; account accessibility/convenience; and, desire to access the global marketplace. In terms of the adoption of mobile phones, typically higher adoption of mobile phones in a country gives rise to the scenario of an individual to make use of online/mobile services provided financial institutions or mobile money providers. By inspecting the number of factors included in the analysis of RQ2, one might be able to assess mobile phone adoption by looking at the internet usage in the country and/or phone call/SMS activity.

Figure 9 ANOVA results with dependent variable mobile check balance with the best predictive variables (loans for home ownership, access, and bill paying) found in the discovery process from the previous analysis using 2017 data via the lm function in R script

```
Analysis of Variance Table

Response: check_bal
                    Df Sum Sq Mean Sq   F value    Pr(>F)    
acc_male             1  57335   57335 1903.4105 < 2.2e-16 ***
acc_in_labor         1     60      60    1.9957 0.1602113    
acc_out_labor        1   3084    3084  102.3980 < 2.2e-16 ***
acc_fem              1    439     439   14.5857 0.0002091 ***
acc_young_adult      1    482     482   15.9894 0.0001078 ***
acc_older_adult      1     11      11    0.3677 0.5453410    
acc_ed_below_hs      1    100     100    3.3049 0.0714472 .  
acc_ed_hs_or_above   1    184     184    6.1225 0.0146770 *  
acc_inc_poorest_40   1   1104    1104   36.6470 1.508e-08 ***
acc_inc_richest_60   1    105     105    3.4860 0.0642147 .  
acc_rural            1      0       0    0.0003 0.9869065    
access               1   7955    7955  264.0943 < 2.2e-16 ***
bill_pay             1   5124    5124  170.1044 < 2.2e-16 ***
Residuals          126   3795      30                        
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Notes: NS denotes not significant at the 0.01 level for a 2-tailed test, S denotes significant at the 0.05 level for a 2-tailed test, MS denotes marginally significant at the 0.05 level for a 2-tailed test, HS denotes highly significant at the 0.01 level for a 2-tailed test.

In terms of the other factors, the presence of non-traditional financial institutions that appear to fill-in the gap created by the absence of larger, more capital-intensive banking and related services may be a good indicator of the ability to access account balances online. In countries where accessibility to local financial institutions is essentially nonexistent, especially in rural and underserved areas (Burgess and Pande, 2005; Turvey et al., 2011), or costs for opening an account in a traditional financial institution are simply too costly, the is a need to provide fundamental financial services. Hence, the presence of other options, such as mobile money providers and auxiliary services, increase the use of financial activity through individuals’ mobile phone. As good metric to assess the presence of non-traditional financial institutions this looking at the population of mobile money accounts owned/shared by a country.

From an economic health perspective, local employment rates certainly can be an important indicator associated with increasing access to financial services. Higher employment rate leads to individuals having a source of income that allow them to participate in activities such as savings, purchasing, accessibility to a quality lifestyle, which essentially all requires a good financial infrastructure as measured via the use of an account from a financial institution or mobile money provider. Low employment rates in countries tend to lead to individuals not having an account, which is especially true for developing countries, resulting the reverse (e.g., a substantially a poorer quality lifestyle). Assessing employment rates by using surveys conducted by nationally based census bureaus that collect nationwide information. It was considered outside the present study; as such detailed information was not available in the EY FinTech Adoption Index, 2017.

Table 1 Four-tiers and associated countries established based on number of financial and/or banking accounts per capita from the EY FinTech Adoption Index 2017 study

Income level (based on GDP)	*Country*
High income	Estonia
High income	Israel
High income	The USA
Upper middle income	Argentina
Upper middle income	Croatia
Upper middle income	Gabon
Lower middle income	Kenya
Lower middle income	Honduras
Lower middle income	Moldova
Low income	Rwanda
Low income	Zimbabwe
Low income	Haiti

Account accessibility/convenience would be a very desirable variable to explore further as individuals with an account as defined in the present study, only measures those who have successfully navigated a FinTech system in its present form, which could be deceiving on its face value. Such a dependent variable does not take into consideration the many barriers that force or discourage others that do not use FinTech often, as the services that are associated with such financial accounts are either too expensive or not convenient enough for them to user in their daily lives. If financial institutions improve the capabilities of the services, they provide with their accounts, which would convince individuals to use their accounts more to perform various financial activities. As previously stated, these data were not included in the EY FinTech Adoption Index, 2017 study and can be assessed conducting individual surveys and collecting feedback from account owners about how they use the account and for what activities they would like to use the account for routine services.

Another important variable that was not encompassed in the present study and not available in the EY FinTech Adoption Index, 2017 dataset is the desire to access the global marketplace via e-commerce. Many items are not available locally as well as less expensive price options are probably available from online sellers/distributors. There was no direct measure of that aspect in the research database, but perhaps using percentage reporting making a purchase over the internet in the last year (B2C) would be a good proxy. Numerous lessons and methods could make FinTech more efficient and reduce costs associated with its application from the manufacturing and service sector. For example, in supply chain management, many uses of Blockchain (e.g., keeping an electronic log of owner associated with goods/services flowing through the supply chain), automatic identification and data capture (AIDC) techniques of RFID and other capture methods may prove useful.

Tabanli and Ertay (2013) completed an in-depth study to demonstrate the value that this technique can add to an organisation; they decided to implement an RFID system on a Kanban system. Typically, RFID technology in production process to improve efficiency, eliminate waste, reduce human errors, and improve overall performance. There are no reasons that these techniques cannot be applied to the FinTech industry. Another technique that was utilised in their case study was the process of value stream mapping (VSM), which as a simple tool to provide an informational and material flow that, in essence, maps the entire process. Applying such as a tool should allow managers to see where the bottlenecks are in the process and where resources are being wasted. In doing so, activities can be prioritised in the process so that it can perform as lean as possible. Once a current-state map has been created, a future-state map can be created by answering questions designed for improvement. Hence, financial organisations use a combination of RFID and VSM to help cut costs while remaining flexible enough to respond to changing customer demand.

Similarly, Long et al. (2010) focuses operational tools on process and capacity design and managing quality of financial services. The authors found that the main bottleneck faced in mid-sized financial service firms is that the lack of effective IT system change control processes used in mid-size accounting firms is resulting in unfavourable working outcomes. These include unplanned downtime, security risks, frustration for the employees working in IT, and compliance issues. All of these results lead to negative productivity, unsatisfied customers, and low performance. Research shows that 80% of unplanned downtime is the cause of IT system changes related to application failures and operation errors. The authors use the Six Sigma methodology as framework to assess firms with potential solutions to this problem. Fixing this will help firms improve the process and technology they are using which will help them produce a better quality of work.

4.2 Managerial implications

A reflection of the analysis and discussion of the four research questions, the statistical analyses may point to several trends on FinTech industry as they try to redefine their roles in shaping the services and products that will improve their profitability as well as improve the standard of living for literary billions of people. As demonstrated in the MLR techniques from RQ1, there are some obvious steps that FinTech can to improve accessibility to much needed financial services. Reducing the barriers and documentation requirements would certainly improve the access to an account, either traditional or mobile, by lowering fees for setting up and maintaining an account. The direct results of the models developed in Figures 3–9 definitely suggest, that most people have immediate financial goals, especially in the developing world, that there should be less emphasis on long-term planning and retirement goals. It was found that even in highly developed countries that have strong investment in public service, quality and affordable/free healthcare, and transportation and senior living infrastructures, long-term planning and retirement goals are not a priority. Certainly, it is advisable that financial institutions offer educational programs or promotional campaigns that promote the benefits of long-term financial planning and stability via FinTech, when these safeguards are missing or poorly developed. From the analysis of RQ1, as populations are relatively young, especially in the developing nations, targeting underserved areas (rural) and segments (young adults) would be growth opportunities for FinTech (Shee et al., 2015).

Another striking trend that can be generated from analysis of the research questions is that FinTech has much improvement in support technologies if it is to better integrate people's routine/daily transactions (e.g., utility and bill pays, transportation, entertainment) via offering more services/features in centralised apps and mobile devices become cheaper and more available. Unfortunately, as cybertheft, fraud, and identity theft become more commonplace, these same financial institutions must offer more security and privacy features when designing their online and mobile services and apps.

5 Summary and conclusions

5.1 Conclusions and recommendations

The EY FinTech Adoption Index 2017 database is an extremely large and comprehensive, fertile for data mining experimentation. The author only picked a very small set of potential set of research questions to analyse. The use of cloud storage was necessary in order to perform the basic statistical correlations and MLR analyses via R-script and R-Markdown. From a detailed analysis of the four research questions, a series of recommendations were created on the results.

1 Ensure access to health insurance in all countries to reduce the percentage reporting having borrowed for medical expenses.

   It is obvious from the analysis that medical expenses are still a dominate reason that people go into debt. Equally true in developing and developed countries, if there is social net and access to affordable insurance, many people are going to fall through the cracks. If access to adequate healthcare facilities with the various modes of transportation are not available and nation-wide financial resources are underfunded, the obvious result with be poor-levels of healthy workers that can participate fully in their economies.

2 Implement cost controls to ensure fair and consistent pricing for medical services/drugs regardless of healthcare insurance coverage to reduce the percentage reporting having borrowed for medical expenses.

   It became equally obvious through an analysis of FinTech in both rich and poor countries, privatisation and deregulation of the medical industry will not pull millions out of poverty. Just as the current dilemma of COVID-19 vaccine nationalism has become a hotly debated issue among rich and poorer nations, there much be a global effort to implement controls that allow everyone access to high quality and accessible. The initial purpose and set of research questions to be discovered and analysed did not have a healthcare focus, it soon become apparent that in a global humanitarian issue that, with governmental support, may be addressed through improved access to financial resources.

3 Require all governments to issue required identification documentation so that citizens may open a banking/financial account.

   Traditionally, many progressive countries have sought to simply identification and tracking of their citizens through national identity cards. In the US, there has been much push back as many politicians feel the pressure from the constituents that feel it is a violation of their rights to privacy. However, especially in developing countries that have low literacy rates or large migrate populations or do not have stable home addresses, many people do not have the proper documentation to receive the benefits of financial or governmentally funded service, such as healthcare.

4 Incentivise financial institutions to offer micro loans in low-income countries for very specific short-term needs, which help in dealing with the most significant barrier to owning an account.

Perhaps the most significant conclusion and related recommendation that many people in developing countries do not have access to micro loans to handle routine emergencies or irregular needs for cash. Having access to buy extra seed when a harvest has been destroyed by bad weather, a healthcare emergency, or an unexpected cash fall are essential to the well-being of any community. Many countries have well-developed FinTech to allow its citizens to purchase on credit. However, with large swards of the population without credit histories or proper documentation, it seems like an impossible luxury. If governmental agencies could create of a system for microloans that do not required such a need for this type of documentation for short-term simple needs, it population would be able to prosper. This as well as related recommendations do require an investment into a national FinTech infrastructure.

5.2 Future research directions

The primary goal was to provide a global perspective on financial technology and usage (FinTech). The initially availability of the EY FinTech Adoption Index 2017 dataset and its published report presented a rare insight to the need for greater levels of financial opportunities to the global population in order to achieve a higher standard of living and basic personal security. This trend is especially true in the historically underserved emerging markets, with China and India leading FinTech adoption across the study. However, it is merely a snapshot in time that has little meaning until its lessons can be chiselled out in data exploration and recommendations made that have some probability of being adapted. Once additional research on this dataset, previous and future similar datasets made and comparisons and trends are compared, a more meaningful set of recommendations can be made and acted upon. Financial security should not be an exclusive right of the privileged few. It should be a basic right of the many if humanity is to prosper and take on the destiny of a greater financial security of its future. Much like a study of asbestos in construction applications of the past, few would argue that its analysis and effects of living systems are fertile grounds for further research opportunities, trouble spots identified, and remediation steps should be undertaken. If we have essentially universal agreement on a static problem of chemicals in the environment, why not something far more dynamic and equally dangerous on other social issues, such as financial equity among the poorest nations circling the global? Although the dangers of insufficient financial resources may be more hidden, its affects may result in an epidemic of homelessness, poverty, illness, disease, and social inequity at an enormous scale. The consequences of loss of global trade, wealth, and opportunity would be almost incalculable. FinTech and its problems of accessibility to capital, is something, like the COVID-19 pandemic, results in disastrous consequences of people so inflicted. Therefore, positive attempts need to be taken to address financial accessibility and social justice that current plague the FinTech industry.

Without a doubt, the financial effects of the global COVID-19 pandemic will be felt for years to come, both directly and indirectly, as unemployment and employment opportunities reshape future cash needs and financial goals. In the U.S., COVID-19 was the third largest contributor to health-related deaths, only preceded by heart disease and cancer, respectively (Ahmad et al., 2021; Howard, 2021), 'potentially overwhelming the healthcare system and causing substantial loss of life' (Woolf et al., 2020). Hence, COVID-19 'marks at least a temporary setback for epidemiology,' (Zhou and Stix, 2020). As the number of Americans who died in January through August 2020 was significantly more than any similar time dating back to 1970. Looking back on the last two years, according to a recently published US Centre for Disease (CDC) report, the domestic death rate from 2019 to 2020 significantly increased (15.9%), from 715.2 to 828.7 deaths per 100,000 (Ahmad et al., 2021).

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