Senior Research

Impact of Mobile Banking Access on Financial Well-being: A Comparative Cross-country Analysis

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Abstract

Ever since the inception of mobile banking services, people have been able to access their financial institution anytime and anywhere. This led to the belief that their quality of life has increased, but does this mean that financial well-being also improves, or does fintech encourage negative behavior? Using previously established theories like the Technology Acceptance Model and Diffusion of Innovation Theory, this study aims to bridge the gap between M-banking, financial well-being, behavior, and literacy at a cross-country scale through Structural Equation Modeling. Results indicate that M-banking has the power to improve well-being, even when knowledge is absent, proving that adopting fintech has a net positive effect. Additionally, the effect of M-banking access is enhanced by proper financial action, as the indirect effect of M-banking on well-being is greater than the direct effect by around three times. This paper hopes to convince financial institutions and governments to emphasize on the ever growing M-banking trend, enhancing people's financial lives.

Introduction

Mobile banking, a global phenomenon that revolutionized the financial industry over the past decade, providing people with real time access to virtually every banking service, anywhere. In Thailand, financial access rose by almost 1.5% within 2016 to 2018 alone, bringing the country's financial access to a shocking 98.7%. In 2017, Promptpay was introduced, effectively removing transfer fees, and increasing the number of banking accounts by over 20 million (Moenjak et al, 2020). This expansion shows the role that M-banking has in advancing financial inclusion, including unbanked areas. However, does this evolution of M-banking actually help improve people's daily lives? This paper aims to cover this exact question.

The primary objective of this study is to identify the relationship between mobile banking access and financial well-being at a cross-country level. This includes factors like financial behavior, and literacy which are stated by past literature to be interrelated with well-being. Additionally, the Technology Acceptance Model will be used in the framework, which the main regression is based on. The TAM theory has been extensively proven in research to explain how mobile banking changes behavior, therefore it will serve as the basis for this study and framework.

For data, multiple trustworthy sources like The World Bank Database and the IMF Database will be used. As mentioned before, this study is a cross-country analysis, meaning that data from 123 countries from the year 2021 will be used. Before the framework and data can be organized though, this paper starts off with a literature review including topics on M-banking, financial behavior, literacy, well-being, and theories related to the field.

Research Question

This paper aims to tackle the question of "Does mobile banking adoption have an effect on financial well-being" through direct and indirect effects of related factors such as financial behavior, financial literacy, and macroeconomic factors by analyzing data at a cross-country level.

Why Mobile Banking?

Throughout history, many use cases have shown that mobile banking leads to easier financial lives in many countries. In Kenya, male workers frequently send money back to their families from urban areas to rural areas. With the help of M-banking, costs significantly reduced by over half compared to mailing options (Medhi et al, 2009). On the other hand, research also proved that mobile financial services led young workers in India to invest and borrow more, improving their financial outcomes (Biswas, 2021). These are but a few out of many cases where M-banking helped better the financial lives of people across the globe.

Literature Review

Briefing

In many regions, the relationship between M-banking and financial well-being involves the interaction of multiple factors, including financial behavior, financial literacy, and social elements. By taking a look at previous studies in this field, this literature review aims to analyze the role of M-banking in influencing these factors through the lens of theories such as Technology Acceptance Model, Diffusion of Innovation Theory, and Stress Coping Theory . In particular, three main themes emerge: the emergence of M-banking, its influence on behavioral and literacy, and the relationship it has with financial well-being. Additionally, this literature review aims to address consistencies as well as the knowledge gap featured in existing research.

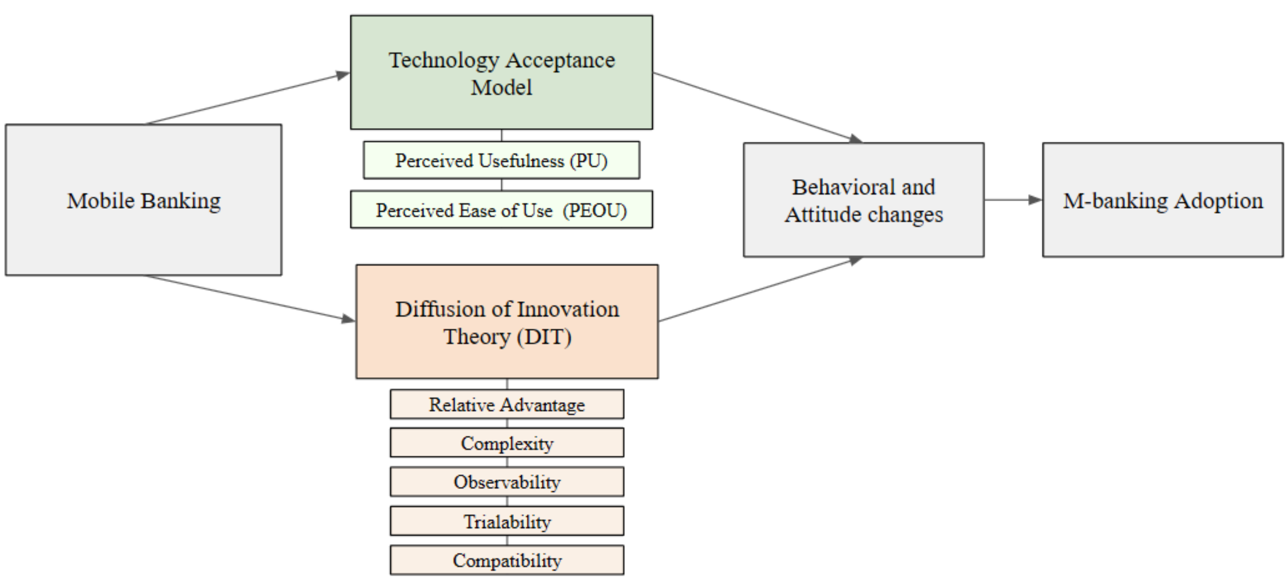
Theme 1: Establishing Mobile Banking Adoption

Multiple studies have defined the term "mobile banking" or "M-banking" in various ways before. A study done in 2016 by Chuchuen defines mobile banking, or M-banking in short, as: "a mobile payment and commerce application that allows customers access to virtual banking at any time and place". Often, with features like merchant and utilities payments, as well as Peer to Peer (P2P), Business to Peer (B2P), Business to Business Transfers (B2B) transfers and long-distance remittances (Chuchuen, 2016). Other works have interpreted M-banking in a similar manner. Thus, M-banking can collectively be defined as a mobile technology or product offered by a financial institute for conducting and accessing financial services; including but not limited to transactions, checking balance, and investment, through a mobile phone or tablet. (Shaikh & Karljaluoto, 2015; Singh et al, 2024)

Correspondingly, the inception and purpose of M-banking has also been extensively researched through the lens of theories like "Technology Acceptance Model" and "Diffusion of Innovation Theory". Studies have used the Technology Acceptance Model or "TAM", proposed by Fred D. Davis in 1985 to explain why people use M-banking in their daily lives. More specifically, the

TAM shows how people perceive the usefulness and convenience of fintech which could change their behavior and daily lives (Ahmad, 2018; Chuchuen, 2016). The research by Audi on mobile banking adoption in Lebanon summarized how TAM measures a technology's relative advantage ("Perceived Usefulness") compared to what people had earlier, and the convenience it brings to their daily lives ("Perceived Ease of Use"). He came to the conclusion that people opt for M-banking due to its usefulness, trustworthiness, and ease of use (Audi, 2016). Another similar theory mentioned in a lot of M-banking literature is the Diffusion of Innovation Theory or "DIT" which seeks to explain why and how technology spread through cultures and whether people choose to accept it by comparing its relative advantage, complexity, compatibility, trialability, and observability (Al-Jabri & Sohail, 2012; Audi, 2016). These models are summarized below.

Framework A



Research suggests and highlights the relative advantage of M-banking through TAM in many examples. In Kenya, a study showed that the nation's high adoption rate was in part due to

M-banking helping families send money back home due to the geographically split nature of the country's work culture, where it helped provide convenience. Additionally, M-banking was 50% cheaper for sending remittance when compared to postal money (Medhi et al, 2009). In similar fashion, research revealed that in Iceland, each log in (to M-banking) contributed to reduced bank fees by $2.24; whereas logging in at least once reduced fees by $19.62. Furthermore, it helped decrease overdraft debt by 14% over a period of 2 years (Carlin et al, 2018). This showed that in a country with over-indebtedness like Iceland, M-banking helped increase access to financial information, inducing positive behavioral changes. However, some studies hint that adoption rate and the TAM model for each country varied greatly, partly due to external factors like social influence and trust (Ahmad, 2018; Audi, 2016; Chuchuen, 2016).

Theme 2: Role of Mobile Banking on Financial Behavior and Literacy

As an enabler of "anytime and anywhere" banking, financial inclusion is inevitable. Many studies have linked M-banking to factors such as financial behavior and financial literacy. Financial behavior being defined as a person or household's ability to manage and control finances (Winarta & Pamungkas, 2021). Meanwhile, financial literacy and knowledge is the key that allows the person to make wise and calculated financial decisions. A study by Singh (2024) defined Financial literacy as "the knowledge, understanding, skills, and confidence to make decisions and financial risk" (Singh et al, 2024). In fact, many works point to financial literacy being one of the most important parts of one's financial life, as it encourages non-impulsive behavior and improves financial decisions (Singh et al, 2024). A study in Northern Ireland revealed that financially literate individuals were better off in the event of a financial shock, as they were more likely to check their income (Panos & Wilson, 2020).

Several literature have highlighted the positive outcome that M-banking had on financial behavior and literacy. Since the adoption of M-banking, many unbanked areas are granted financial services which can potentially improve a person's ability to save, transfer, and manage, which increases convenience and gives the person a better sense of control (Zhang, 2023). Additionally, fintech features such as real time alerts and banking tools may improve financial habits by allowing the person to monitor their spending patterns whenever they like. (Shaikh & Karljaluoto, 2015). Previous research also concluded using the TAM model that Fintech innovations can lead to behavioral changes which affect attitude, leading to knowledge seeking behavior. This then leads to producers creating new innovations, causing a feedback loop between Fintech, financial behavior and knowledge (Moenjak et al, 2020).

On the other hand, some studies also found the opposite to be true. A study done by Zhang (2023) found that Fintech, particularly mobile applications, were negatively correlated to positive financial behavior. Rather than consulting an institution or financial expert, they may make impulsive financial decisions, leading to mismanagement. This suggests that while M-banking provides the necessary tools for financial engagement, financial literacy and responsibility is crucial to make financial behavior positive and avoid hasty decisions, especially under pressure (Panos & Wilson, 2020; Zhang, 2023).

Theme 3: Role of Mobile Banking on Financial Well-being

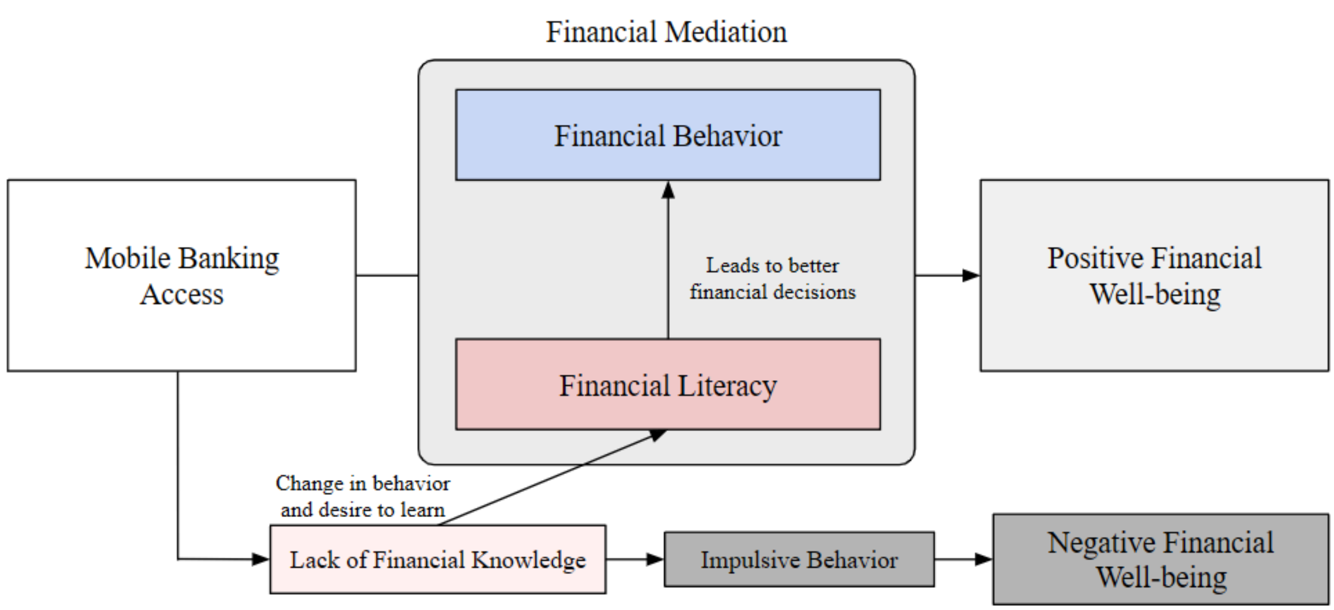
It is in human nature to cope under stress. The Stress and Coping Theory (SRT) by Lazarus and Folkman (1984) attempts to explain this phenomenon by stating that coping mechanisms are strategies individuals use to manage stress. A study by Zhang showed that M-banking acts as a coping mechanism for financial stress by letting people control and manage their finances (Zhang, 2023).

Before looking into the relationship with M-banking, the concept must be defined. Financial well-being has been extensively defined throughout research. Collectively, it can be defined as a state where individuals can meet financial obligations, absorb financial shocks, commit to long-term financial commitments, and feel secure about their financial future, allowing them to enjoy life. (CFPB, 2015; Desello, 2024; Sabri et al, 2023; Singh et al, 2024)

Despite the fact that people have used M-banking as a way to cope, a majority of papers have determined the relationship between mobile banking and financial well-being to be multifaceted. M-banking alone does not have a clear positive relationship with financial well-being, as there are many other factors that prey on individuals to make irrational decisions and spend their money (Sabri et al, 2023). As a matter of fact, Zhang (2023) suggested the opposite, that people who rely too much on solely their application often lacked proper financial advice which prevented them from making optimal financial decisions, hindering their financial well-being.

Regardless of split opinion on M-banking's influence on wellbeing, a majority of literature agreed that only the coexistence of positive financial behavior, financial literacy, and M-banking can bring about positive financial well-being; with either factor being a mediator. A study by Balatif (2024) suggested that fintech acts as an enabler and solution for people with financial education to effectively manage finance (Balatif et al, 2024). In a similar manner, other literature mentioned that financial literacy and behavior acts as a mediator for M-banking to improve financial well-being. One study found that fintech helped reduce impulsive behavior through the use of financial literacy (Singh et al, 2024). Another study proposed financial behavior as a mediator between financial literature and wellbeing by using technology as a means. With the latter acting as an enabling ecosystem but requires responsible use to have a positive effect. (Sabri et al, 2023). This relationship is further represented in *Framework B*.

Framework B



Summary and Knowledge Gap

To summarize, this literature review investigated multiple definitions of M-banking and relevant terms, its role in inclusion, and relationship with financial behavior, literacy and well-being. While M-banking has an ever important role to play in the financial industry, its impact on financial well-being remains unclear. Some papers highlight M-banking as a crucial tool that has helped reduce banking fees and a way to cope with financial stress, while others found that fintech - without other factors, actually dealt harm as it incentivises impulsive behavior. Despite this, it is clear that the nature of the relationship is highly complex, as it involves financial behavior or literacy as a mediator for effective M-banking use, resulting in a positive relationship with financial well-being.

While existing research has extensively explored M-banking's role on financial inclusion, behavior, and education, the impact that mobile banking access has on financial well-being has yet to be fully investigated. Particularly, the paper by Zhang & Fan (2024) highlighted fintech utilization's effect on well-being, but not global M-banking access. This means there is no research on this multifaceted relationship on a cross-country scale yet, as previous works focused on a single concentrated region such as the US, Malaysia, Lebanon, Kenya, Saudi Arabia, India and many more. Furthermore, these nations feature varying social aspects and culture, which may influence the impact on variables, leading to different conclusions for each study. Addressing these gaps may provide a more comprehensive understanding of how M-banking adoption impacts financial well-being across different global contexts.

Data and Methodology

Indicator	Role	Sub-Definitions	Variable	Data Definition	Source
Mobile Banking Adoption	Independent	-	MB	% of active mobile money service accounts in the past year	World Bank - The Global Findex Database
Financial Well-being (FWB)	Dependent	The ability to absorb shocks	FWB_1	% of people who are able to come up with emergency funds in 30 days	World Bank - The Global Findex Database
		The ability to meet current obligations	FWB_2	Natural log of GDP per capita	World Bank - World Economic Outlook Database
		The ability to meet long term obligations	FWB_3	Household debt as a % of GDP	IMF - Global Debt Database
		The ability to enjoy life, risk free	FWB_4	Out-of-pocket health expenditure % of national health exp.	World Bank - World Economic Outlook Database
Financial Mediators (FBL)	Dependent	Financial Literacy	FL_1	% of people who can use a bank or financial institution without help	World Bank - The Global Findex Database
			FL_2	% of people who used a credit or debit card	
	Dependent	Financial Behavior	FB_1	% of people who saved any money	
			FB_2	% of people who borrowed any money	
Inflation	Control	-	Inflation	% change in CPI	World Bank - World Economic Outlook Database
Unemployment	Control	-	Unemployment	% change in unemployment	
Economic Growth	Control	-	GDPGrowth	% change in annual GDP	
Government Spending	Control	-	GovtSpend	Final total general govt. spending % of GDP	
Internet Access	Control	-	InternetAccess	% of internet access	

Data Table

This study sources cross-sectional data from multiple sources from the year 2021 to analyze the relationship between mobile banking adoption and financial well-being through other important variables in 123 countries. In particular, the paper utilizes data from the World Bank Global Findex Database, World Bank World Economic Outlook Database, World Health Organization UHC Coverage Index, and IMF Global Debt Database. Primary data is merged based on available countries in 2021 using *IBM SPSS* and *Microsoft Excel*. Please note that missing data, primarily in variables where some cross-country data is not available, was estimated using Maximum Likelihood Estimation to make SEM regression possible. Although, this is only for FWB_3 where there is missing data.

Methodology

This paper employs a quantitative method which includes a combination of theoretical and empirical approaches used in conjunction to perform a quantitative analysis. Unlike normal linear regressions which can only account for observed variables, this study features multiple "latent variables" which are used to explain concepts. For this purpose, the Structural Equation Modeling Regression (SEM) is used, as it allows for latent constructs and helps establish direct and indirect cause between variables. In fact, much research done on financial well-being, behavior and literature also utilizes this method (Sabri et al, 2023; Zhang & Fan, 2024). The Framework illustrated in *Appendix B* serves as the main concept for regressions. Additionally, SEM was constructed through *AMOS 28 SPSS*. Furthermore, causality between M-banking and financial mediation was tested through 2SLS Instrumental Variable Regression using *gretl*.

Defining SEM Methodology

Before the hypothesis can be tested, the objective and methods must be defined. According to Geffen's guidelines on Structural Equation Modeling, he defined it as a "multivariate econometrics technique, using multiple regression and factor analysis to estimate relationships simultaneously". In short, it does this by running multiple regressions through Maximum Likelihood Estimation to find the regression weights (β) until it stabilizes, and values are obtained (Gefen et al, 2000). Its main advantage over other linear regressions is that it can estimate "factors" (also called "latent constructs") which are concepts that cannot be measured. Instead, these constructs are explained through multiple "observed variables" and loading factors (λ) which work similarly to β in a normal regression. After constructing the relationship paths by following the framework, a Confirmatory Factor Analysis (CFA) is run to test theoretical relationships.

Hypothesis Testing

H_0: Mobile banking adoption has no significant effect on financial well-being

H_1: Mobile banking adoption has a direct positive effect on financial well-being

H_2: Mobile banking adoption has a direct negative effect on financial well-being

H_3: Mobile banking adoption has an indirect positive effect on financial well-being through financial behavior and financial literacy

H_4: Mobile banking adoption has an indirect negative effect on financial well-being through financial behavior and financial literacy

Confirmatory Factor Analysis

Simplified Formula:

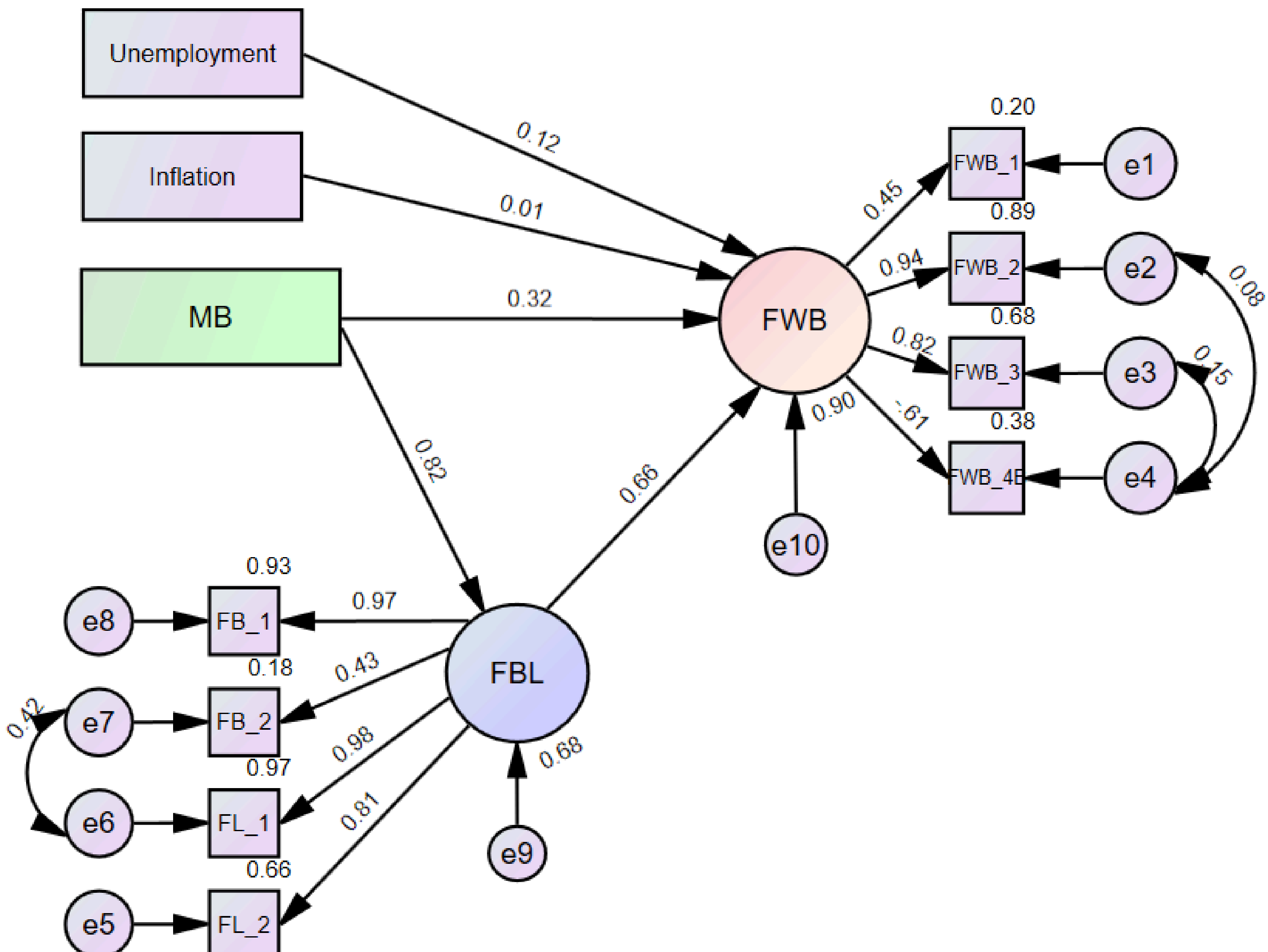
$$FWB = \beta_0 + \beta_1 MB + \beta_2 FBL + \beta_3 Unemployment + \beta_4 Inflation + \varepsilon$$

Constructs:

$$FBL = \lambda_0 + \lambda_1 FL1 + \lambda_2 FL2 + \lambda_3 FB1 + \lambda_4 FB2 + \gamma$$

$$FWB = \lambda_0 + \lambda_1 FWB1 + \lambda_2 FWB2 + \lambda_3 FWB3 + \lambda_4 FWB4 + \gamma$$

Diagram 1: SEM regression with 2 controls (AMOS 28 SPSS)



Justification and Validation

Diagram 1 shows the CFA of the SEM regression where the factor loadings are standardized. From the literature review, mobile banking adoption affects both the financial mediators (FBL) and financial well-being (FWB) itself, represented through regression paths (MB → FBL; MB → FWB; FBL → FWB). Here, the direct and indirect effects that mobile banking has on each construct are estimated. Furthermore, latent constructs such as the financial mediators and financial well-being can be represented through multiple observed variables through factor loadings (FBL → FB_1, FB_2, FL_1, FL_2; FWB → FWB_1, FWB_2, FWB_3, FWB_4). Additionally, control variables such as inflation and unemployment were added to reduce confounding bias and improve model fit.

The error terms were also estimated. It is to note that the covariation in the error terms can be justified to improve model fit. For [e3 ↔ e4], out-of-pocket health spending is significantly related to household debt according to research. A study in 2023 showed that OOP expenses led to increased household debt, likely because medical bills accumulate debt and borrowing which reduces financial well-being (Bernard et al, 2023). For [e2 ↔ e4], research justifies that on average, higher income countries spend more on OOP expenses due to increased costs (Wagstaff et al, 2020). This is also reflected in the dataset where Switzerland's OOP expenditure is somewhat high compared to others at 22.7%. For [e6 ↔ e7], it can be said that financial literacy influences the behavior, including actions like borrowing (Singh et al, 2024).

Assessing Model Validity

In SEM, there are numerous methods to validate the model in various aspects. The two main dimensions that are tested in research are construct validity and model validity. According to Gefen's guidelines for SEM, construct validity is measured through the convergent validity, and discriminant validity tests (Gefen et al, 2000). It is used to see if the latent constructs and its observed variables are valid or not. Meanwhile, model validity checks the fit of the whole regression and can be checked by model fit indices, the most common being CFI, TLI, and RMSEA (Schumacker & Lomax, 2015; Shi et al, 2019).

Construct Validity: Convergent Validity Test

To make sure that the observed variables are actually related to the latent construct, the convergent validity test must be performed. Many studies suggest the golden rule that if: Average Variance Extracted (AVE) > 0.5 and Composite Reliability (CR) > 0.6, then it is validated and the construct has great internal consistency (Fornell & Larcker, 1981; Hair et al, 2019; Shrestha, 2021). AVE and CR and calculated by:

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n} = \frac{\Sigma(Factor\ Loadings^2)}{n}$$

$$CR = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{[(\sum_{i=1}^{n} \lambda_i)^2 + \sum_{i=1}^{n} var(e_i)]} = \frac{(\Sigma Factor\ Loadings)^2}{[(\Sigma Factor\ Loadings)^2 + \Sigma Error\ Variance]}$$

From *Table 1* obtained from the SEM regression, the AVE and CR values all exceed their threshold, validating the convergent test, meaning that the model constructs are consistent.

Construct Validity: Discriminatory Validity Test

This test makes sure that each latent construct is “distinct” from each other. Multiple studies follow the method of comparing the square root of AVE to the standardized regression weights of the latent construct (Rönkkö & Cho, 2022; Sabri et al, 2023).

$$\sqrt{AVE} > Correlation\ between\ latent\ constructs$$

$$(\sqrt{0.537} = 0.733 > 0.66; \sqrt{0.687} = 0.829 > 0.66\ )$$

From Table 1 and Diagram 1, the AVE of both FWB and FBL exceeds the correlation between constructs. This proves that the latent constructs are distinct enough from each other to validate the model.

Table 1: Factor loadings for AVE and CR calculation

Observed Variables	Standardized Factor Loadings (λ)	Error Term Variance	AVE > 0.5	CR > 0.6
FWB_1	0.448	0.005	**0.537**	**0.904**
FWB_2	0.944	0.230		
FWB_3	0.823	0.034		
FWB_4	-0.614	0.020		
FL_1	0.984	0.002	**0.687**	**0.995**
FL_2	0.813	0.034		
FB_1	0.967	0.003		
FB_2	0.429	0.013		

Model Validity: Fit Indices

The standard guideline for validating model fit is used in this study. Many researchers and studies collectively agree that when the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI or NFI), and the Incremental Fit Index (IFI) is greater than 0.90, it means that the model is well-fitted, while 0.95 shows an excellent fit (Gefen et al, 2000; Afthanorhan et al, 2020). Another common measure is the RMSEA which should be between < 0.06 - 0.10. However, recent studies have shown that taking this index into consideration while having a small sample size (n < 200) is highly misleading. This is because the chi-squared measure heavily penalizes a small sample, leading to model "misspecification" (Shi et al, 2019). Thus, looking at the chi-squared/df to make sure that it is below 3 can be a feasible alternative for evaluating model fit (Schumacker & Lomax, 2015).

From *Table 2*, the chi-squared, CFI, TLI, and IF all meet the required threshold. However, the RMSEA is slightly above 0.10, which might indicate a poor fit. However, this is potentially because the sample size is low (due to the cross-country nature of the research), leading to lower values of chi-squared and consequently, higher RMSEA. Recent studies suggest that completely ignoring the RMSEA and looking at other values is advisable when the df is small. Not only that, in small models, it is common for RMSEA to exceed the cutoff, even when it is correct (Kenny et al, 2015; Shi et al, 2019). Thus, the RMSEA in this study will be ignored, and other indices will be taken into consideration instead. Therefore, taking this assumption into account, the model fit appears to be acceptable within the standard.

Table 2: Model fit indices of Diagram 1

Model Fit Indices	**Criteria**	**Value**
χ^2/df	< 3.0	**2.431**
CFI	> 0.90	**0.945**
TLI	> 0.90	**0.922**
IFI	> 0.90	**0.946**
RMSEA** Ignored due to small n	< 0.06 - 0.10	**0.108**

Discussion and Results

Table 3: Regression weights and significance

Regression Paths	**Unstandar-dized Regression Weights**	**Standardized Regression Weights (β)**	**Standard Error**	**Critical Value (t)**	**P-value (p)**	**Significance**
MB → FWB	0.045	0.317	0.013	3.429	***	*Significant*
MB → FBL	0.829	0.824	0.075	10.998	***	*Significant*
FBL → FWB	0.094	0.662	0.021	4.479	***	*Significant*
Inflation → FWB	0.000	0.011	0.001	0.268	0.789	Not Significant
Unemployment → FWB	0.077	0.117	0.030	2.595	0.009	Significant at the 95% CI

Please note that: *** $p < 0.001$

From Table 3, it is clear that mobile banking adoption has a significant effect on both financial mediators, and financial well-being itself. In fact, it can be said that the access to M-banking has a significant positive effect on financial behavior and literature ($\beta = 0.829$, $t = 10.998$, $p < 0.001$); and that the financial mediators also show a significant positive effect on financial well-being ($\beta = 0.662$, $t = 4.479$, $p < 0.001$). The key takeaway here is that M-banking adoption greatly positively impacts financial behavior and literacy, which then strongly influences financial well-being. Although, the effect that mobile banking has on FBL is slightly more than the effect FBL has on FWB. This can mean that MB substantially contributes to improving people's financial behavior and literacy by building awareness, tracking features, and other products. This matches the Technology Acceptance Model theory mentioned in the literature review, where people perceive M-banking as useful in their daily lives so they begin to change their behavior according to MB adoption (Audi, 2016; Chuchuen, 2016). Since the relationship between FBL and FWB is slightly weaker, it may show that people may not apply their financial knowledge correctly, or it may also mean that psychological factors like stress and impulsive behavior played a part in the relationship, further supporting previous research (Zhang, 2023). Additionally, unemployment is significant at the 95% CI level ($\beta = 0.117$, $t = 2.595$, $p = 0.009$), albeit with a very small positive effect. Despite initial contradictions, unemployment had a small positive effect on FWB possibly due to the context of the COVID-19 pandemic in 2021. This may be because many governments like the US, China, and Thailand provided benefits, insurances, and job search efforts which helped offset the damage (Williams, 2020). Additionally in 2020, almost 20% of adults in the US actually found new jobs due to the pandemic, suggesting that unemployment was balanced by employment benefits (Acs & Karpman, 2020). However, inflation has no significant effect on financial well-being. In addition, M-banking by itself also impacts financial well-being positively, albeit significantly less than FBL ($\beta = 0.317$, $t = 3.429$, $p < 0.001$). This means that despite being positive, simply having access to mobile banking does not improve FWB directly, only slightly. Furthermore, this also aligns with existing literature where many examples from many countries showcase that having access can improve people's lives, only if they understand financial principles (Klapper et al, 2015). In India, a study revealed that individuals using mobile banking apps were more likely to engage with financial activities like investing and borrowing. This suggests that MB influences behavior which contributes to financial well-being (Biswas, 2021). In contrast, this finding differs from existing papers that state that fintech usage by itself contributes negatively to financial well-being in the US due to stress and lack of proper financial behavior (Zhang, 2023). This indicates that just having M-banking access may have a positive effect on people's lives around the world.

Table 4: Direct, indirect effects and R-squared

Direct/Indirect Effects	**MB**	**FBL**	**R-Squared**
FBL	0.824	-	0.679
FWB	0.546 + 0.317	0.662	0.900
FB_1	0.797	0.967	0.935
FB_2	0.353	0.429	0.184
FL_1	0.811	0.984	0.968
FL_2	0.670	0.813	0.660
FWB_1	0.387	0.297	0.201
FWB_2	0.815	0.626	0.892
FWB_3	0.710	0.545	0.677
FWB_4	-0.530	0.407	0.377

From *Table 4*, M-banking adoption has a stronger indirect effect than the direct effect on financial well-being (β = 0.546 > 0.317), with both being positive. This proves that financial behavior and literacy acts as the key to financial well-being, while mobile banking acts as the enabler. Interestingly, this differs from previous research in the US which found that fintech utilization alone led to negative financial well-being (Zhang & Fan, 2024). Results are further enhanced by the R-squared estimates which show that the model was able to explain 67.9% and 90% of FBL and FWB respectively. MB having a strong indirect effect follows existing literature which often stated that having access to banking services did not improve decision-making without proper financial literacy and usage (Cole et al, 2011; Zhang & Fan, 2024).

Looking at other indirect effects reveals that M-banking adoption had the most effect on FL_1, which is the % of individuals who were able to use banking services without help. This shows that mobile banking leads to a behavioral change of people learning to use the service, as it becomes a part of their daily lives. Moreover, both MB and FBL have the greatest indirect effect on FWB_2, the GDP per capita measure. This can be interpreted as countries with higher adoption rates indirectly led to an increase in GDP per capita through financial behavior and literacy. Nevertheless, the connection to FWB_1, the ability to come up with emergency funds, remains weaker and might reflect the change in saving patterns in this day and age. In particular, a study in 2023 found that Gen Y, a huge part of the working force, tends to splurge and not save, which might lead to insufficient funds for saving (Xie et al, 2023). Additionally, FWB_4 or the OOP health expenditures were actually negative. This follows the OECD's reports, showing that spending more money out-of-pocket can lead to financial hardships and worse financial stability

(OECD, 2023). Particularly, the research by Bolongaita highlighted that at least 34 low-middle income countries are at risk of "catastrophic health expenditure", leading to financial stress (Bolongaita et al, 2023). To summarize findings, we reject the null and support the H_3 hypothesis, as M-banking acts as an enabler for financial behavior and literacy to improve financial well-being, while having a small positive effect on financial well-being by itself in the global context.

Alternative Regression CFA (Robustness Check)

Simplified Formula:

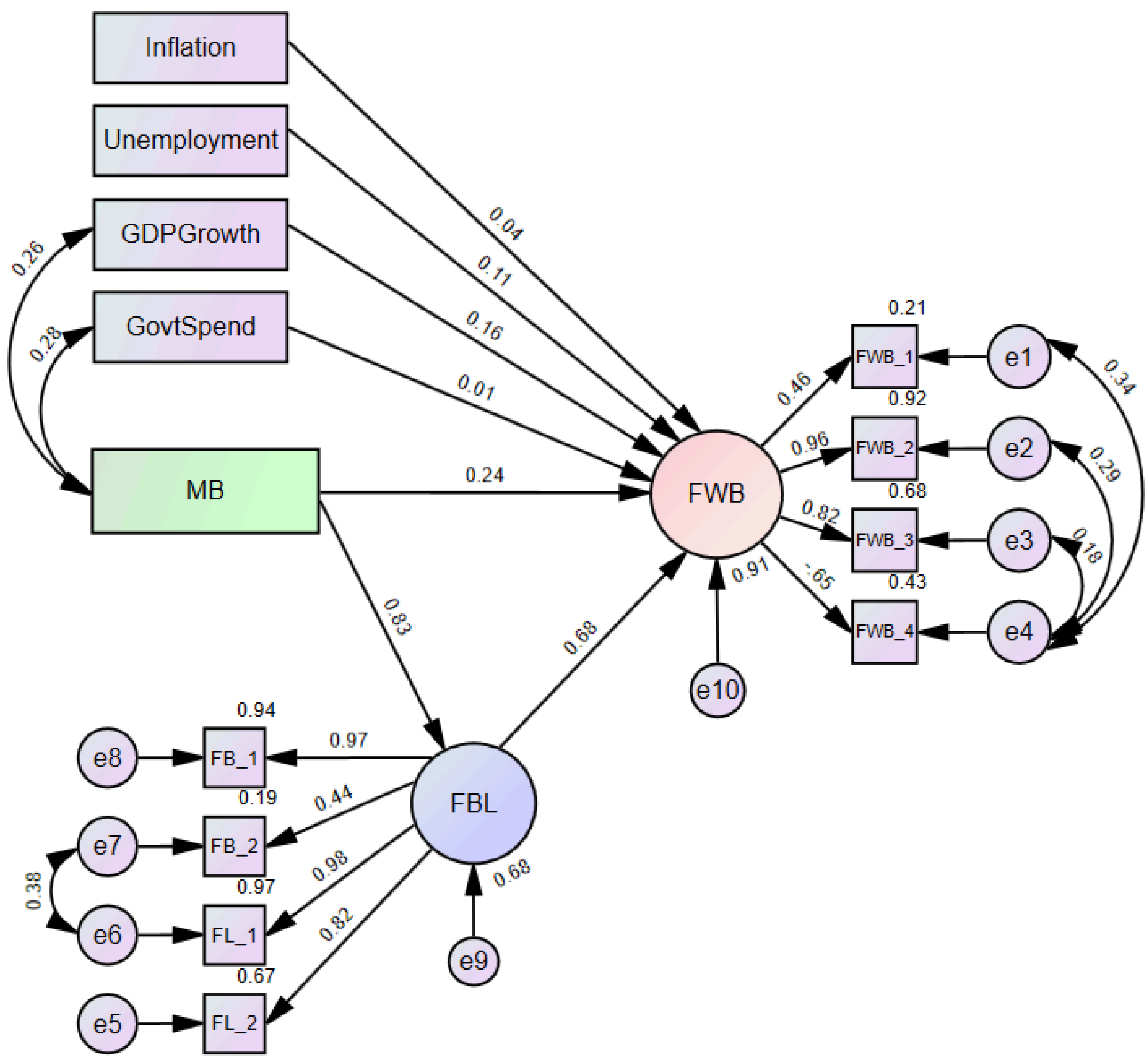
$$FWB = \beta_0 + \beta_1 MB + \beta_2 FBL + \beta_3 Unemployment + \beta_4 Inflation + \beta_5 GDPGrowth + \beta_6 GovtSpend + \varepsilon$$

Constructs:

$$FBL = \lambda_0 + \lambda_1 FL1 + \lambda_2 FL2 + \lambda_3 FB1 + \lambda_4 FB2 + \gamma$$

$$FWB = \lambda_0 + \lambda_1 FWB1 + \lambda_2 FWB2 + \lambda_3 FWB3 + \lambda_4 FWB4 + \gamma$$

Diagram 2: SEM regression with 4 controls (AMOS 28 SPSS)



Results of Alternative CFA

Alternatively, a regression was done with 4 control variables (adding GDP growth and government spending) in an attempt to better explain the relationship between mobile banking access and well-being. Additionally, covariation between [e1 ↔ e4] was added to improve fit. However, the model fit indices still yielded worse values for every category, meaning that adding more variables actually made the model worse in terms of explaining the relationship as shown in *Table 5*. That being said, the relationship and values still show similar results regarding direct and indirect relationships, regression weights, and factor loadings which tell the same story and prove the same points as *Diagram 1*. The key parts being that MB has a stronger indirect effect, showing the importance of financial mediators, and that without it, the effect on financial well-being is significantly reduced. Therefore, *Diagram 1* will be used as the main result for this research, as both with or without controls showed similar findings.

Table 5: Model fit indices of Diagram 2

Model Fit Indices	**Criteria**	**Value**
χ^2/df	< 3.0	**2.721**
CFI	> 0.90	**0.910**
TLI**	> 0.90	**0.877**
IFI	> 0.90	**0.912**
RMSEA** Ignored due to small n	< 0.06 - 0.10	**0.119**

Causality Test

Now that the relationship between access to mobile banking and financial well-being has been established at a cross-country scale, how can the relationship between M-banking and financial mediation also be proven? In other words, how can we know that access to mobile banking leads to improved financial behavior and literacy?

Due to the nature of this study being cross-sectional data, the amount of options and methods for proving causality becomes limited. Thus, an instrumental variable regression was done to establish causality in this case, as it prevents endogeneity. The dependent variables are the financial mediators (FBL), while M-banking (MB) access serves as the independent variable along with control variables including: unemployment, inflation, GDP growth, government spending, and internet access.

First Stage

$$MB = \gamma_0 + \gamma_1 Z + \gamma_2 InternetAccess + \gamma_3 Unemployment + \gamma_4 Inflation + \gamma_5 GDPGrowth + \gamma_6 GovtSpend + e$$

Second Stage

$$FBL = \beta_0 + \beta_1 MB + \beta_2 InternetAccess + \beta_3 Unemployment + \beta_4 Inflation + \beta_5 GDPGrowth + \beta_6 GovtSpend + \varepsilon$$

Diagram 3: F-statistic Results of IV Regression

```
Weak instrument test -
  First-stage F-statistic (5, 117) = 29.074
  Critical values for TSLS bias relative to OLS:

     bias       5%      10%      20%      30%
    value    18.37    10.83     6.77     5.25
```

After a Two-Stage Least Squares regression was done, the First Stage F-statistic results yielded a value of 29.07 (shown in *Diagram 3*), exceeding 10, which was the rule of thumb for establishing causality (Staiger & Stock, 1997; Stock & Yogo, 2002). This shows that M-banking does lead to better financial knowledge, proving the framework and regression to be valid.

Implications and Contributions

The significance of this paper implies that policymakers and governments can choose to improve and promote financial knowledge and positive behaviors in order for mobile banking to have the most effect on people's financial well-being. They can do this through various policies including subsidies to the financial education industry, pushing for financial inclusion like PromptPay in Thailand, or providing unbanked areas like rural states with proper access. Moreover, banks can help customers avoid financial slipups and impulsive behavior by providing immediate financial knowledge in their apps.

Limitations

It is important to note though, that this study has some limitations. Firstly, data is taken from cross-sectional sets in a single time period which might be affected by bias. Particularly, the COVID-19 pandemic which shook the global economy and forced new policies, which may have affected people's financial well-being. Secondly, some data samples are quite limited, as The

World Bank Database is incomplete for some counties and time periods, especially before 2021. Additionally, latent constructs such as "financial behavior" are open to interpretations which are limited by the data taken by World Bank Findex surveys. Having a more specific measure may greatly improve data clarity and provide a better understanding. Lastly, due to the nature of this paper being a cross-country analysis, only the whole summary of the country was taken into account, possibly ignoring the differences between rural and urban areas.

Future studies can focus on a specific region like Southeast Asia or Northern Europe, and use panel data over time for clearer insights into the relationship. Additionally, countries can be grouped based on their M-banking access to make data more uniform.

Conclusion

In summary, it is evident that mobile banking access acted as a key enabler for countries to achieve financial well-being through the help of the right knowledge and behavior. At least in the year 2021, M-banking alone had the power to improve people's daily lives including higher GDP per capita and less out-of-pocket expenditures. However, if people choose to lead the right decisions and avoid impulse behavior, the effect on financial well-being is drastically improved. Overall though, this study showed that countries that had more access to mobile banking led to better lives and financial outcomes.

Interestingly, the results show that M-banking alone does improve financial well-being at a global scale, while past literature stated the change to be negative (particularly in the US), without proper actions and knowledge. However, keeping the limitations in mind, future research can update the situation by using data post-COVID, as many macroeconomic aspects have changed.

Nonetheless, this study offers a cross-country insight on mobile banking's relationship with financial well-being in the digital age, which may provide valuable implications for banking firms and government bodies to improve quality of life and maximize positive financial outcomes.

To conclude this paper: with the right financial behavior and knowledge, financial well-being can be achieved not only for the wisest or the wealthiest, but for everyone.

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Appendix

**Please note that OOPExp = FWB_4

AMOS 28 SPSS SEM Regression Estimates

Diagram 1

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
FBL	<---	MB	.829	.075	10.998	***	
FWB	<---	FBL	.094	.021	4.479	***	
FWB	<---	MB	.045	.013	3.429	***	
FWB	<---	Unemployment	.077	.030	2.595	.009	
FWB	<---	Inflation	.000	.001	.268	.789	
FWB_1	<---	FWB	1.000				
FWB_2	<---	FWB	37.798	7.129	5.302	***	
FWB_3	<---	FWB	7.344	1.440	5.100	***	
OOPExp	<---	FWB	-3.024	.676	-4.476	***	
FL_2	<---	FBL	1.000				
FL_1	<---	FBL	.870	.059	14.689	***	
FB_2	<---	FBL	.210	.043	4.852	***	
FB_1	<---	FBL	.748	.052	14.290	***	

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
MB	.065	.008	7.810	***	
e9	.021	.004	5.342	***	
Unemployment	.003	.000	7.810	***	
Inflation	2.045	.262	7.810	***	
e10	.000	.000	2.065	.039	
e1	.005	.001	7.713	***	
e2	.230	.066	3.497	***	
e3	.034	.005	6.899	***	
e4	.020	.003	7.215	***	
e5	.034	.004	7.520	***	
e6	.002	.001	2.574	.010	
e7	.013	.002	7.726	***	
e8	.003	.001	4.708	***	

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
FBL	<---	MB	.824
FWB	<---	FBL	.662
FWB	<---	MB	.317
FWB	<---	Unemployment	.117
FWB	<---	Inflation	.011
FWB_1	<---	FWB	.448
FWB_2	<---	FWB	.944
FWB_3	<---	FWB	.823
OOPExp	<---	FWB	-.614
FL_2	<---	FBL	.813
FL_1	<---	FBL	.984
FB_2	<---	FBL	.429
FB_1	<---	FBL	.967

Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
FBL	.679
FWB	.900
FB_1	.935
FB_2	.184
FL_1	.968
FL_2	.660
OOPExp	.377
FWB_3	.677
FWB_2	.892
FWB_1	.201

Total Effects (Group number 1 - Default model)

	MB	Inflation	Unemployment	FBL	FWB
FBL	.829	.000	.000	.000	.000
FWB	.124	.000	.077	.094	.000
FB_1	.620	.000	.000	.748	.000
FB_2	.174	.000	.000	.210	.000
FL_1	.721	.000	.000	.870	.000
FL_2	.829	.000	.000	1.000	.000
OOPExp	-.374	-.001	-.232	-.285	-3.024
FWB_3	.907	.002	.563	.692	7.344
FWB_2	4.669	.010	2.898	3.563	37.798
FWB_1	.124	.000	.077	.094	1.000

Standardized Direct Effects (Group number 1 - Default model)

	MB	Inflation	Unemployment	FBL	FWB
FBL	.824	.000	.000	.000	.000
FWB	.317	.011	.117	.662	.000
FB_1	.000	.000	.000	.967	.000
FB_2	.000	.000	.000	.429	.000
FL_1	.000	.000	.000	.984	.000
FL_2	.000	.000	.000	.813	.000
OOPExp	.000	.000	.000	.000	-.614
FWB_3	.000	.000	.000	.000	.823
FWB_2	.000	.000	.000	.000	.944
FWB_1	.000	.000	.000	.000	.448

Standardized Total Effects (Group number 1 - Default model)

	MB	Inflation	Unemployment	FBL	FWB
FBL	.824	.000	.000	.000	.000
FWB	.863	.011	.117	.662	.000
FB_1	.797	.000	.000	.967	.000
FB_2	.353	.000	.000	.429	.000
FL_1	.811	.000	.000	.984	.000
FL_2	.670	.000	.000	.813	.000
OOPExp	-.530	-.007	-.072	-.407	-.614
FWB_3	.710	.009	.096	.545	.823
FWB_2	.815	.010	.110	.626	.944
FWB_1	.387	.005	.052	.297	.448

Standardized Indirect Effects (Group number 1 - Default model)

	MB	Inflation	Unemployment	FBL	FWB
FBL	.000	.000	.000	.000	.000
FWB	.546	.000	.000	.000	.000
FB_1	.797	.000	.000	.000	.000
FB_2	.353	.000	.000	.000	.000
FL_1	.811	.000	.000	.000	.000
FL_2	.670	.000	.000	.000	.000
OOPExp	-.530	-.007	-.072	-.407	.000
FWB_3	.710	.009	.096	.545	.000
FWB_2	.815	.010	.110	.626	.000
FWB_1	.387	.005	.052	.297	.000

Diagram 2

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
FBL	<---	MB	.830	.075	11.110	***	
FWB	<---	FBL	.100	.021	4.744	***	
FWB	<---	MB	.036	.012	3.084	.002	
FWB	<---	GovtSpend	.008	.024	.331	.741	
FWB	<---	GDPGrowth	.131	.038	3.416	***	
FWB	<---	Unemployment	.076	.027	2.777	.005	
FWB	<---	Inflation	.001	.001	1.147	.251	
FWB_1	<---	FWB	1.000				
FWB_2	<---	FWB	37.807	6.822	5.542	***	
FWB_3	<---	FWB	7.192	1.359	5.293	***	
OOPExp	<---	FWB	-3.147	.751	-4.191	***	
FL_2	<---	FBL	1.000				
FL_1	<---	FBL	.867	.058	14.829	***	
FB_2	<---	FBL	.212	.043	4.950	***	
FB_1	<---	FBL	.748	.052	14.490	***	

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
MB	.066	.008	7.851	***	
e9	.021	.004	5.364	***	
GovtSpend	.003	.000	7.810	***	
GDPGrowth	.002	.000	7.810	***	
Unemployment	.003	.000	7.810	***	
Inflation	2.045	.262	7.810	***	
e10	.000	.000	2.125	.034	
e1	.005	.001	7.716	***	
e2	.179	.061	2.927	.003	
e3	.035	.005	7.046	***	
e4	.019	.003	7.094	***	
e5	.033	.004	7.507	***	
e6	.002	.001	2.940	.003	
e7	.013	.002	7.730	***	
e8	.002	.001	4.683	***	

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
FBL	<---	MB	.826
FWB	<---	FBL	.682
FWB	<---	MB	.243
FWB	<---	GovtSpend	.012
FWB	<---	GDPGrowth	.156
FWB	<---	Unemployment	.112
FWB	<---	Inflation	.041
FWB_1	<---	FWB	.462
FWB_2	<---	FWB	.959
FWB_3	<---	FWB	.823
OOPExp	<---	FWB	-.655
FL_2	<---	FBL	.816
FL_1	<---	FBL	.983
FB_2	<---	FBL	.435
FB_1	<---	FBL	.969

Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
FBL	.683
FWB	.907
FB_1	.938
FB_2	.190
FL_1	.965
FL_2	.666
OOPExp	.428
FWB_3	.677
FWB_2	.919
FWB_1	.213

Total Effects (Group number 1 - Default model)

	MB	Inflation	Unemployment	GDPGrowth	GovtSpend	FBL	FWB
FBL	.830	.000	.000	.000	.000	.000	.000
FWB	.119	.001	.076	.131	.008	.100	.000
FB_1	.621	.000	.000	.000	.000	.748	.000
FB_2	.176	.000	.000	.000	.000	.212	.000
FL_1	.720	.000	.000	.000	.000	.867	.000
FL_2	.830	.000	.000	.000	.000	1.000	.000
OOPExp	-.373	-.003	-.240	-.411	-.025	-.314	-3.147
FWB_3	.853	.008	.548	.940	.057	.717	7.192
FWB_2	4.482	.041	2.883	4.943	.298	3.771	37.807
FWB_1	.119	.001	.076	.131	.008	.100	1.000

Standardized Direct Effects (Group number 1 - Default model)

	MB	Inflation	Unemployment	GDPGrowth	GovtSpend	FBL	FWB
FBL	.826	.000	.000	.000	.000	.000	.000
FWB	.243	.041	.112	.156	.012	.682	.000
FB_1	.000	.000	.000	.000	.000	.969	.000
FB_2	.000	.000	.000	.000	.000	.435	.000
FL_1	.000	.000	.000	.000	.000	.983	.000
FL_2	.000	.000	.000	.000	.000	.816	.000
OOPExp	.000	.000	.000	.000	.000	.000	-.655
FWB_3	.000	.000	.000	.000	.000	.000	.823
FWB_2	.000	.000	.000	.000	.000	.000	.959
FWB_1	.000	.000	.000	.000	.000	.000	.462

Standardized Total Effects (Group number 1 - Default model)

	MB	Inflation	Unemployment	GDPGrowth	GovtSpend	FBL	FWB
FBL	.826	.000	.000	.000	.000	.000	.000
FWB	.806	.041	.112	.156	.012	.682	.000
FB_1	.800	.000	.000	.000	.000	.969	.000
FB_2	.360	.000	.000	.000	.000	.435	.000
FL_1	.812	.000	.000	.000	.000	.983	.000
FL_2	.674	.000	.000	.000	.000	.816	.000
OOPExp	-.528	-.027	-.073	-.102	-.008	-.446	-.655
FWB_3	.664	.034	.092	.129	.010	.561	.823
FWB_2	.773	.039	.107	.150	.012	.654	.959
FWB_1	.373	.019	.052	.072	.006	.315	.462

Standardized Indirect Effects (Group number 1 - Default model)

	MB	Inflation	Unemployment	GDPGrowth	GovtSpend	FBL	FWB
FBL	.000	.000	.000	.000	.000	.000	.000
FWB	.564	.000	.000	.000	.000	.000	.000
FB_1	.800	.000	.000	.000	.000	.000	.000
FB_2	.360	.000	.000	.000	.000	.000	.000
FL_1	.812	.000	.000	.000	.000	.000	.000
FL_2	.674	.000	.000	.000	.000	.000	.000
OOPExp	-.528	-.027	-.073	-.102	-.008	-.446	.000
FWB_3	.664	.034	.092	.129	.010	.561	.000
FWB_2	.773	.039	.107	.150	.012	.654	.000
FWB_1	.373	.019	.052	.072	.006	.315	.000

AMOS 28 SPSS Regression Model Fit Indices

Diagram 1

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	38	94.802	39	.000	2.431
Saturated model	77	.000	0		
Independence model	22	1063.063	55	.000	19.328

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.108	.081	.136	.001
Independence model	.388	.367	.408	.000

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.911	.874	.946	.922	.945
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Diagram 2

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	47	155.090	57	.000	2.721
Saturated model	104	.000	0		
Independence model	26	1169.061	78	.000	14.988

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.119	.097	.141	.000
Independence model	.339	.322	.356	.000

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.867	.818	.912	.877	.910
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Gretl Causality Check

Diagram 3

```
gretl: model 2

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Model 2: TSLS, using observations 1-123
Dependent variable: FL_1
Instrumented: MB
Instruments: const GDPGrowth GovtSpend InternetPenetration Inflation
  Unemployment

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       -0.318884    0.0468231    -6.810    4.02e-10 ***
  MB           0.840248    0.0643507    13.06     7.45e-25 ***

Mean dependent var   0.271413   S.D. dependent var   0.227190
Sum squared resid    2.212144   S.E. of regression   0.135212
R-squared            0.665457   Adjusted R-squared   0.662692
Chi-square(1)        170.4939   p-value              5.77e-39

Hausman test -
  Null hypothesis: OLS estimates are consistent
  Asymptotic test statistic: Chi-square(1) = 8.16069
  with p-value = 0.00428082

Sargan over-identification test -
  Null hypothesis: all instruments are valid
  Test statistic: LM = 19.9079
  with p-value = P(Chi-square(4) > 19.9079) = 0.000520741

Weak instrument test -
  First-stage F-statistic (5, 117) = 29.074
  Critical values for TSLS bias relative to OLS:

     bias       5%      10%      20%      30%
    value    18.37    10.83     6.77     5.25

  Relative bias is probably less than 5%

  Critical values for desired TSLS maximal size, when running
  tests at a nominal 5% significance level:

     size      10%      15%      20%      25%
    value    26.87    15.09    10.98     8.84

  Maximal size is probably less than 10%
```