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Telemedicine Acceptance during the COVID-19 Pandemic: An Empirical Example of Robust Consistent Partial Least Squares Path Modeling

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Abstract: The explanation of behaviors concerning telemedicine acceptance is an evolving area of study. This topic is currently more critical than ever, given that the COVID-19 pandemic is making resources scarcer within the health industry. The objective of this study is to determine which model, the Theory of Planned Behavior or the Technology Acceptance Model, provides greater explanatory power for the adoption of telemedicine addressing outlier-associated bias. We carried out an online survey of patients. The data obtained through the survey were analyzed using both consistent partial least squares path modeling (PLSc) and robust PLSc. The latter used a robust estimator designed for elliptically symmetric unimodal distribution. Both estimation techniques led to similar results, without inconsistencies in interpretation. In short, the results indicate that the Theory of Planned Behavior Model provides a significant explanatory power. Furthermore, the findings show that attitude has the most substantial direct effect on behavioral intention to use telemedicine systems.

Keywords: telemedicine; technology acceptance; robust partial least squares path modeling

1. Introduction

Partial least squares path modeling (PLS) has been widely used to analyze data associated with complex phenomena [1]. The characteristics of PLS have managed to be seen by some social sciences researchers as a fundamental tool to try to explain causal relationships among concepts of the real world [2]. Many enhancements have been incorporated into PLS throughout the years. Among them, it is worth mentioning the following, multigroup analysis [3], identifying and treating unobserved heterogeneity [4], measures of model fit [5], predictive power assessment [6], and consistent PLS (PLSc) [7]. Despite the several enrichments of PLS [8], handling outliers in the context of PLS has been broadly ignored [9]. Johnson and Wichern [10] referred to an outlier as an observation in a dataset that appeared to be inconsistent with the rest of that dataset.

Commonly, two types of outliers are observed. Some outliers arise following no pattern, i.e., unsystematic outliers. Other outliers arise systematically, being part of a population different from the rest of the observations [11]. Considering that outliers are often found in empirical social sciences research, ignoring outliers is extraordinarily likely to lead to inaccurate results and debatable conclusions. Considering the above, robust PLS has recently been proposed to address this problem [9]. A highly robust estimator designed for elliptically symmetric unimodal distributions is central to this proposal. This option is considered to be a better approach for only identifying and manually removing outliers, which has two drawbacks. First, outliers may not be easily identified by visualization or statistical methods. Second, even if this is possible, removing outliers would imply information lost and the sample size decreasing [9]. On the basis of the robust PLS proposal, this study is aimed at evaluating a social phenomenon where the analysis should be as free as possible from outlier-related bias. This research addresses a current social phenomenon, telemedicine acceptance during the COVID-19 pandemic, comparing the two known models, the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM). Therefore, in the following paragraphs, we develop both the telemedicine and technology acceptance concepts.

First, telemedicine refers to healthcare services provided by healthcare providers in a patient-centered manner, from a geographical distance, and using digital technologies [12]. Over the last decade, a technology shift has created a rise in the accessibility to technology and mobile services, including mobile health services [13]. However, although telemedicine technology has been in use for over five decades, it has still not moved past a pilot stage, with traditional in-person service preferred [14]. Global statistics back up this claim, as only ten percent of people have ever used telemedicine. Within this group of people, their approval level is positive, with two out of three individuals stating they would use the service again [15]. The usage of telemedicine is not the same across the globe. There is higher usage in developing countries within Asia and the Middle East (31% in Saudi Arabia, 27% in India, 24% in China, and 15% in Malaysia). However, in Europe, telemedicine is less common (2–4% in Belgium, Serbia, Russia, France, Spain, and Hungary) [15]. The current global COVID-19 crisis adds a new layer to the literature surrounding telemedicine and its usage. The onset of the virus has highlighted the ability of health providers to manage patient visits triaged to telemedicine services. It has also shown the importance of connectivity and how quickly the logistics behind these services could be put into place [16]. Telemedicine allows patients with mild conditions to obtain the attention that they need while minimizing their exposure to other patients with more severe conditions [17]. The ability to support healthcare workers during this time is a significant focus, as they are battling with pressure from the virus, which not only presents itself as a high rate of occupied resources but also a high rate of resources being removed due to exposure [18]. Concern regarding this quick spread of telemedicine is related to how long the measures in place will last past the pandemic. While the pre-pandemic adoption was not high, the telemedicine model greatly benefits both the patient and the provider from a business standpoint (e.g., [19]). Providers with better telemedicine services aim to gain a better competitive advantage, from which patients can significantly benefit [20]. This competitive advantage is more critical than ever at a time when governments are struggling to minimize both the death toll and the virus' economic impact [21].

Second, multiple authors have explored telemedicine acceptance using models rooted in technology acceptance theories or behavioral theories [14]. In general, these studies indicate that technology acceptance models perform better than behavioral models when it comes to telemedicine acceptance [14,22,23]. The TPB and the TAM are the two most popular models to explain the use of systems [24–26] and, in particular, within the adoption of telemedicine systems, their utilization has been highlighted separately [27–31] or in a complementary way [32]. Previous ideas led us to choose TPB and TAM in the present study as a research framework. The TPB originated from the Theory of Reasoned Action (TRA) [33]. The TRA proposed that attitude toward behavior and subjective norms surrounding that behavior directly affects the individual's behavioral intention. Attitude relates to how individuals perceive behavior. If the behavior is perceived as beneficial to themselves, they are more likely to partake in the behavior. Social norms are the way that individuals perceive others' beliefs regarding their behavior. If individuals see the behavior as viewed to be beneficial by those around them, then, they are more likely to partake in the behavior. Lastly, behavioral intention is how likely they are to participate in the observed behavior. The TPB adds a new concept to the TRA, i.e., perceived behavioral control [25]. Perceived behavioral control is the individual's perceived ability to perform the observed behavior. It considers if the individual believes that participating in this behavior is within their capabilities. If they believe that the behavior is within their reach, then they are likely to have a higher intention to take part in the behavior. Similar to the TPB, the TAM proposed by Fred Davis [25] also had its roots in the TRA. The TAM looks at how users accept a technology through the same measure as the TRA and the TPB, i.e., behavioral intention. However, the TAM proposes different variables in order to predict behavioral intention. In the TAM, attitude, perceived use, and perceived ease-of-use are used to measure the individual's behavioral intention to use technology. Perceived use relates to how individuals perceive that the technology will be useful to them; perceived ease-of-use is how much effort the individual perceives that the technology requires to use it [25]. The TPB and the TAM both assume that once an individual develops an intention to partake in a behavior or use technology, they can carry out this behavior. This intention is the most significant predictor of this occurrence [25]. Since models are abstractions of a phenomenon within a context, their explanatory capabilities must be systematically tested to determine their usefulness in new settings. Therefore, comparing which model best explains telemedicine adoption in the current context emerges as a necessary action.

In this context, the objective of this study is to determine which model, TPB or TAM, provides greater explanatory power for the adoption of telemedicine addressing outlier-associated bias.

The main contributions of this study are three-fold. First, from a practical viewpoint, this research provides empirical evidence of the application of the robust PLS proposal to test the outlier bias effects in a PLS model based on primary data. Second, from an academic viewpoint, this study contributes by testing the technology acceptance theories' applicability in a new social context, validating the circumstances where these theories can be supported. Third, from a social perspective, this study gives an exploratory baseline to define public policies that support telemedicine implementation in a pandemic context.

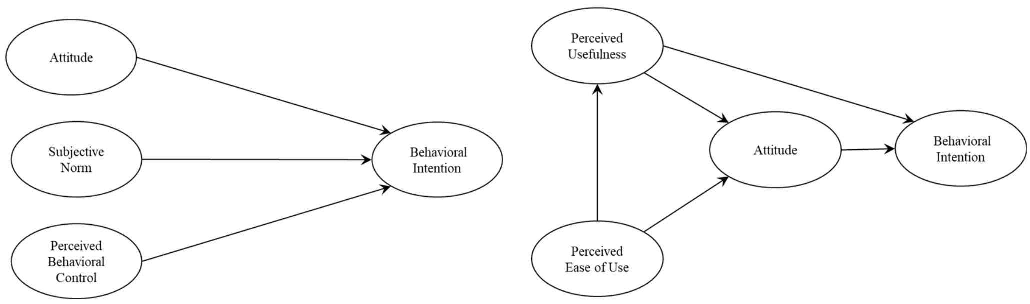
The organization of this paper is as follows: In Section 2, we explain the data collection process and methods used to analyze the data; in Section 3, We present the results of this data analysis; in Section 4, we offer a discussion of these results; and finally, in the last section, we provide a summary of the outcome of this study.

2. Methods

2.1. Data

A cross-sectional study was carried out between January and June 2020. A convenience sampling technique was used to collect data from Brazilian adults. The anonymity of the respondents was guaranteed in the data collection process. According to standard socioeconomic studies, no ethical concerns were involved other than preserving the participants' anonymity.

Specifically, the data was obtained through an online questionnaire for current and future adult telemedicine users in Brasilia. The scales were adapted from Jen and Hung [32]. A 7-point Likert scale was used with answers ranging from 1 (strongly disagree) to 7 (strongly agree). Table 1 shows the questions that were included in the online questionnaire. Figure 1A,B represents the variables and relationships associated with the models under study.



(**A**) TPB Model (**B**) TAM Model

Figure 1. (**A**) Theory of Planned Behavior (TPB) model; (**B**) Technology Acceptance Model (TAM) model.

Table 1. Questions included in the study questionnaire.

Latent Variable	Item	Description
Subjective norms	SN1	The experts who influence my behavior would think that I should use telemedicine services.
	SN2	My family would think that I should order the telemedicine service.
	SN3	My friends would think that I should order the telemedicine service.
Perceived behavioral control	PBC1	I have the knowledge and ability to operate the telemedicine service.
	PBC2	I think I can handle the telemedicine service.
	PBC3	Using the telemedicine service is entirely within my control.
Attitude	ATT1	Using the telemedicine service is a good idea.
	ATT2	The telemedicine service increases the healthcare service quality.
	ATT3	The adoption of telemedicine reduces the risks associated with health
	ATT4	The telemedicine service is valuable.
Perceived usefulness	PU1	The telemedicine service will be beneficial to the care of people.
	PU4	Using the telemedicine service will reduce the psychological burden of people.
	PU3	The advantages of the telemedicine service will outweigh the disadvantages.
Perceived ease of use	PEOU1	Instructions for using equipment in the telemedicine service will be easy to follow.
	PEOU2	It will be easy to learn how to use the telemedicine service.
	PEOU3	It will be easy for people to operate the equipment in the telemedicine service.
Behavioral intention	BI1	I am glad to present the telemedicine service to my close ones.
	BI2	I will adopt the telemedicine service.
	BI3	I will adopt the telemedicine service based on my close ones' necessities.

2.2. Partial Least Squares Path Modeling and Robust Partial Least Squares Path Modeling

Traditional and robust PLS were utilized to test the proposed research models. Two models define PLS, i.e., the measurement model and the structural model [34]. The first model examines the instrument's reliability and validity, and the second model evaluates the relationships among the latent variables. Figure 2 shows the PLS algorithm; a detailed description of the algorithm can be found in [35].

In the PLS procedure, a Pearson correlation matrix is a relevant input, even though Pearson estimates are highly sensitive to unsystematic outliers, which can finally conclude in distorted PLS results. To cope with this shortcoming, Schamberger et al. proposed using a robust correlation coefficient to define a robust PLS [9]. The minimum covariance determinant (MCD) was central to their approach [36]. The MCD estimator is a highly robust estimator of multivariate location and scatter, being the one with the highest asymptotic breakdown point (BP), see Figure 3. The MCD is designed for elliptically symmetric unimodal distributions. The MCD has been used to develop robust multivariate techniques, such as principal component analysis, factor analysis, and multiple regression [37]. In summary, the MCD coefficient estimates the variance-covariance matrix of a sample set based on a subsample of the total observations with the smallest positive determinant. The robust

PLS algorithm uses the MCD correlation as an input, maintaining unaltered the subsequent PLS steps, and therefore confronts the outlier issues without removing them from the sample set [9].

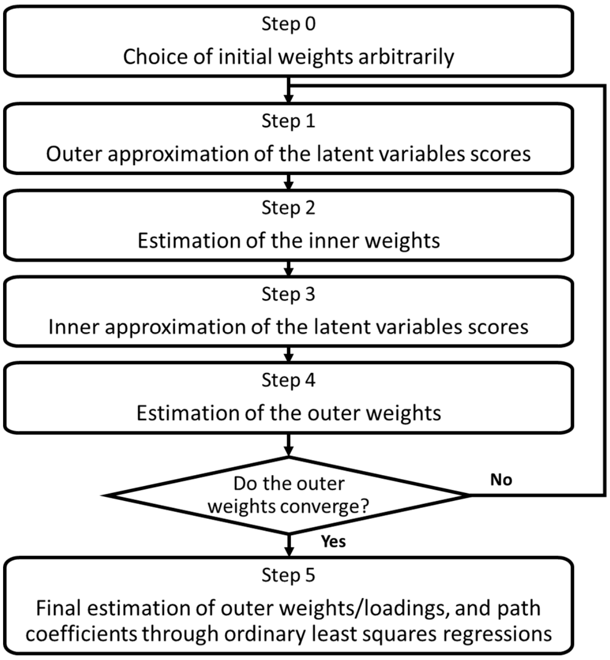


Figure 2. Flowchart of the partial least squares path modeling (PLS) algorithm.

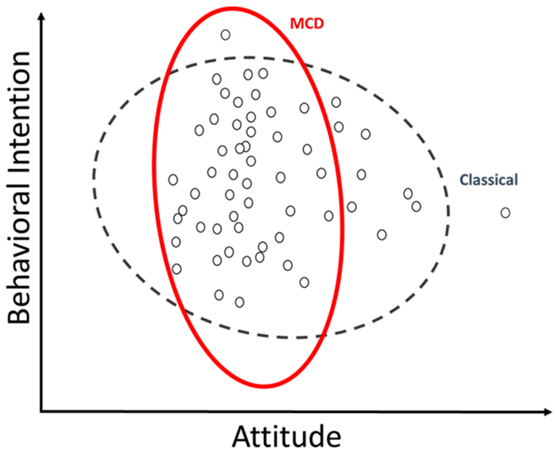


Figure 3. Compare classical and minimum covariance determinant (MCD) covariances.

All calculations were performed using the statistical programming environment R [38]. In particular, an ad hoc script was built based on the simplePLS function from the SEMinR package [39] to integrate the MCD correlation. MCD estimates were determined by the cov.rob function from the MASS package [40]; Figure 4 shows the MCD algorithm. These modifications affect Steps 2 and 4 of the PLS algorithm. Since the models contained common factors and followed the literature [41], the consistent PLS (PLSc) method was applied. The PLSc method applies a correction for attenuation to consistently estimate factor loadings and path coefficients among common factors [7,42]. The following section shows the results associated with these analyses for the empirical study.

```
i ← 1
repeat
  Uniformly sample an initial subset
  Compute T_i (mean matrix) and S_i (covariance matrix)
  Compute the determinant of S_i. det (S_i)
until det (S_i) <> 0
repeat
  i ← i +1
  Compute the Mahalanobis distance for all n points
  Construct a new subset which contains samples with smaller distances
  Update the estimates of T_i and S_i using the extracted samples
  Compute det (S_i)
until det (S_i) = det (S_{i-1}) or det (S_i) = 0
Compute the mean and covariance only using select samples
```

Figure 4. Pseudocode of the MCD algorithm.

2.3. Statistical Analysis Plan

First, a primary analysis was carried out. This analysis consisted of the description of the characteristics of participants in the study and the preliminary evaluation of data using descriptive statistics. Next, a PLS analysis was carried out [34] which consisted of two broad phases. These phases applied to both the traditional [7] and the robust PLSc method [9]. The first phase was the measurement model analysis of TPB and TAM. Two analyses were carried out in this phase. First, the reliability analysis of the indicators and constructs associated with the models; second, we analyzed the convergent and discriminant validity of these same constructs. The second phase was the structural model analysis of TBP and TAM. This phase evaluated the relationships among the variables, considering the determination coefficients and the strength of the relationships. Finally, a resampling procedure evaluated the statistical significance of the estimates associated with the strength of the relationships.

3. Results

3.1. Primary Analysis

A total of 200 surveys were completed for the study. The majority of the completed surveys were from males (56%), and the average age was 39.9 years old. See Table 2 for more details of the distribution of the variables of interest.

Table 2. Distribution of the variables of interest.

Variable	N	%
Gender		
Male	111	56
Female	89	44
Total	200	100
Age	Mean 39.9 ± 16.65 Range 18–85 years	

Table 3 shows the descriptive statistics of the items that integrate the measurement models for TPB and TAM.

Table 3. Descriptive statistics.

Item	Average	SD	Asymmetry	Kurtosis
SN1	3.68	1.403	−0.055	0.020
SN2	3.52	1.378	−0.462	−0.590
SN3	3.61	1.421	−0.326	−0.526
PBC1	4.24	1.184	−0.174	−0.090
PBC2	4.46	1.267	−0.231	−0.064
PBC3	4.33	1.216	−0.148	−0.149
ATT1	5.00	1.315	−0.724	0.836
ATT2	4.66	1.358	−0.555	0.246
ATT3	4.21	1.286	−0.456	0.140
ATT4	4.98	1.260	−0.632	1.260
PU1	4.97	1.361	−0.618	0.591
PU4	3.96	1.256	−0.093	0.367
PU3	4.46	1.424	−0.314	−0.266
PEOU1	4.52	1.613	−0.530	−0.244
PEOU2	4.98	1.428	−0.675	0.347
PEOU3	4.64	1.698	−0.606	−0.211
BI1	4.23	1.448	−0.398	0.088
BI2	4.60	1.315	−0.356	0.241
BI3	3.99	1.470	−0.280	−0.141

3.2. Partial Least Squares Path Modeling (PLS) Analysis

3.2.1. Measurement Models Analysis

Table 4 indicates the assessment of the measurement models. The table shows the following two indicators: (1) Composite reliability which is a measure of internal consistency reliability that does not assume equal indicator loadings, in their place, it considers indicator loadings in its calculation and values greater than 0.7 are adequate [34] and (2) Average variance extracted (AVE) which is a measure of convergent validity, defined as the degree to which a construct explains the variance of its indicators, values exceeding 0.5 are acceptable [34]. In addition, the discriminant validity assessment using the Fornell–Larcker criterion indicates acceptable values [34].

Table 4. Assessment of the measurement models.

Model/Latent Variable	Traditional PLSc		Robust PLSc	
	Composite Reliability	AVE	Composite Reliability	AVE
TPB				
Behavioral intention	0.822	0.588	0.834	0.594
Attitude	0.908	0.693	0.910	0.694
Subjective norms	0.901	0.744	0.897	0.743
Perceived behavioral control	0.906	0.747	0.912	0.751
TAM				
Behavioral intention	0.824	0.589	0.834	0.594
Attitude	0.905	0.692	0.906	0.692
Perceived usefulness	0.869	0.646	0.914	0.652
Perceived ease of use	0.905	0.740	0.896	0.739

3.2.2. Structural Models Analysis

To indicate an intermediate result of the structural analysis, Figure 5 shows the plot of the score values for the two models, at the top with traditional PLSc and the bottom with robust PLSc.

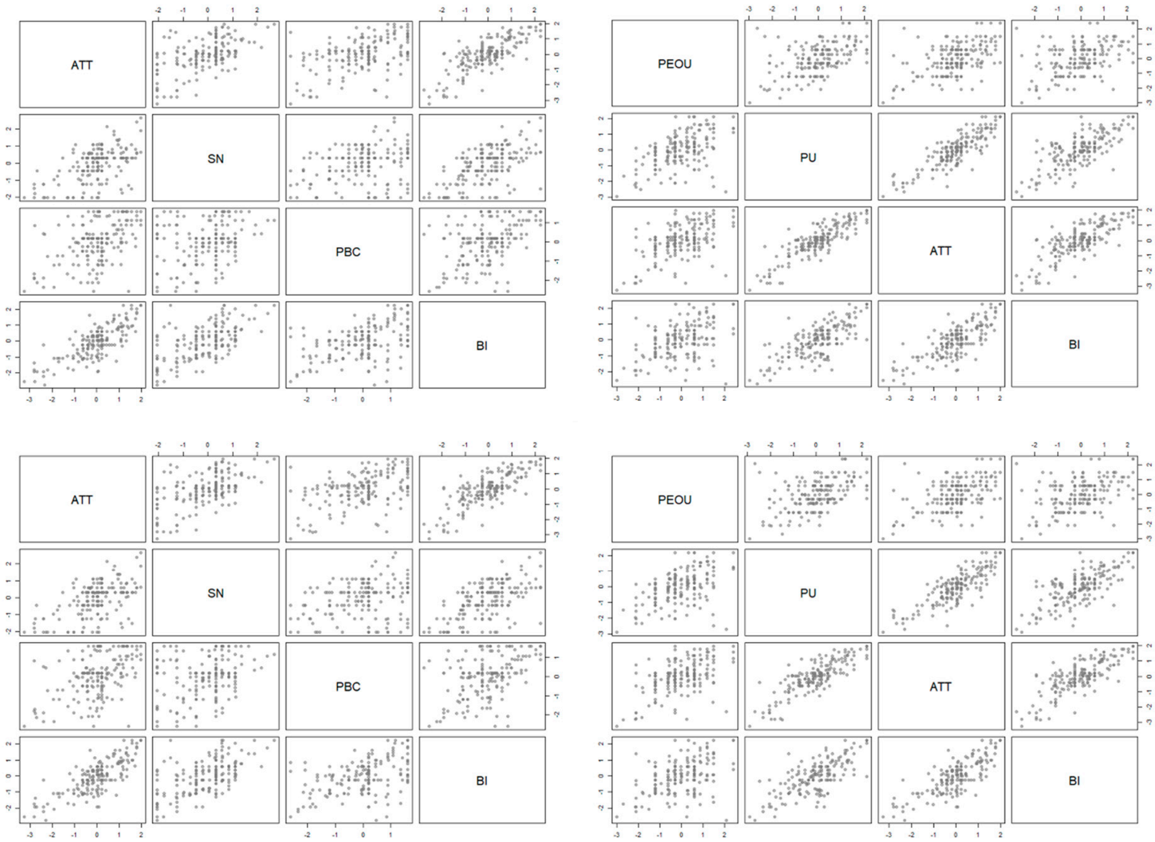


Figure 5. The plot of the score values for the two models. Traditional consistent partial least squares path modeling (PLSc) at the top and robust PLSc at the bottom. ATT, attitude; SN, subjective norms; PBC, perceived behavioral control; BI, behavioral intention; PEOU, perceived ease of use; PU, perceived usefulness.

The results concerning the analysis of the two research models are indicated in Table 5a,b. The coefficient of determination (R^2) indicates the amount of the variance of the dependent variables that is explained by the variables that predict it. The path coefficients (β) express the extent to which the independent variables contribute to the explained variance of the dependent variables. The significance of the β coefficients was calculated using bootstrapping. Bootstrapping is a resampling technique used to determine standard errors of coefficient estimates to evaluate the coefficient's statistical significance without relying on distributional assumptions. We used 999 bootstrap samples. Both estimation techniques lead to similar results without inconsistencies in interpretation. The analysis using traditional PLSc indicates that the TPB explains 85.8% of the intention to use telemedicine, whereas the TAM explains 81.5%. The analysis using robust PLSc indicates very similar results (84.5% versus 80.8% with TAM). In both methods, the TAM analysis indicates that none of the variables in that model which explain behavioral intention is statistically significant.

Table 5. (**a**) Structural results (coefficient of determination). (**b**) Structural results (path coefficients).

(**a**)

Model/Independent Variable	Traditional PLSc	Robust PLSc
	R^2	R^2
TPB		
Behavioral intention	0.858	0.845
TAM		
Perceived usefulness	0.336	0.310
Attitude	0.932	0.840
Behavioral intention	0.815	0.808

(**b**)

Model/Relationship	Traditional PLSc					Robust PLSc				
	Original	Boot Mean	Boot SD	Perc 0.025	Perc 0.975	Original	Boot Mean	Boot SD	Perc 0.025	Perc 0.975
TPB										
Attitude -> behavioral intention	0.713	0.707	0.075	0.546	0.838	0.712	0.709	0.079	0.534	0.851
Subjective norms -> behavioral intention	0.243	0.248	0.075	0.107	0.395	0.240	0.249	0.076	0.110	0.389
Perceived behavioral control -> behavioral intention	0.084	0.087	0.061	−0.034	0.206	0.080	0.084	0.064	−0.034	0.216
TAM										
Perceived ease of use -> perceived usefulness	0.579	0.576	0.084	0.403	0.732	0.557	0.580	0.084	0.397	0.729
Perceived ease of use -> attitude	0.031	0.025	0.075	−0.136	0.168	0.103	0.020	0.077	−0.134	0.169
Perceived usefulness -> attitude	0.947	0.953	0.055	0.843	1.063	0.855	0.956	0.058	0.844	1.071
Perceived usefulness -> behavioral intention	0.044	0.214	6.813	−2.819	2.563	0.121	−0.140	10.396	−2.215	2.743
Attitude -> behavioral intention	0.860	0.689	6.814	−1.634	3.691	0.787	1.043	10.395	−1.850	3.092

4. Discussion

This study was presented as the proper context to justify the use of robust PLSc. In this sense, we must highlight two elements. First, the differences between the results of both techniques are minimal, which rules out bias due to outliers in the models' estimations. Although all the estimates decrease when robust PLSc is applied instead of traditional PLSc, the variations are minimal. On the one hand, for the TPB model, the determination coefficient of the behavioral intention varies by 1.5%, and the maximum variation in the path coefficient is 1.2%. On the other hand, for the TAM model, the maximum variation in the path coefficients is 9.7%. Moreover, while this makes the following paragraphs of this discussion possible, we believe that this result is partly due to the TPB model's parsimony and broad application. Second, the robust PLSc approach has a significant challenge related to the extended computation time of the estimates, especially in the bootstrapping process. This problem calls into question the use of this technique beyond exploratory purposes if the sample size is large.

Our results show that the TPB model has significant explanatory power, while the TAM model does not. This outcome indicates that in the sample context, the TPB model is more parsimonious than the TAM model, meaning that we can have significant results with fewer measures. The TAM model does not explain the behavioral intention of using telemedicine. One possible explication is related to the fact that the current study is based on a concept to use technology rather than a demonstration of the technology itself. Since the TAM variables rely on the perceived usefulness and ease of use, the lack of specifications with respect to what the technology will look like could affect these results. Another possible explanation is related to telemedicine being a broader field than just the technology. There are more external variables that affect the behavioral intention to participate in telemedicine. Last but not least, the application of non-consistent PLS methods could be the cause of explanatory power lacking; the literature provides examples of the application of these methods [43,44].

The TPB-based results highlight four points. First, the determination coefficient of the behavioral intention variable (R^2 = 0.84), which results from applying robust PLSc, can be described as substantial [2]. This result implies that its predictor variables determine a high variability of the behavioral intention construct. This result must be supported by recent studies about the adoption of telemedicine in emerging countries, however, in general, the explanatory power of these studies has been moderate. This characteristic is evidenced in the following examples. On the basis of a sample of physicians and nurses in public hospitals in Malaysia, a TAM-based model explained 41.5% of the acceptance of telemedicine [45]. In Nigeria, using the data of physicians and nurses, a model based on the unified theory of acceptance and use of technology explained 49.7% of the variation in intention to use telemedicine [46]. On the basis of a sample of Pakistani patients, a TAM model explained a total of 62% of the variance of the intention to use telemedicine [43]. Second, the attitude variable was the most significant predictor of behavioral intention (β = 0.71, robust PLSc). This result is concordant with previous patient-based research [47]. Third, the subjective norms variable was a significative predictor of behavioral intention (β = 0.24, robust PLSc). In previous patient-based studies, the subjective norms factor had a significant effect on the intention to use [43,47], which contrasted with its effect on physician-based studies [48]. Fourth, the perceived behavioral control factor does not affect behavioral intention. This last result is in line with both previous patient-based and physician-based studies [48,49].

Telemedicine has been useful in crisis outbreaks in the past [50]. Today, telemedicine is displaying its potential in the COVID-19 pandemic, for example, e-triage, e-consultations, remote monitoring of the intensive care unit, and patients being attended to remotely by health personnel, including those currently in quarantine [51]. Unfortunately, telemedicine has not been promoted and scaled-up homogeneously in all countries [52]. For example, Italy did not include telemedicine at a fundamental level when the pandemic started. In comparison, France actively fostered the use of telemedicine [50]. COVID-19 is creating a great deal of learning about telemedicine's effectiveness in times of crisis. However, nation-wide telemedicine programs, especially in developing countries, cannot be designed and implemented overnight [16,17]. According to this research's results, the attitude toward telemedicine is the most relevant variable to explain the intention of using these services by patients. A practical implication of this study is that communication strategies should focus on showing the benefits of these technologies, initially with vicarious experiences, and then stimulating engagement with these services. This promotion of engagement is associated with patients and also with family members or caregivers, as well as health service providers.

The outcomes of this study can serve as a good starting point for future research about telemedicine usage intention in developing countries. Future research could include larger sample sizes and different population samples. It would be noteworthy to see the difference between a population sample from a country that has many COVID-19 cases and a sample of a country with a low number of cases.

Some limitations must be considered in the present study. First, telemedicine adoption in developing countries, particularly at the COVID-19 pandemic, is an unexplored research area. Thus, the results of this investigation should not be lightly generalized to other settings. Second, this study used a convenience sampling technique appropriate for an initial exploratory research such as this one, but which limits the generalization of the findings. Third, this study used the more traditional versions of the TAM and the TPB. Although only the TPB model provides good explanatory power, these results indicate the necessity of considering other antecedent variables concerning developing countries, such as cultural values, hedonic motivation, self-efficacy, and habit. In this vein, future studies could make comparisons with extended models explicitly developed for telemedicine adoption.

5. Conclusions

This study was aimed at determining which model, TPB or TAM, provided greater explanatory power for the adoption of telemedicine addressing the outlier-associated bias. We carried out an empirical study on a sample of Brazilian adults. From the responses, we tested both the TPB and the TAM models to explain the behavioral intention to use telemedicine.

According to the results of both PLSc and robust PLSc analysis, the TPB provides significant explanatory power. Both estimation techniques lead to equivalent results without inconsistencies in interpretation. Additionally, the TPB structural results show that attitude has the strongest effect on behavioral intention to use telemedicine systems.

Our global findings suggest that statistical notions and methods associated with robustness can be effortlessly implemented in standard techniques used by social scientists. However, the community has not been readily receptive to these improvements. We hope that this study will be useful to advance in that sense.

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