



Analytical study on users' awareness and acceptability towards adoption of multimodal biometrics (MMB) mechanism in online transactions: a two-stage SEM-ANN approach

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Abstracts

The study analyses user awareness of multimodal biometrics and its acceptability for online transactions in the current dynamic world. The study was performed on the five underlying perspectives: User Acceptability, Cognizant Factors towards Biometrics, Technological factors, Perceptual Factors (Fingerprints, Iris, Face Recognition and Voice) and Data Privacy Factors. A questionnaire was prepared and circulated to the 530 biometrics users; on that basis, the corresponding answer was obtained for analysis. SEM is first employed to gauge the research model and test the prominent hypothesized predictors, which are then used as inputs in the neural network to evaluate the relative significance of each predictor variable. By considering the standardized significance of the feed-for-back-propagation of ANN algorithms, the study found a significant effect of DPF_3 (93%), DPF_2 (50%) and DPF_4 (34%) on the adoption of MMB. In the Perceptual construct, PRF_2 (49%) and PRF_3 (33%) was relatively the most important predictor, whereas, in User Acceptability, UAC_2 (37%), UAC_3 & UAC_5 (41%) was vital to be considered. Only one item, TCF_2 (35%), from Technological Factors, followed by Cognizant factors, i.e., CFG_1 (33%), confirmed the best fit model to adopt MMB. The research is a novel effort when compared to past studies as it considered cognizant and perceptual factors in the proposed model, thereby expanding the analytical outlook of MMB literature. Thus, the study also explored several new and valuable practical implications for adopting multimodal instruments of biometrics along with certain limitations.

Keywords Multi-model biometrics (MMB) · Biometrics adoption (BA) · Fusion · CFA · ANN

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1 Introduction

A human-machine interface is the key research area of contemporary computational technologies [1]. According to [2, 3], the primary aim of the research advancement is to serve humankind and create an eco-system of continuous support for the betterment of the world. In the words of [4, 39], interaction with machines for a different purpose is visible. Its success depends upon user acceptability and ease of application. Data privacy and security are also paramount factors in this digital era that is unpredictable in the fast-changing technical development process, especially in financial transactions [5]. Scholarly evidence [6, 7] stated that the use of biometrics authentication for offline transactions ensures that the use of biometrics authentication in the authenticated user's presence while operating at the point of sale. Moreover, during online transactions, the authentication and verification process enhances reliability and improves security for the user and service providers [8].

According to [10, 11], biometric systems are traditionally classified into two key areas, i.e., Unimodal and Multimodal biometrics. Unimodal is a system based on a single biometric trait, unlike a multimodal system where more than one physiological or behavioral trait is used to recognize the person. Popular physiological traits are the face, ear, iris, fingerprint, finger vein, and knuckle, whereas behavioral traits are gait, keystroke, voice, eye movement, facial gradient etc. Over the years, quality datasets of all traits have been developed for research purposes and are available for experimental testing for academic and commercial uses. Researchers have combined multiple traits for identification problems to improve performance and better data security, known as Multimodal biometric (MMB) fusion. Due to its incredible efficiency, cheap cost, and convenience, biometric technology has become the most extensively used human identification and authentication technology in public and private sectors [12]. Biometric systems, also known as Identity Certification (IC) systems, are the art of constructing authentication procedures using biometric traits to identify automatically, measure, and validate a living human [13]. The biometric system is based on the concept that everyone is unique in cognitive and behavioral characteristics. Identifiers are permanent, one-of-a-kind, and distinct from one another. Developing such systems is to improve the digital world's safety and security. Science, security, surveillance, identifying information, and commerce require biometric recognition systems to ensure user authentication and identification. Because it is difficult for an imitator to detect and skit a registered person's biometric modality, biometric technologies have grown popular due to their universal framework (see Fig. 1). High accuracy rates and the difficulty of spoofing are the significant criteria that separate old security solutions [14].

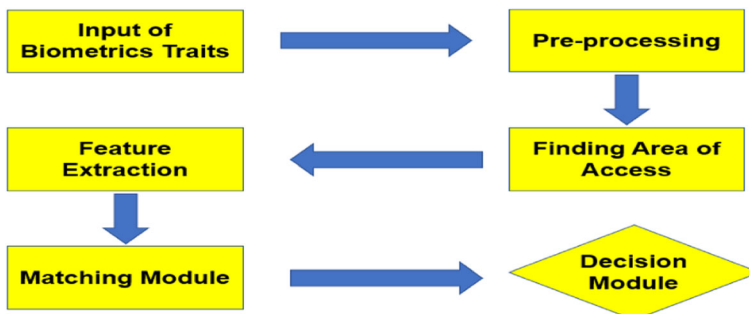


Fig. 1 Universal framework of biometric system

Similarly, MMB has shown better results in online trade transactions in terms of more reliability, enhanced security, and safe transaction [15]. On the other hand, the unimodal process where single traits are utilized for authentication is comparatively more prone to imposter attacks and has higher chances of eye dropping [13]. According to [16–18], the last decade has been a transition period for electronic payment-based applications and commercial uses. The wild development of processors and high-speed internet has provided a foundation for digital payment systems in this era. However, traditional methods like memory-based password gateway are not safe to give such transactions high security and reliability. Instead of fusion of face, ear, iris, keystroke, voice, and fingerprint provides a robust mechanism for authentication (see Fig. 2). Related work [19, 20, 22] also stated that various fusion techniques classify into different categories, such as rank level, score, decision level, and feature level. Advantages and challenges associated with these different categories compete in terms of performance parameters. For applications requiring rich information for decision making, feature-level methods are used. The terminology depends upon the level of fusion and feature extraction positions [23].

According to [24], “supervised learning and pattern acknowledgement are critical research areas in information retrieval, data engineering, medical image processing, and intrusion recognition”. This work aims to identify a robust classifier and consider a network-based intrusion detection system. Another incredible research has been done by [28], using the dataset of 858 budding cancer patients to corroborate the performance based on the combinations of iForest with SMOTE and iForest with SMOTETomek. Besides, the study used a


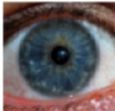

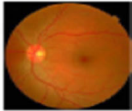

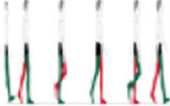




Fingerprint		Iris	
Finger Vein		Retina	
Facial		Gait	
Palm Vein		Hand Geometry	
Handwriting		Speech	

Fig. 2 Typical biometric attributes

mobile application that can gather data on cervical cancer risk factors and delivers results from CCPM for immediate and appropriate accomplishment at the early phase of cervical cancer.

2 Review of literature

A systematic review of the literature effectively coordinates and deduces facts relevant to a particular research question rationally, descriptive, dependable, and accurate. [21, 29, 30] studied multimodal biometrics which is based on a fusion of different physical and behavioral traits like face, ear, iris, gait, keystroke, voice etc. [4] presented a detailed study on types of fusion methods for MMB. They have highlighted various scoring fusions: min, max, average, mode, and others. Feature and sensor levels come under the first category score, whereas decision & rank level fusion is in the second category. The recent studies viz. [26, 31, 32] advocated that a combination of unimodal and multimodal biometrics features is helpful for text and voice output accuracy. [33] used unimodal score and multimodal score to compare performance for different conditions. They found MMB has the advantage of a more secure and reliable process at the cost of increased complexity.

In the words of [34–36], multimodal biometrics outperformed unimodal in multiple experiments with different feature extraction algorithms. However, authors have used a different combination of face, ear, iris, fingerprint, palm print, and palm knuckle to confine the results. [38] stated fused fingerprint, retina and finger vein at feature level and used RSA key generation to achieve FAR (false acceptance rate) .01, 95.3% GAR (genuine acceptance rate). Modified RSA (Rivest, Shamir and Adleman) is the contribution made by the authors to improve GAR, FAR from 90% & 2.06%, respectively. Individual unimodal GAR FAR compared with the MBM results. RSA with fingerprint GAR of 80.2% and FAR of 3.25%, RSA with retina GAR of 84.2% and FAR of 2.2%, RSA with finger vein GAR of 87.6% and FAR of 0.52% were obtained. [15] reported fast and robust biometrics system design using Ear trait. Later it was combined with other characteristics and compared in precision, recall rate, accuracy, ease of use. The ear has stable features for long tenure and is comparatively less affected by age and other factors. [37] studied the computerized progression of classifying skin disease using deep learning MobileNet V2. They specified that the projected system could assist general practitioners in diagnosing skin conditions proficiently and reduce complications and indisposition. In a similar line of research [40] developed a consolidated tree construction (CTC) algorithm to create a sound sample from a high-class imbalanced dataset at the detector's pre-processing phase. The outcomes delineated the accuracy of 99.96%, reflecting the CICIDS2017 dataset and the NSL-KDD data frame using thirty-four topographies.

Scholarly evidence [41, 42] a robust and efficient ear-based biometric system using AdaBoost-based ear detection, local features extraction, and stereo matching-based recognition algorithm proposed in this work outperforms multimodal biometrics [32]. [43] outlined IITD, UND-F, USTB databases used for experimental purposes and comparison. The results were compared with other methods where SVM, plane Adaboost, MNN and the proposed method generated accuracy of 96.20%, 94.40%, 96.40% and 98.50%, respectively. [36] highlighted the feature level fusion-based method, where correlation analysis is done in class and intraclass feature sets. Discrete correlation analysis is adopted for feature fusion to get a more pairwise correlation. DCA also reduces class correlation to create a clear boundary. The experimental results have shown better performance than other LCA methods in similar environments. [44] outlined the detailed status of contemporary biometric system design issues, prospects,

commercial uses, and market demand and supplied part of unimodal vs multimodal biometrics systems. A significant portion of the current market is occupied by a unimodal system which is getting tough competition from multimodal systems. Moreover, users are changing priorities from user-friendliness to security and fraud protection. Some previous studies viz. [33, 45, 46] studied various applications of biometrics in school attendance systems, public place access, office/institute access, airports, and sensitive regions like border crossing points. At the same time, online commercial benefits like purchase, banking transactions, stock trading, shopping, and non-commercial online parts such as necessary access like defence lab systems or high-security areas access are studied in detail [47]. Certain authors [1, 12] highlighted the increasing impact of artificial intelligence and deep learning in biometric system design. Using AI-based algorithm testing and deployment part is becoming smooth. Moreover, smart devices like phones and other tablets are now using multimodal biometric algorithms to enhance user experience.

[13] conducted a brief review on the research dimension of multimodal biometrics. It was reported that MBS could be classified into two major areas synchronous and asynchronous systems. In the first case, two or more biometric systems are under the same authorization systems. In contrast, asynchronous category two, the biometrics process, is used one after another. Further, subdivisions are serial (cascade), parallel, and hierarchical modes. [41] categorized the fusion schemes into two categories like fusion before and after matching: feature level, score level, decision, rank level, and hybrid levels. Soft biometrics is another vital aspect of a user-friendly system where age, gender, height, eye color, skin color, and hair color input are added with other traits. It is convenient for the user and enhances the perceived ease of service. The pattern matching process is also vital in an extensive database. Some prominent techniques, such as k-d & k-d-b, are frequently used. [48] used a convolution neural network for advanced biometric system design with cancellable biometrics rules. Their previous work used braided CNN for speech classification, which generated a high accuracy of 97.5%, 98.8%, and 98.06% for US8k, GSCv1, and GSCv2 datasets. Later in the cited work, they utilized cancellable biometrics for upgrading the security and protection of in-ear biometrics. This shows the path to use cancellable biometrics in MBS design to improve safety and privacy. CNN and SVM combination are utilized for feature extraction and classification part. SHA 3 hashing algorithm is used for secure ear templates where 12.5 EER were obtained on AWE dataset. As SHA 3 is noninvertible, process intrusion is almost impossible.

For multimodal biometrics, gait is essential as user acceptance and ease of data collection are very high. In 2014 [34], successfully presented a novel approach to obtaining gait identification from low-quality videos where the frame rate was 1fps and resolution was 32*22. To reduce error large number of weak classifiers (ensemble of classifiers) were used over average gate image (AGI), and it is noted that performance was highly correlated with diversity. The experiment was conducted on outdoor and indoor databases like USF and OU-ISIR-D. Different kinds of fusion strategies are used to cope with less information, where features matching scores from other spaces of the same trait were fused. In 2018, a detailed survey on Unimodal and Multimodal biometrics was carried out by [36]. They explained the biometric system's modules like sensors, feature extractors, pre-processing, matching modules, and decision modules. Various biometric systems like face, ear, iris, fingerprint, voice, manner, and palmprint have been mentioned. The fusion methods were classified into three categories such as rule-based method, classification-based, and estimation-based fusion methods. Kalman filter and particle filter had been explained for the estimation-based fusion

category. This work gives an excellent introduction to biometric studies and the fundamental technologies used. In recent years, CNN-based biometric system design is becoming popular as traditional feature extractions/ classification methods are less efficient in large datasets [49]. Also, it removes the need to pre-process the inputs, as multiple filters inside the network layers perform the task automatically in the state of the artwork, invalidating the significance of sample size in biometrics identification. The proposed multivariate copula models for correlated biometric acquisitions demonstrated the calculation of minimum numbers of samples required for the authentication process. The CNN-based system manages such tasks with more excellent performance [48].

[13] delineated an excellent analytical outlook on customer awareness of the biometric mechanism of unimodal and multimodal systems in online transactions. It motivates system designers to improve system performance and integration with modern e- platforms such as banking sites, e-commerce platforms and device access. More than 100, 93.4% of users have shown high interest in multimodal biometrics systems based on online transactions in the selected sample size. Furthermore, a multidimensional questionnaire was floated among users from different classes regarding their profession, gender, age etc. According to [50], 68.87% of customers reflected confidence in the online purchase if platform authentication is MBS equipped. By analyzing the previous outcomes of biometrics behavioral studies in a recent survey, it has been observed that several studies have subsumed the adoption of technology through a notion of a single theory. A single theory cannot attempt a comprehensive view of the research matter, so a model of several theories is conducive and advantageous for panoramic in-depth research. Ideas from earlier studies were used as part of the literature study, and this material was filtered and aggregated to derive a broad range of previously found factors. Several studies focus on the organization's internal and external conditions and technological aspects in analyzing drivers for new technology diffusion [51]. The TOE framework [52] considers multidimensional factors when studying technology adoption. It yields a greater explanatory power than other adoption models, such as the Technology Acceptance Model [53]. The manifests selected in this study also mapped with the Theory of Planned Behavior (Ajzen 1991) matrix, the Unified Theory of Acceptance and Use of Technology [47]. Comprehensive usages of these models may help establish whether MMB is appropriate in facilitating the delivery of online financial transactions. The extended model fit describes how suitable MMB is for delivering services, and this may be tested by determining how user-friendly and secured the tasks are. In the current Covid 19 era, researchers are working on touchless biometrics and remote authentication processes using AI-ML models [55]. These technologies are more user-friendly, robust, and reliable for commercial use and high-security asset access. Moreover, users are becoming more convenient with the advanced version of the process. However, the previous studies based on literature review did not support any theory and were not empirically validated in MMB [54].

The paper is meticulously framed to get inside factors influencing biometrics adoption in the present scenario where people are restricted from moving freely due to Covid-19. To fulfil the research objectives, the following section is conducive to comprehension. Section 2 portrays the literature review, research gap, theoretical constructs, and development of hypotheses. Section 3 outlines the research frame and methodology to assess customer awareness and acceptability of biometrics transactions. Section 4 illustrates data analysis, SEM, and hypotheses testing, followed by ANN modelling, sensitivity analysis and interpretation with the help of statistical tools. The last section considers practical implications, limitations, future scope, and conclusions.

2.1 Research gap, conceptual model, and novelty

The model's constructs were evaluated using artefacts found in the existing literature. A literature review of previous works creates the measurement constructs, and the present study seeks to identify and determine the factors influencing cloud computing implementation in LMS [56]. The notion of biometrics adoption was assessed using 21 items (five-point Likert scale) from published sources. Thus, theoretical constructs viz. technological factors, perceptual factors (fingerprints, iris, face recognition and voice), cognizant factors towards biometrics, user acceptability and data privacy factors extracted from previous research [5, 10, 13].

This research contributes to a survey related to customer awareness and acceptability of biometric mechanisms while transacting online. As a result, the proposed questionnaire is prepared and receives responses from various customers. Based on feedback received from technical experts/users, hypotheses of the proposed model are tested by framing SEM and followed by ANN. This is one of the few studies investigating the factors that affect MMB adoption. As a result, the established model contributes to the literature in this field—similarly, few studies quintessence on the adoption of BA from users' perspectives (see Fig. 3).

3 Theoretical constructs and development of hypotheses

The research examines factors of adopting multimodal biometrics mechanisms in online transactions. Analysis was done based on the survey to find out the degree to which they are embraced. To examine the objectives- user acceptability, cognizant factors, technological factors, perceptual factors, and data privacy were exercised to determine the impact on the adoption performance of the virtual consumers. Distributions of essential variables were included in the investigation reported in previous studies. Table 1 highlights the constructs and their reported significance in the literature. In different phrases, primary and higher-level data analysis is done on the selected constructs.

There is stepwise extraction of manifests from past research work, i.e., users' acceptability criterion towards biometrics usage while performing the online transaction, the notion of the cognizant factors towards Biometrics usage by the users, and technological factors that evoke

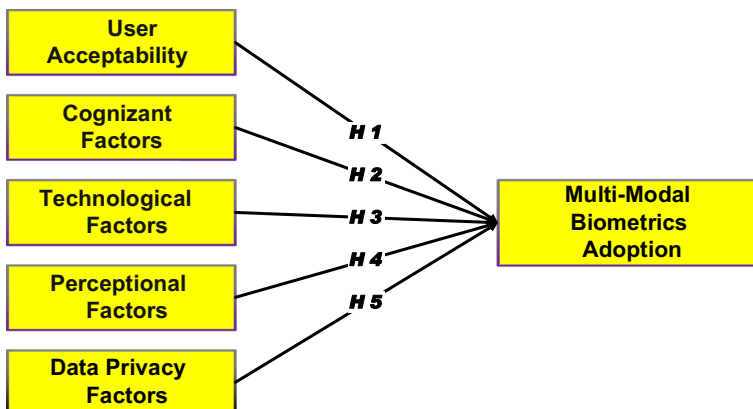


Fig. 3 Conceptual framework of the study

Table 1 Multi-Model Biometrics and Execution Measures

Constructs	Instruments for survey	Sources
User Acceptability	UAC_1: Acquaint the protection of online privacy. UAC_2: Accuracy and flexibility of biometrics mechanism. UAC_3: Biometrics would help make living wills more eagerly accessible. UAC_4: Control over personal information released online. UAC_5: Acquaint how information is shared with other companies.	[13, 45, 57, 59]
Cognizant Factors towards Biometrics	CGF_1: Level of relying on biometrics during an online transaction. CGF_2: Recognition level of Biometrics mechanisms. CGF_3: Using biometrics for safety and privacy. CGF_4: Biometrics is a better tool during Covid.	[27, 44, 60]
Technological Factors	TCF_1: Capability for gaining a competitive advantage. TCF_2: Biometrics provide a flexible and robust solution during an online transaction. TCF_3: Biometrics is conducive to the existing legacy systems. TCF_4: Accessibility of IT support and infrastructure.	[52, 61, 64]
Perceptual Factors (Fingerprints, Iris, Face Recognition and Voice)	PRF_1: Facial biometrics need different tactics such as voice and posture. PRF_2: Using MMB is valuable and safe. PRF_3: Biometric authentications ensure virtual security. PRF_4: There is a need to incorporate more specific variables in MMB.	[20, 44, 64]
Data Privacy Factors	DPF_1: Aware of the privacy concerns associated with biometric traits. DPF_2: Willing to purchase a high-priced item online in biometrics mode. DPF_3: Concerns about your privacy while making an online purchase. DPF_4: Security of online transactions should improve by biometrics.	[6, 10, 12, 13, 29, 45, 49]

the practices of biometrics applications. Subsequently, perceptual factors (Fingerprints, Iris, Face Recognition and Voice) influence MMB, followed by data privacy & security while using biometrics submission.

3.1 Hypotheses for the research

The following hypotheses are proposed based on the literature review and conceptual model:

- H₁: There is a connotation between user acceptability and MMB while transacting online.
- H₂: There is subsume association between technical factors and MMB adoption.
- H₃: There is evidence of cognizant Factors that influence MMB.
- H₄: Perceptual Factors (Fingerprints, Iris, Face Recognition and Voice) are strongly associated with MMB.

H₅: There is an association between data privacy factors and the adoptive operation of biometrics operations.

4 Research methodology

The study is a perfect blend of a quantitative-qualitative frame conducive to exploring the determinants of adoption of biometrics mechanisms from users’ viewpoint. All the elements used to quantify the study variables were adapted from previous research, with slight terminology adjustments to acclimate them to the unique biometrics context from the users’ perspective [49]. The adopted process flow is presented in the Fig. 4.

4.1 Survey instruments and data collection

Nevertheless, the survey instruments were finalized by focus group discussions and walk-through evaluations of selected respondents who indulged in biometrics features while conducting online transactions. This confirmed the content validity of the questionnaire used to gauge each unobserved variable depicted in Table 1. This objective was accomplished using the observational approach of focus groups [65]. In this instance, a few focus groups were formed comprised of individuals with a working knowledge of biometrics applications. The

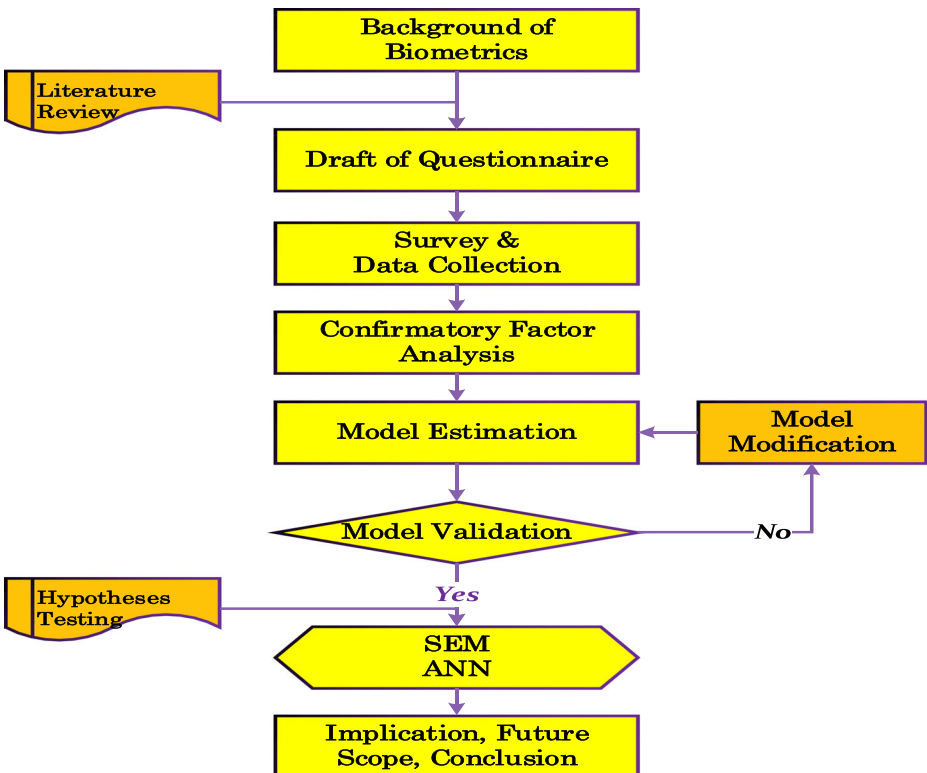


Fig. 4 Methodology of research

study's subject was assigned to the selected groups to familiarize them with biometrics terminology before filling out the final questionnaire. The questionnaire survey was developed using these inputs and previous research findings.

Assembly 530 samples handle the procurement of relevant primary data by virtue of using Google form from plentiful individuals concerning the online transaction. In addition, a personal interview was conducted to obtain the required answer, i.e., biometrics data. This personal interview cleared the doubts of the respondents about an acquaintance of the question based on biometrics awareness. Therefore, the reliability of the responses can be enhanced. Similarly, the sample size of the study is based on the following calculation that 530 respondents are a good fit for further study [66]:

$$n = \frac{(Q_{\alpha} - Q_{\beta})\sigma^2}{\mu_1 \pm \mu_2}$$

where:

n number of sample size.

σ standard deviation as considered at 1.2 based on prior studies.

Q_{α} upper tail in the SND. corresponding to $Q_{\alpha} = 1.96$, p value-0.05.

Q_{β} lower tail in the SND. corresponding to $Q_{\beta} = -0.84$ at $\beta = 0.2$.

μ_1 and μ_2 difference in means.

4.2 Measurement used in the study

To elucidate the degree of correlation among the variables in an array of data sets, EFA is a conducive technique to examine a factor structure. It facilitates the performance of certain functions, i.e., exploring the pattern of data configured, illustrating the relationship among various patterns, and extracting valid data to the next level of analysis [67, 71]. CFA is used to test the core hypothesis and evaluate the association between observed variables underlying their latent constructs to confirm the observed variables in a set of factor structures. CFA is a significant and vital part of the modelling structure equation [9]. It is advantageous and apt to formulate observed variables for measuring and validating the hypothesized model of latent constructs [72]. The researchers use the relevance of items representing the proposed theory, empirical or scientific research, postulate the association framework a priori and confirm hypotheses. Thus, CFA is a unique specified factor conjoint technique widely used to validate the model supported by any previous theory [73].

A priori model, number of factors, item loading on each factor, fit indices, error term, and standard regression weights on items are elucidated by SEM. The goodness of fit (GoF) should be considered to conceptualize the model practically. Moreover, GoF is inversely interrelated to sample size and the number of variables in the model. Therefore, it is vital and mandatory to view reliability in terms of Cronbach Alfa, followed by establishing convergent and discriminant validity of a model [74, 75]. With the assistance of SPSS and AMOS tools, the recorded data was listed, analyzed, and interpreted. Having considered 530 respondents from various respondents, mostly bankers, technical experts and engineers, the researcher intends to test the convergent

and discriminant validity of the group variables. Therefore, the questionnaire consists of two sections. The first part encompasses six questions about the all-purpose profile of the experts and actors using biometrics while doing online transactions. The second part entails five major constructs along with 22 variables. The research took place from January to April of 2021.

5 Data analysis and interpretation

The researcher instigated the data analysis by examining responses to survey questions intended to measure awareness and acceptability towards adopting the MMB Mechanism while doing online transactions. Prima facie, discussing well-versed users' demographic profiles and becoming acquainted with the biometric application is pertinent (Table 2).

The above table enunciates that the sample comprised 52.80% male and 47.20% female; principally, 47.70% of respondents were below the age set of 30 years, and 43.60% were between 30 and 40 years, 08.70% persons were above the age of 40. Besides, most technical respondents were UG, i.e., 62.30%, PG professionals, 19.80%, and others were only 17.90%. 44.30% of experts had work experience of fewer than two years, 34.30% were 2–5 years, and 21.40% share above five years. Among the respondents, a significant share of 42.80% of service class, businesspersons were 40%, and share statistics of professional was 17.20%. Eventually, most defendants were from the junior management level, i.e., 36.80%, middle management scored 46.40%, and top management share was 16.80%. Prima facie, the research aims to test the reliability of selected items that have already been discussed; Cronbach's Alpha expressed the score of 0.825, summarized that the observed variables were reliable enough for confirmatory statistical analysis.

Table 2 Demographic profile

Factor	Classification	Frequency	%
Gender	Male	280	52.80
	Female	250	47.20
Age		530	100.00
	Below 30	253	47.70
	30–40	231	43.60
	Above 40	46	08.70
Education		530	100.00
	UG	330	62.30
	PG	105	19.80
	Others	95	17.90
Work Experience		530	100.00
	Less than two years	235	44.30
	2–5 years	182	34.30
	Above five years	113	21.40
Occupation		530	100.00
	Service	227	42.80
	Business	212	40.00
	Professional	91	17.20
Management Level		530	100.00
	Junior Management	195	36.80
	Middle Management	246	46.40
	Top Management	89	16.80
		530	100.00

5.1 Harman's single variable test

The statistical distribution of the constructs used in the analysis outlines in Table 3. Skewness and kurtosis were determined to ascertain the symmetry distribution and peakedness of the gathered data. In general, skews are considered within the spectrum of alternatives $+1/-1$, and the values are usually distorted [76, 77]. The analysis outlines those respondents prioritize user acceptability (20.31), perceptual factors such as fingerprints, iris, facial recognition, speech etc. (15.54), technical factors (15.33), and cognizant factors towards biometrics (12.80) as primary reasons for embracing MMB, followed by data privacy factors (11.84). All in all, there is an asymmetrical distribution of results when it comes to biometric adoption. According to Harman's single factor test, just 24% of the variance in all variables is explained by a single factor, demonstrating that CMV is not a problem in this analysis. Another test was run to ensure that no similarities were greater than 0.90, which may mean skewed data [62]. As a result, none of the measured correlations surpasses the suggested threshold, indicating that CMV is not a severe concern in this analysis.

5.2 Measurement model

Determinants of biometrics mechanism adoption were used in research to evaluate the users' acceptance and awareness while transacting online. Exploratory factors were used to understand biometric behavioral, knowledge and adoption. Moreover, the Kaiser-Mayo-Olkin score was used to gauge the sample size's adequacy. The measured score of 0.874 intended that the

Table 3 Statistical distribution of constructs

Constructs	N	X	σ	Vari.	Skew.	Kurt.
User Acceptability (Cum. Mean=20.3132)						
UAC_1	530	4.0887	1.00550	1.011	-.817	-.127
UAC_2	530	4.1509	0.97213	0.945	-.889	0.004
UAC_3	530	4.0679	1.05926	1.122	-1.027	0.334
UAC_4	530	4.0453	1.10585	1.223	-1.049	0.245
UAC_5	530	3.9604	1.08797	1.184	-.708	-.423
Technological factors (Cum. Mean=15.3358)						
TCF_1	530	4.2434	0.93817	0.880	-1.357	1.466
TCF_2	530	4.1038	1.02270	1.046	-1.550	2.390
TCF_3	530	3.5849	1.16233	1.351	-.377	-.565
TCF_4	530	3.4038	1.04130	1.084	-.736	-.032
Cognizant Factors towards Biometrics (Cum. Mean=12.8075)						
CGF_1	530	3.0245	1.33350	1.778	-.146	-1.141
CGF_2	530	3.6094	1.41965	2.015	-.605	-.987
CGF_3	530	2.8906	1.42464	2.030	.217	-1.304
CGF_4	530	3.2830	1.33128	1.772	.351	-1.016
Perceptual Factors (Fingerprints, Iris, Face, and Voice) (Cum. Mean=15.5491)						
PRF_1	530	3.4623	1.24332	1.546	.420	-.888
PRF_2	530	3.9943	1.19939	1.439	1.005	-.072
PRF_3	530	4.0491	1.13104	1.279	1.017	.002
PRF_4	530	4.0434	1.25561	1.577	1.037	-.207
Data Privacy Factors (Cum. Mean=11.8453)						
DPF_1	530	3.2226	1.21563	1.478	-.357	-.696
DPF_2	530	2.9849	1.25853	1.584	.154	-.945
DPF_3	530	3.0208	1.26070	1.589	.097	-1.008
DPF_4	530	2.6170	1.19486	1.428	.325	-.772

samples were adequate for the factor analysis. Determinants of MMB were analyzed, and Table 4 enunciated the G'F'I (0.936), A'G'F'I (0.812) along with N'F'I (0.866) and R'F'I (0.833) whereas C'F'I (0.920), Tucker-Lewis delineates 0.918. The value of RMSEA was 0.035, which specifies that the anticipated model is a decent fit [67, 78].

The model exposed a good fit measurement i.e., $\lambda^2 = 951.69$, $df = 195$, $CMIN/df = 4.88$, at significant level $p = 0.038$. As illustrated in Table 5, the factor loading, Cronbach alfa, AVE, and CR of all factors were highly significant [79].

Possible options for normality, linearity, cointegration and homoscedasticity were conducted before evaluating the proposed model. The data was then subjected to CFA to see if it matched the proposed theoretical model and confirm the gauged constructs' validity and reliability. The factor correlation among latent items has to be less than the square root of the average variance explained by each factor [4]. With all figures, it has been inferred that the model meets the standards of reliability, the validity of substance, convergent validity, and discriminant validity. In this way, it was succeeded by testing the structural equation model.

The discriminant validity infers the degree to which dormant items are varied from other dormant variables in the selected frame. Also, the construct correlation among dormant items must be less than the square root of the AVE of every factor [80]. With these all standards, it has been confirmed that the model estimates the criteria of reliability and the rationality of matter with convergent validity (Table 6). In this way, it was accomplished by perusing the SEM.

Figure 5 revealed the standard estimates of confirmatory model in which six factors depicted their item and eventually examined the proposed hypotheses, structural model fit, and path analysis. Confirmatory factor analysis (CFA) is a multivariate statistical procedure for determining how well measured variables represent the number of constructs. The rationalized SEM model exhibits theorized connotation among the latent variables. The assessment of standardized regression loads was applied to fetch an appreciation concerning the proposed disposition, as signified by (Agrawal, 2019; Rakesh Kumar Birda & Manish Dadhich, 2019; Singhal, 2020). In the table below, β , S. Er, Cri. ratios were positive, and eventually, null hypotheses could be rejected. The computed p-values of all five projected hypotheses were less than 0.05, viz. user acceptability and biometrics adoption (0.035), technical factors and adoption of multi-model biometrics adoption (0.045), Cognizant Factors towards Biometrics (0.040), Perceptual Factors (0.020), and Data Privacy (0.001) for the adoptive operation of biometrics. Most of the constructs were consistent with the previous studies. Hence, it validates the proposed model good fit. Eventually, expressed hypotheses were supported and accepted (Tables 7 and 8).

The researchers used CFA to validate the hypotheses of the research model, as discussed in section 1. Besides, the researcher opted to perform an additional research tool ANN to rate the normalized value of the significant predictors based on the SEM analysis. Due to nonlinear correlations between the independent and outcome variables, the two-stage SEM-ANN methodology entails getting a precise classification of performing predictors for biometrics adoption

Table 4 Goodness-of-Fit for MMB Adoption

Particulars	G'F'I	A'G'F'I	N'F'I	R'F'I	C'F'I	T'L'I	RMSEA
Ceiling value	>0.900	>0.905	>0.985	>0.906	>0.910	>0.910	>0.01
Achieved value	0.936	0.812	0.866	0.833	0.920	0.918	0.035

Table 5 Validity and reliability test of standards

Statements	FL.	Cron. α	A-V-E	C-R
UAC_1	0.866	0.902	0.785	0.942
UAC_2	0.802			
UAC_3	0.725			
UAC_4	0.895			
UAC_5	0.816			
TCF_1	0.795	0.887	0.876	0.856
TCF_2	0.815			
TCF_3	0.866			
TCF_4	0.796			
CGF_1	0.812	0.891	0.785	0.839
CGF_2	0.782			
CGF_3	0.769			
CGF_4	0.785			
PRF_1	0.712	0.856	0.806	0.826
PRF_2	0.882			
PRF_3	0.912			
PRF_4	0.885			
DPF_1	0.722	0.887	0.881	0.823
DPF_2	0.882			
DPF_3	0.802			
DPF_4	0.795			

[39, 83]. These two methods complement each other because the SEM is idyllic for hypothesis testing of linear relationships but cannot describe the relationship of nonlinearity, whereas the ANN can detect nonlinear relationships and is not suitable for hypothesis testing [14, 84].

5.3 Analysis of neural network

In the word of [85, 86], ANN is an incredibly analogous scattered processor composed of computational units with a natural propensity for storing experimental data and improving its usability. Moreover, ANN seems to be a more advanced and typically stable method that offers a higher level of precision than traditional tools. Nodes or neurons store the information that is referred to as synaptic weights. Further, it has already been proved by some prominent studies [39, 87] that the advantage of this methodology is that the neural network model can learn intricate linear and nonlinear relationships between predictors and the adoption decision. At the outset, SEM is applied to evaluate the overall research model and test the significant hypothesized predictors, which were further used as inputs in the neural network model to assess the relative significance of each predictor item. Input nodes, hidden/black box, and

Table 6 Fornell-larcker criterion for discriminant validity

Variables	AVE	User Acceptability	Technological factors	Cognizant Factors	Perceptual Factors	Data Privacy Factors
User Acceptability	0.785	0.595				
Technological factors	0.876	0.614	0.672			
Cognizant Factors	0.785	0.526	0.543	0.662		
Perceptual Factors	0.806	0.679	0.748	0.479	0.405	
Data Privacy Factors	0.881	0.426	0.469	0.269	0.559	0.225

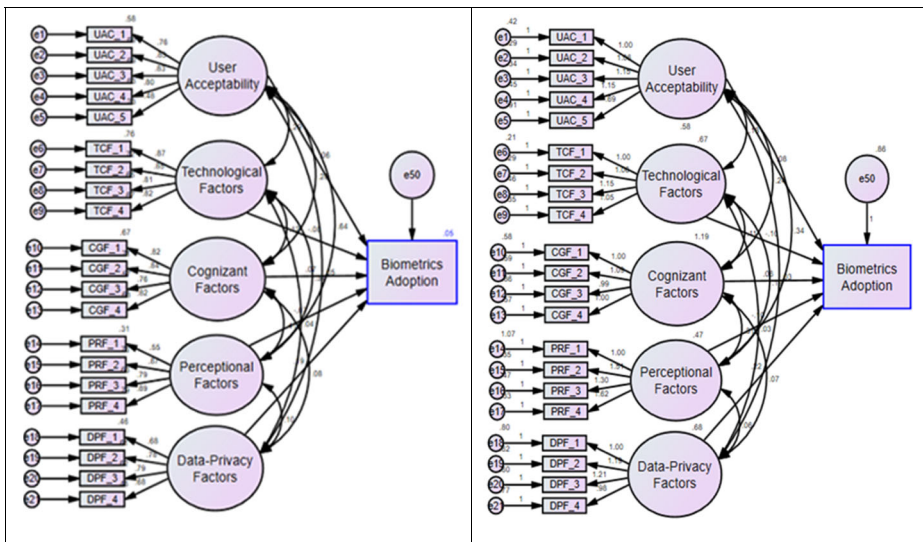


Fig. 5 Estimates of CFA model

output layer make up a neural network. Data are projected into the input layers, generating the output information in the output layers. Synaptic weights are assigned to each input and passed to the hidden layers. Using applied weights, a nonlinear activation process uses these values

Table 7 Summary of standard regression weights of constructs

Items	Direction	Esti.	Std.-Er.	Cri. Ratio	Sig.	
UAC_1	<---	Users Acceptability	1.000	—	—	
UAC_2	<---	Users Acceptability	1.056	0.055	19.372	0.001
UAC_3	<---	Users Acceptability	1.152	0.059	19.405	0.003
UAC_4	<---	Users Acceptability	1.151	0.062	18.509	0.000
UAC_5	<---	Users Acceptability	0.686	0.064	10.770	0.008
TCF_1	<---	Technological Factors	1.000	—	—	
TCF_2	<---	Technological Factors	1.061	0.043	24.452	0.015
TCF_3	<---	Technological Factors	1.154	0.051	22.836	0.020
TCF_4	<---	Technological Factors	1.047	0.045	23.310	0.010
CGF_1	<---	Cognizant Factors	1.000	—	—	
CGF_2	<---	Cognizant Factors	1.090	0.051	21.430	0.042
CGF_3	<---	Cognizant Factors	0.986	0.052	18.849	0.006
CGF_4	<---	Cognizant Factors	1.002	0.048	20.934	0.005
PRF_1	<---	Perceptual Factors	1.000	—	—	
PRF_2	<---	Perceptual Factors	1.513	0.112	13.508	0.002
PRF_3	<---	Perceptual Factors	1.303	0.101	12.914	0.001
PRF_4	<---	Perceptual Factors	1.619	0.119	13.627	0.042
DPF_1	<---	Data Privacy Factors	1.000	—	—	
DPF_2	<---	Data Privacy Factors	1.190	0.083	14.420	0.008
DPF_3	<---	Data Privacy Factors	1.205	0.083	14.499	0.000
DPF_4	<---	Data Privacy Factors	0.982	0.075	13.043	0.002
BMO_1	<---	Users Acceptability	0.076	0.079	0.964	0.035
BMO_1	<---	Technological Factors	0.097	0.056	1.723	0.045
BMO_1	<---	Cognizant Factors	0.062	0.044	1.407	0.040
BMO_1	<---	Perceptual Factors	0.101	0.094	1.066	0.020
BMO_1	<---	Data Privacy Factors	0.217	0.056	3.907	0.001

Table 8 Estimation of the hypotheses and comparison

S. N.	Statements	Consistent with	Inconsistent with	Remarks
H ₁	There is a connotation between the user acceptability and biometrics adoption while transacting online, ($\beta=0.076$, S. Er=0.079, Cri. ratio=0.096)	[36, 44, 81]	[58]	Confirmed ($p<0.05$)
H ₂	There is subsume association between technical factors and adoption of multi-model biometrics adoption, ($\beta=0.097$, S. Er=0.056, Cri. ratio=1.72)	[33, 38, 48]	[82]	Confirmed ($p<0.05$)
H ₃	Cognizant Factors towards Biometrics have influenced on BA, ($\beta=0.062$, S. Er. = 0.044, Cri. ratio=1.40)	[5, 6, 23]	[42]	Confirmed ($p<0.05$)
H ₄	Perceptual Factors (Fingerprints, Iris, Face Recognition and Voice) have a strong association with MMB, ($\beta=0.101$, S. Er. = 0.094, Cri. ratio=1.06)	[3, 8]	–	Confirmed ($p<0.05$)
H ₅	There is an association between Data Privacy Factors and adoptive operation of biometrics operations, ($\beta=0.217$, S. Er. = 0.056, Cri. ratio=3.90)	[10, 14, 15]	[26]	Confirmed ($p<0.05$)

into an output value. There are numerous other types of neural networks, but the researcher employs one of the most common and well-known instruments, i.e., the feed-forward back-propagation MLP [14, 88] (Fig. 6).

A typical neural network has multiple hierarchical levels, including one input, one or more hidden layers, and one output layer. Any incessant function can be represented with one hidden layer, but discontinuous functions can be described with two hidden layers. However, only one hidden layer is commonly employed in technology acceptance neural network models [89]. Each layer comprises neurons that connect with neurons in the next layer, and each link is represented by a synaptic weight that can be adjusted. Radial basis, recurrent networks, multi-layer perceptron, and Feed-forward neuronal functional networks are the four significant kinds of ANN. The research applied the MLP model to study users’ awareness and acceptability of adopting a multimodal biometrics mechanism in online transactions. The synaptic weights of the relationships will be changed through an iterative training process while using the training samples to train the network [73].

The research employed 10 Epochs of training and testing of the selected manifests. For the initial iteration, the Initial Learning Rate of the model was 0.4, Momentum-0.9, and Interval Offset ± 0.5 , which was suggested by previous work [14, 25, 29, 40]. The

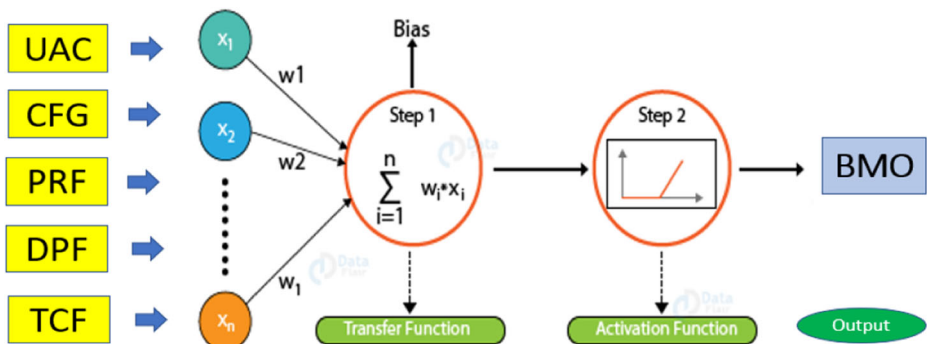


Fig. 6 Analysis of ANN function

study used the customized architecture tool of SPSS. The hyperbolic tangent has been used as a hidden layer activation function to yield appropriate output layer activation identify, which was empirically validated by prior studies [8, 31, 35, 49]. Dark blue lines in the above figure confirm the higher synaptic weight of CGF, PRF, DPF and TCF to achieve and explain biometric adoption (Fig. 7).

In step 1, Inputs of $X_1, X_2,$ and X_3 are associated with their respective weights, $W_1, W_2,$ and W_3 . The output Y of the neuron is computed as shown in the above figure. Step 2, $f,$ is a nonlinear process titled the activation function (AF). The (AF) aims to initiate nonlinearity into the output of a neuron, which is vital since the real-world data are mostly nonlinear.

$$\mu_k = \sum_{i=1}^n W_{ki}X_j$$

and

$$Y_k = \varphi(\mu_k + D_k)$$

Where μ_k is the linear combiner output because of input signal k. W_{kj} ($j = 1, 2, \dots, n$) is the respective weights of neuron k, where φ is the activation function.

The code used for the in-built ANN algorithm in SPSS:

Input: # Data Preprocessing of the indicator’s variables viz. User Acceptability: UAC, Technological factors: TCF, Cognizant Factors: CGF, Perceptual Factors: PRF, Data Privacy Factors: DPF.

- Import the Libraries
- Load the Dataset
- Split Dataset into X and Y
- Encode Categorical Data
- Split the X and Y Dataset into the Training set and Test set
- Build ANN Model
- Initialize the ANN

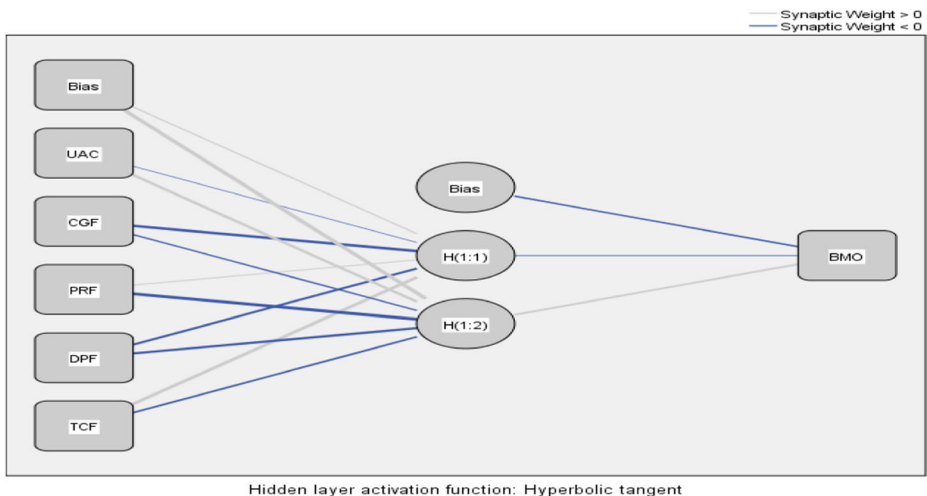


Fig. 7 Analysis of output activation function

- Add the input layer and the first hidden layer
- Train and compile the ANN
- Fit the ANN to the Training setting

Output: # Predict the Test Set of Multimodal Biometrics (MMB).

The pre-processed dataset from SEM is again used as an input variable for ANN and transformed into numerical representation to adopt Multimodal Biometrics analysis (see Table 9).

5.4 Results of neural network modeling

The neural network approach was examined using the widely used statistical program SPSS. The statistically relevant determinants from the SEM analysis were inserted into this model. From the findings of the structural equation, five constructs have been considered vital for further research. As a result, these items were rendered as input variables in the input layers. In this case, biometrics were chosen as the output layer's dependent variable. Furthermore, a cross-validation tool was used to overcome the over-fitting issue of the model [35, 45].

In the ANN model, [90] proposed that hidden nodes should be in the range of 1–10. 10% of the data were used for experimentation during the study process, while 90% were used for training, as suggested by earlier established studies [20, 29, 58, 63]. Similarly, there was no documentary evidence and empirical study of holding the data set. Table 9 shows the RMSE values for both training and testing data points and the mean and standard deviation. The outputs show that the mean RMSE values for the training and testing model are 0.694 and 0.084, respectively, whereas the σ of training data are 0.012 and 0.081 for testing data (see Fig. 8). The RMSE values with comparatively small σ indicate higher accuracy in the statistical results [64]. We, thus, affirm that the model is a good fit. Using a similar approach as [61] applied, the researcher computed the R^2 of 0.87%, and the result reveals that the ANN model predicts multimodal biometrics adoption with an accuracy of 87%. The results also show that the ANN mined very secure connections between the significant predictors and the output variables. Furthermore, in evaluating meaningful work, the sensitivity analytics were determined with the average importance of the predictor. The normalized relative significance

Table 9 RMSE value for training and testing data (N-530)

Sample size (Tr.)	SSE	RMSE	Sample size (test.)	SSE	RMSE	RMSE (Tr.-Test.)	Total Sample
466	214.870	0.683	64	25.113	0.652	0.030	530
468	219.101	0.688	62	23.20	0.638	0.050	530
467	229.522	0.705	63	31.686	0.739	0.034	530
474	237.420	0.711	56	13.711	0.519	0.193	530
467	236.439	0.715	63	25.445	0.662	0.053	530
471	222.779	0.691	59	24.461	0.673	0.018	530
475	216.567	0.679	55	18.539	0.609	0.070	530
462	215.448	0.687	68	39.887	0.796	0.109	530
473	221.310	0.688	57	16.193	0.558	0.130	530
465	219.682	0.691	65	29.767	0.704	0.013	530
Mean	223.717	0.694	Mean	24.248	0.084	0.057	–
σ	8.324	0.012	σ	7.739	0.081	0.057	–

Note: SSE-Sum of error, RMSE-Root-mean-square of errors, N-sample size

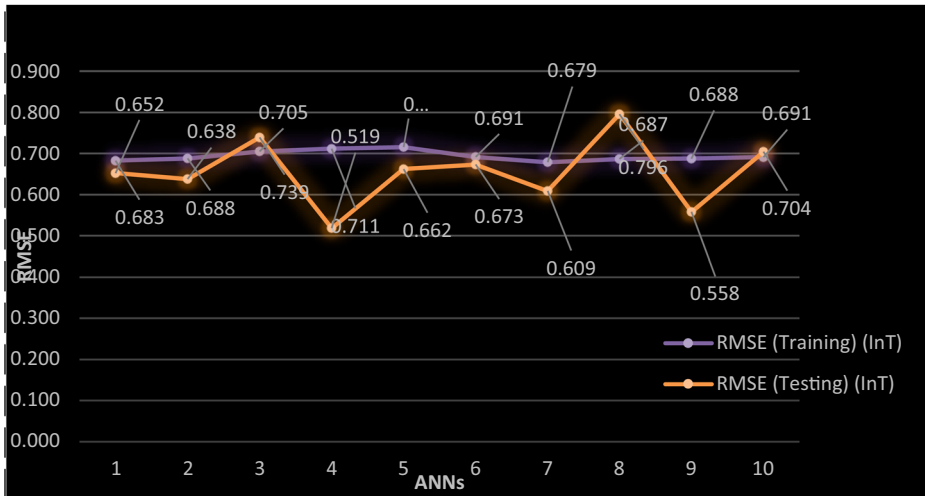


Fig. 8 RMSE statistics of training and testing

of each forecast in the model was calculated by dividing each predictor's relative importance by the highest predictor. Table 10 shows each predictor's Normalized and Sensitivity Assessment. The results of the ANN, however, outline that the average explanation of the data privacy construct was significant, i.e., DPF_3 (93%), DPF_2 (50%) and DPF_4 (34%). Perceptual construct-PRF_2 (49%) and PRF_3 (33%) was relatively most important predictor of BA, whereas in user acceptability-UAC_2 (37%), UAC_3 & UAC_5 (41%), technological factors- TCF_2 (35%), followed by cognizant factors- CFG_1 (33%) towards biometrics adoption (see Table 10). Thus, the model confirms the best fit from both CFA-ANN approaches.

6 Practical implications

Regarding the quantitative outcomes, this study's results contribute to advancing the literature on biometrics and its awareness among various segments of users. Furthermore, this study contributes significantly to our understanding of biometrics adoption at the virtual level. In this study, integrating certain constructs, i.e., cognizant and perceptual factors, has rendered a new theoretical contribution to the issues influencing biometrics adoption. Although these factors' application was ubiquitous in marketing research, there is a lack of studies that examined its comprehensive effects with other variables. Thus, this is perhaps the first research encompassing five constructs and 21 variables to explicate biometrics adoption in the present chaotic scenario. Contrary to current linked studies using linear models, the study adopted a two-stage SEM-ANN approach consisting of a linear and nonlinear ANN model. It is a new technique since a decrease in one predictor can be neutralized by increasing another predictor in a linear compensatory model. The study has effectively resolved the weakness of linear models and has made an innovative theoretical contribution to established literature using the ANN model. In summary, the study aims to provide a systematic, in-depth, and consistent understanding of biometrics's direct and indirect effect on online transactions, which may be helpful for researchers, administrators, and academicians while developing frameworks to deal

Table 10 Normalized and sensitivity analysis

Neural Network	UAC_1	UAC_2	UAC_3	UAC_4	UAC_5	TCF_1	TCF_2	TCF_3	TCF_4	CFG_1	CFG_2
NI (i)	30%	19%	52%	19%	16%	23%	58%	31%	17%	39%	16%
NI (ii)	21%	73%	88%	50%	50%	38%	63%	42%	43%	50%	22%
NI (iii)	28%	37%	31%	49%	48%	37%	18%	19%	14%	16%	6%
NI (iv)	45%	31%	47%	24%	34%	42%	54%	13%	25%	28%	30%
NI (v)	31%	43%	37%	58%	59%	28%	22%	21%	25%	57%	57%
NI (vi)	25%	20%	34%	18%	28%	22%	13%	51%	28%	23%	34%
NI (vii)	44%	62%	26%	18%	28%	19%	50%	18%	31%	34%	21%
NI (viii)	22%	8%	14%	22%	23%	34%	9%	24%	13%	24%	34%
NI (ix)	18%	47%	42%	14%	24%	6%	39%	15%	33%	9%	19%
NI (x)	77%	26%	43%	74%	75%	40%	24%	41%	21%	55%	67%
Average	34%	37%	41%	34%	41%	29%	35%	27%	25%	33%	31%
Norm. Val.	36.6%	39.8%	44.1%	36.5%	44.1%	31.1%	37.6%	29.1%	26.8%	35.4%	33.3%

Neural Network	CFG_1	CFG_2	CFG_3	CFG_4	PRF_1	PRF_2	PRF_3	PRF_4	DPF_1	DPF_2	DPF_3	DPF_4
NI (i)	39%	16%	15%	21%	10%	100%	28%	65%	27%	55%	73%	41%
NI (ii)	50%	22%	62%	39%	31%	51%	45%	27%	65%	13%	100%	57%
NI (iii)	16%	6%	31%	20%	20%	58%	16%	21%	20%	46%	100%	26%
NI (iv)	28%	30%	16%	13%	34%	28%	24%	35%	51%	31%	100%	37%
NI (v)	57%	57%	22%	44%	66%	26%	25%	22%	27%	42%	75%	21%
NI (vi)	23%	34%	19%	40%	18%	38%	10%	23%	16%	43%	100%	29%
NI (vii)	34%	21%	12%	26%	24%	99%	27%	73%	21%	84%	100%	55%
NI (viii)	24%	34%	24%	35%	24%	13%	50%	32%	9%	79%	100%	23%
NI (ix)	9%	19%	10%	17%	35%	23%	21%	10%	11%	11%	91%	45%
NI (x)	55%	67%	70%	24%	33%	54%	85%	10%	33%	100%	91%	70%
Average	33%	31%	28%	28%	30%	49%	33%	32%	28%	50%	93%	34%
Norm. Val.	35.4%	33.3%	30.1%	30.1%	32.2%	52.6%	35.5%	34.4%	30.1%	53.7%	100%	36.5%

with complex technological changes. Existing research has predominantly focused on the drivers of MMB. Adoption at the virtual platform; however, this study takes it a step further by developing and testing hypotheses about continent-level factors that affect the use and adoption of biometrics techniques for online operation.

7 Limitations and future research

Even though the findings of this study have significant consequences for researchers and practitioners, it has the following limitations: First, the representative sample for this empirical research is minimal. By gathering more data, future research would provide more credible scientific findings. Second, SEM was used in this research to analyze the research model. Even though SEM is a standard statistical technique in information management research, it does not hierarchically evaluate independent variables. Future research should consider computational methods such as AI-ML, which can isolate variables at the personal and organizational levels. Third, this work conducted an empirical investigation using a survey approach. In the future, an in-depth interview or qualitative methods and measurement can be used to get more feasible and meaningful findings in terms of theoretical contributions. Fourth, the research focused exclusively on educational organizations located on a single continent. It is recommended that future cross-country research on MMB can be done to generalize the findings. Fifth the insignificant variables of this study can be removed, and new manifests can be included to improve the validity of the proposed model. Sixth, a new practical model can also be implemented, which will be theory-driven [88–90]. Finally, the study delineated users' knowledge and willingness to adopt the MMB in a limited time frame.

8 Conclusion

The numerous applications of biometrics are gaining traction in business and society. The study focuses on analyzing user awareness of MMB and its acceptability for online transactions in the current dynamic world under pandemics. The study was conducted on the five underlying perspectives named user acceptability, cognizant factors towards biometrics, technological factors, perceptual factors (fingerprints, iris, face recognition and voice) and data privacy. The study illustrates the relationship between previously used constructs and evaluates a multimodal biometrics adoption. A questionnaire was prepared and circulated to the 530 biometrics users; on that basis, the corresponding answers were obtained for analysis. The collected replies were just from the professionals/experts who had performed online tasks of MMB. SEM is first employed to gauge the wholesome research model and test the prominent hypothesized predictors, which are then used as inputs in the neural network to evaluate the relative significance of each predictor variable. SEM-ANN analysis was used to identify the inclusive link among variables, including linear-nonlinear and non-compensatory correlations [39, 48, 54, 78]. Additionally, the researcher extended the prior study by incorporating two new constructs, i.e., cognizant and perceptual factors, with tested elements like user acceptability, technological considerations, and data privacy. The study is a unique and comprehensive attempt compared to past studies, as it considered cognizant and perceptual factors, thereby extending the analytical outlook of MMB literature. Thus, the study also explored several new and valuable theoretical implications for adopting multimodal instruments of biometrics adoption.

Dataset Availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest First Author Himanshu Purohit, Second Author Manish Dadhich, and Third Author Pawan K Ajmera respectively declare that they have no conflict of interest.

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