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Predicting the Intention to Use the Investment Aggregate Functionality in the Context of Open Banking Using the Artificial Neural Network Approach

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Abstract

This study investigates the determining factors influencing the intention to use investment aggregator functionality in the context of Open Banking. A survey involving 167 participants was conducted, employing an in-depth analysis through Artificial Neural Networks (ANN). The findings reveal that the construct of "innovativeness" is the most influential factor for individuals' intention to utilize investment aggregator functionality. Furthermore, "trust," "social influence," "optimism," and "perceived usefulness" were identified as additional significant factors. Notably, individuals already engaged in investment activities, including variable income or fixed income investments, exhibited a higher inclination to adopt technology. These findings contribute to companies and banks considering the implementation of Investment Aggregator technology by providing valuable insights for effective adoption strategies. Additionally, this study offers technical contributions to Open Banking technology and aggregating tools, expanding knowledge in the field and presenting practical recommendations for companies to successfully apply this technology. Moreover, the study contributes to the deepening of the theme and the advancement of knowledge in non-linear methods, enriching the understanding of this evolving field.

Keywords: Open Banking; investment aggregator; intention to use; technology; Artificial Neural Networks

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1. Introduction

Open Banking has emerged as a mechanism to open systems and databases, granting third parties access to customers' banking information with their explicit consent. The primary objective is to facilitate the provision of personalized products and foster increased competition within the banking sector [1,2]. Figure 1 illustrates the process, whereby the customer generates data through their bank account. Subsequently, a third-party provider is granted authorized access to this data via an API request. The bank digitally verifies the customer's approval for data exchange and proceeds to fulfill the request.

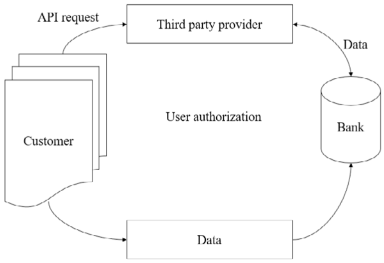

Fig. 1. Exemplified flow of Open Banking operation
Source: (Broby, 2021, p. 12).

Open Banking revolutionizes the financial landscape by granting customers access to a diverse range of financial services through data sharing. This accessibility not only facilitates credit risk assessment but also enhances user convenience by automating form filling processes, enabling seamless requests without the need for manual input. Furthermore, Open Banking significantly improves personalized offerings and enhances operational efficiency, enabling banks and financial institutions to make more accurate decisions [1]. One notable outcome of Open Banking is the emergence of investment aggregator functionality, as exemplified by Íon, an investment application offered by Itaú bank (Fig. 2). In its latest update, Íon introduced the ‘Investment Aggregator’ feature, a tool built within the framework of Open Banking. This functionality empowers users to view multiple portfolios, including those from accounts held with Itaú, other banks, and brokerage houses, all consolidated into a single comprehensive panel.

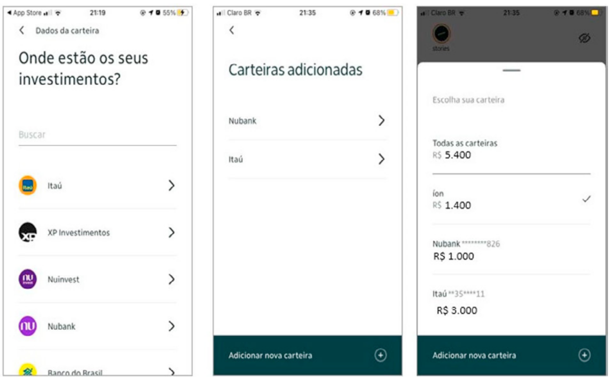

Fig. 2. Investment Aggregator Application

The introduction of the investment aggregator functionality by the banking institution marks a significant milestone as the first of its kind in the industry. This feature aims to provide users with a comprehensive overview of their investments across various financial products. The key advantage lies in the ability to closely monitor portfolio profitability, volatility, and diversification [4].

Consequently, the primary objective of this article is to predict the intention to use the investment aggregator functionality within the Open Banking context by analyzing its determining factors. Specifically, the study focuses on assessing the importance of factors such as Innovativeness [5,6], Perceived Usefulness [7], Social Influence [8–10], Optimism [5,6], Trust [7] and Intention to Use [8,10,11]. Additionally, the study aims to explore whether individuals already engaged in investment activities are more inclined to adopt this technology. The theoretical model proposed in this study is illustrated in Figure 3.

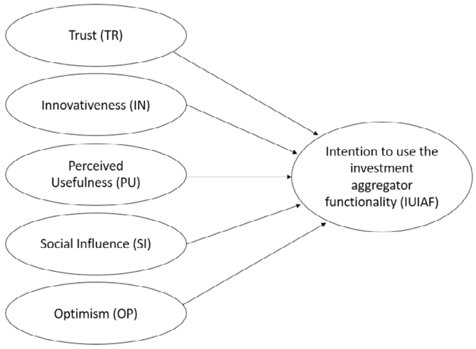

Fig 3. Proposed theoretical model.

2. Related Work

2.1. Expanding Business Opportunities through Open Banking

The study of Open Banking is highly justified due to its significance in empowering users to take control of their financial data sharing, thereby promoting competition between traditional banks and fintech firms—a key objective of regulatory bodies[12,13]. Additionally, it is essential to highlight the user experience benefits associated with utilizing platforms that aggregate various financial aspects in one place. By accessing user data, institutions authorized by the Central Bank of Brazil can offer personalized products and services, ultimately benefiting the consumers. It is worth noting that Open Banking in Brazil aligns with the European Open Banking model. However, in addition, the Central Bank of Brazil introduced a novel approach known as Open Finance, encompassing Open Insurance and Open Investment, in addition to Open Banking [14].

This expanded framework creates a favorable environment for technological advancement across various sectors. Open Banking contributes to cost savings through standardized open APIs, promoting efficiency and interoperability. Moreover, the API economy brings further benefits, such as the concept of "Bank as a Platform" and "Bank as a Service". Banks can act as net consumers of partner APIs, integrating their traditional services with digital innovations and novel offerings from third-party partners. This collaborative approach enables banks to rapidly offer new services or expand into new markets by leveraging the expertise of ecosystem partners [2]. Encouraged by the Central Bank, API standardization ensures enhanced communication and seamless interoperability between institutions.

2.2. Artificial Neural Networks (ANN)

To address the existing gap in understanding the factors that contribute most to the adoption of Open Banking functionality, this study adopts an Artificial Neural Networks (ANN) approach. Unlike traditional linear methods such as PLS-SEM, CB-SEM, NCA, etc., ANN does not rely on multivariate assumptions, such as linearity, normality, or homoscedasticity. Instead, it can identify both linear and nonlinear relationships [15]. In analyzing the proposed theoretical model, the selected ANN method does not rely on predefined hypotheses, as it does not inherently establish causal relationships. Rather, its focus is on evaluating the level of importance of each independent variable for the dependent variable, thus providing valuable insights into the results [16,17].

3. Method

The research employed an exploratory and descriptive approach. Data collection was carried out through a survey (where n=167) distributed across various digital platforms, including LinkedIn, WhatsApp groups, and Instagram, utilizing the QuestionPro platform. The survey was conducted in late 2022, and the majority of participants were located in São Paulo, one of the major cities in Brazil. The questionnaire comprised statements adapted from different scales that were relevant to the study's context. The final version of the questionnaire consisted of 53 questions, each rated on a five-point Likert-type scale, ranging from 1 – "totally disagree" to 5 – "totally agree." To ensure the validity and reliability of the research instrument, the questionnaire was reviewed by three senior academic experts in the field, serving as judges. Additionally, a pre-test was conducted with 15 individuals to assess the questionnaire's clarity and effectiveness[18]. The collected data were tabulated in an electronic spreadsheet, and subsequent analysis involved employing exploratory factor analysis to validate the scale within the sample context. IBM SPSS 25 software was utilized for data analysis.

4. Results Analysis

4.1. Sample characterization

In order to capture diverse sociodemographic profiles, the sample collection process aimed to ensure representation across various characteristics. The gender distribution within the sample was well-balanced, with 49.7% male respondents (n=83) and 50.3% female respondents (n=84). The average age of the participants was approximately 37 years, indicating the involvement of individuals from different stages of adulthood.

Regarding financial investments, it was observed that 50.6% of male respondents (n=42) reported some form of investment. However, among female respondents, 58.3% (n=49) stated that they did not engage in any form of investment, while 41.7% (n=35) reported engaging in some form of investment.

4.2. Exploratory Factor Analysis (EFA)

In this study, an EFA was employed to examine the dataset and identify the interrelationships among the integrated concepts represented by the group items. Each item comprising the selected scales was analyzed, with a focus on identifying common factors underlying the observed variables. The varimax rotation statistical technique was used to clarify the relationship between these factors, adjusting the coordinates derived from the principal component analysis. The initial analysis focused on the scales of innovativeness, trust, perceived usefulness, social influence, and optimism. The commonality matrices of these scales were examined, and the Kaiser-Meyer-Olkin (KMO) criterion and Bartlett's Test of Sphericity were utilized. The KMO values indicated excellent results for all scales, as a value above 0.8 is considered favorable. Additionally, Bartlett's Test of Sphericity yielded significant results for all scales, with $p<0.001$.

Following these procedures, cross-factor loadings were observed, and certain variables were excluded based on their extraction value (h^2) to minimize complex factors and maximize the variance of the factor loadings. Subsequently, the results demonstrated unidimensionality (with a score >0.5 in the respective factor) and low cross-loading (with a score <0.4 in other factors) for the remaining variables. Furthermore, all variables exhibited appropriate adjustments due to commonality (with $h2<0.5$) and demonstrated strong coefficients (>0.4). Consequently, the factor loadings of the scale items were adjusted to a single factor for each respective scale. These adjustments resulted in satisfactory values for explaining the total variance of the sample and were confirmed through reliability analysis using Cronbach's Alpha (refer to Table 1). All factor loadings were ⩾ 0.70, indicating excellent reliability according to [15]. Finally, the four factors exhibited acceptable total explained variance above 60%, as indicated in Table 1.

Table 1. Results obtained by exploratory factor analysis

Factors	number of items	KMO	Sphericity Test	% total variance	α
Trust (TR)	6	0.876	p<0.001	87.98%	0.973
Innovativeness (IN)	7	0.920	p<0.001	82.69%	0.963
Perceived Usefulness (PU)	4	0.832	p<0.001	87.48%	0.951
Social Influence (SI)	4	0.836	p<0.001	82.15%	0.927
Optimism (OP)	5	0.914	p<0.001	85.60%	0.958
Intention to use the investment aggregator functionality (IUIAF)	3	0.779	p<0.001	94.87%	0.973

4.3. Application Artificial Neural Networks (ANN)

Due to the limitations of linear methods in capturing non-linear relationships, the ANN approach was employed in this study to identify both linear and non-linear associations and leverage the learning capabilities of neural networks [17,19]. This approach allows for the utilization of nonlinearity in predictive models. An illustration of the network model can be seen in Figure 4. The covariates are the five independent variables of the model (IN, PU, SI, OP, TR), while the dependent variable is the IUIAF. The multi-layer perceptron (MLP) training algorithm was used to train the neural networks. The MLP has five independent imputed variables (TR, IN, PU, SI, and OP), three hidden layers (automatically calculated by software; usually, the number of hidden layers represents 2/3 of the number of imputed variables), and an output layer, which would be the dependent variable – IUIAF. To normalize the items of each variable $\bar{v}_i$ the average of the items was rescaled to the range [0, 1] using the following expression:

$$\bar{x}_i = \frac{\bar{v}_i - 1}{4} \quad (1)$$

Among the various activation functions available in neural networks, the sigmoid function was chosen to activate neurons in both the hidden and output layers [16]. The sigmoid function converts the input values into a binary space and is particularly effective in introducing non-linearity. Its notable advantage lies in the fact that its derivative is maximal when x is close to 0, which helps drive the training process towards the extremities of the range [0, 1]. In the output layer, the sigmoid function is a suitable choice for producing probabilities in binary classification problems, as the values within the range [0, 1] can be interpreted as the probability of a given instance belonging or not belonging to a specific class.

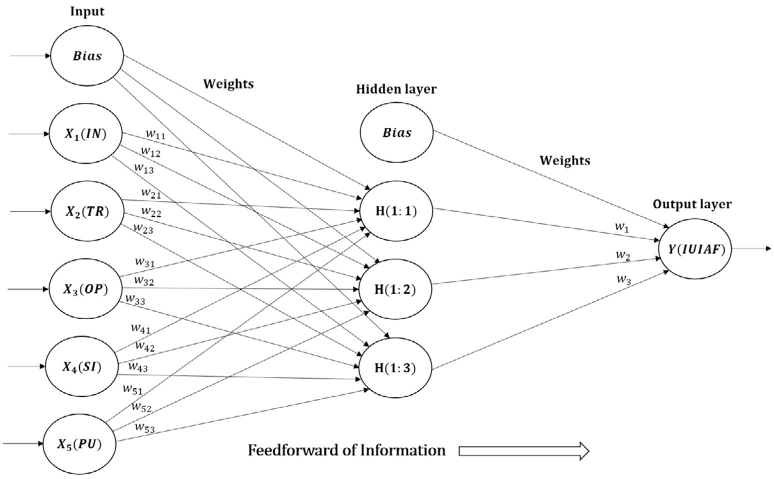

Fig 4. ANN Model Hidden Layers

The ANN model utilizes a supervised learning process, where the outputs are utilized in the training phase, employing a gradient descent optimization algorithm. The gradient descent algorithm is an optimization technique employed to minimize functions by iteratively moving in the direction of steepest descent, as determined by the negative gradient. It is commonly used in machine learning models to update the parameters of the model [20].

For prediction and classification purposes, the feedforward propagation back-propagation (FFBP) algorithm was employed, which can be seen as an advanced form of multiple regression analysis (MRA) capable of handling complex and non-linear relationships. The sigmoid curve function was utilized to activate both the hidden and output layers, providing an effective means to model non-linear behaviors. This activation function assumes values between 0 (representing non-activation) and 1 (representing activation). To assess the accuracy of the model, the Root Mean Square Error (RMSE) was employed. The RMSE is calculated using the following expressions.

$$\mathrm{SSE} = \sum_{t=1}^{n}(Q_t - \hat{Q}_t)^2 \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\mathrm{SSE}}{n}} \tag{3}$$

4.4. Measurement by Artificial Neural Networks (ANN)

To evaluate the performance of the models, a thirty-fold cross-validation approach was employed. This involved splitting the data into 90% for training the neural network and 10% for testing and measuring the accuracy of the trained network. This process was repeated thirty times, with different data splits each time. The test set accounted for 10% to 25% of the total sample size, as suggested by previous studies [19,21]. The Root Mean Square Error (RMSE) values for each model are presented in Table 2.

The average RMSE values for the training and testing of the models were found to be 0.090 and 0.091, respectively. These low RMSE values indicate that the network models are reliable in capturing the numerical relationships between the predictors and the output variable [16,17,21,22]. The small RMSE values suggest that the models can provide highly accurate predictions, with values around 0.10 indicating a very accurate prediction [16,23]. In Fig. 4, the results confirm the predictive relevance of the weight resistances, as each input neuron is connected to the three hidden neurons through non-zero synaptic weights. To assess the sensitivity of the models, a sensitivity analysis was performed by calculating the average importance of the covariates in predicting the output variable across the thirty networks. The results of the sensitivity analysis are presented in Table 3. Predictor importance measures how much the predicted value of the network model changes for different values of the predictor variables. The importance values were normalized by dividing them by the highest importance value and presented as a percentage.

Table 2. RMSE Values

Training			Test				
n	SSE	RMSE	n	SSE	RMSE	total	RMSE(Training)-RMSE (Test)
147	1.187	0.090	20	0.179	0.095	167	0.005
152	1.362	0.095	15	0.031	0.045	167	0.049
149	1.272	0.092	18	0.127	0.084	167	0.008
147	1.004	0.083	20	0.315	0.125	167	0.043
150	1.287	0.093	17	0.142	0.091	167	0.001
153	1.316	0.093	14	0.091	0.081	167	0.012
149	1.122	0.087	18	0.188	0.102	167	0.015
149	1.038	0.083	18	0.366	0.143	167	0.059
149	1.097	0.086	18	0.195	0.104	167	0.018
151	1.222	0.090	16	0.094	0.077	167	0.013
150	1.131	0.087	17	0.248	0.121	167	0.034
150	1.128	0.087	17	0.152	0.095	167	0.008
150	1.252	0.091	17	0.106	0.079	167	0.012
144	0.989	0.083	23	0.284	0.111	167	0.028
151	1.356	0.095	16	0.063	0.063	167	0.032
145	1.046	0.085	22	0.277	0.112	167	0.027
145	1.018	0.084	22	0.222	0.100	167	0.017
156	1.23	0.089	11	0.037	0.058	167	0.031
145	1.367	0.097	22	0.223	0.101	167	0.004
149	1.457	0.099	18	0.098	0.074	167	0.025
144	1.520	0.103	23	0.113	0.070	167	0.033
152	1.238	0.090	15	0.112	0.086	167	0.004
147	1.121	0.087	20	0.14	0.084	167	0.004
151	1.804	0.109	16	0.039	0.049	167	0.060
155	1.263	0.090	12	0.021	0.042	167	0.048
156	1.152	0.086	11	0.146	0.115	167	0.029
146	1.117	0.087	21	0.171	0.090	167	0.003
157	1.030	0.081	10	0.253	0.159	167	0.078
152	1.269	0.091	15	0.166	0.105	167	0.014
164	2.681	0.128	3	0.008	0.053	167	0.075
average	1.269	0.091	average	0.154	0.090		0.026
standard deviation	0.318	0.009	standard deviation	0.091	0.028		0.022

Table 3. Relative Importance - 30 neural networks

Relative Importance					
Artificial Neural Networks (ANN)	IN	PU	SI	OP	TR
ANN (i)	0.277	0.028	0.260	0.269	0.166
ANN (ii)	0.304	0.073	0.133	0.150	0.340
ANN (iii)	0.501	0.037	0.208	0.025	0.229
ANN (iv)	0.374	0.040	0.152	0.113	0.320
ANN (v)	0.405	0.121	0.162	0.112	0.199
ANN (vi)	0.410	0.068	0.116	0.170	0.236
ANN (vii)	0.388	0.026	0.149	0.120	0.317
ANN (viii)	0.426	0.040	0.149	0.167	0.218
ANN (ix)	0.388	0.037	0.100	0.169	0.305
ANN (x)	0.435	0.074	0.174	0.051	0.266
ANN (xi)	0.375	0.161	0.239	0.072	0.152
ANN (xii)	0.312	0.059	0.143	0.181	0.305
ANN (xiii)	0.332	0.055	0.205	0.161	0.247
ANN (xiv)	0.314	0.041	0.172	0.164	0.308
ANN (xv)	0.352	0.081	0.179	0.192	0.196
ANN (xvi)	0.295	0.079	0.163	0.209	0.254
ANN (xvii)	0.347	0.043	0.190	0.173	0.248
ANN (xviii)	0.444	0.007	0.150	0.108	0.291
ANN (xix)	0.319	0.086	0.270	0.173	0.152
ANN (xx)	0.252	0.185	0.045	0.238	0.280
ANN (xxi)	0.267	0.169	0.209	0.113	0.242
ANN (xxii)	0.375	0.103	0.212	0.053	0.256
ANN (xxiii)	0.465	0.027	0.092	0.141	0.275
ANN (xxiv)	0.136	0.153	0.259	0.234	0.219
ANN (xxv)	0.449	0.052	0.143	0.042	0.314

ANN (xxvi)	0.446	0.007	0.190	0.069	0.288
ANN (xxvii)	0.439	0.024	0.192	0.114	0.230
ANN (xviii)	0.356	0.025	0.153	0.147	0.319
ANN (xxix)	0.338	0.112	0.288	0.059	0.203
ANN (xxx)	0.289	0.205	0.124	0.150	0.232
Average Importance	0.360	0.074	0.174	0.138	0.254
Normalized Importance (%)	1.000	0.099	0.938	0.969	0.598

5. Discussion

The Artificial Neural Networks successfully captured both linear and non-linear relationships among the variables of innovativeness, trust, social influence, optimism, perceived usefulness, and intention to use the investment aggregator technology. The results indicated that innovativeness ($\bar{x}_{IN} = 36\%$) had the highest importance as a predictor for the intention to use the technology, followed by trust ($\bar{x}_{TR} = 25.4\%$), Social Influence ($\bar{x}_{SI} = 17.4\%$), Optimism ($\bar{x}_{OP} = 13.8\%$) and Perceived Usefulness ($\bar{x}_{PU} = 7.4\%$).

The examination of the “innovativeness” construct highlighted a significant difference in behavior between individuals who invest and those who do not invest ($t_{(165)}$=5.967; p<0.001). The investing group showed a higher inclination towards adopting technology, as indicated by an average score of 4.33, compared to 3.39 for the non-investing group. This finding suggests that individuals with a higher degree of innovativeness are more likely to embrace technological advancements and tolerate uncertainties associated with them. Companies and banks planning to implement investment aggregator technology should target innovative users, as they are more inclined to adopt such technologies and exhibit lower resistance to change.

Regarding the “perceived usefulness” construct ($t_{(165)}$=4.623; p<0.001 it was observed that individuals who already have investment knowledge are more inclined to perceive the value of investment aggregator technology. Perceived usefulness plays a crucial role in determining user satisfaction and long-term intention to use the technology. To ensure the successful adoption of the technology, companies and banks should effectively communicate the utility and benefits of the technology, enabling users to understand how it can help them achieve their financial goals. The average response for the investing group was 4.31, while for the non-investing group, it was 3.56.

The “social influence” construct also showed a better performance among individuals who already invest ($t_{(165)}$=4.096; p<0.001 This finding indicates that social influence plays a positive role in technology adoption, with the social environment and peer recommendations influencing individuals’ decisions. However, for successful adoption, users need to have some familiarity with or exposure to the investment world. Leveraging digital influencers followed by the target users on social networks can be an effective strategy to encourage the use of technology. The average response for the investing group was 4.19, while for the non-investing group, it was 3.55.

“Optimism” regarding technology ($t_{(165)}$=5.060; p<0.001) was more pronounced among individuals who already invest. Optimism acts as a facilitator and positive influencer in technology adoption, and it is particularly prevalent among individuals already involved in investments. The average response for the investing group was 4.46, compared to 3.69 for the non-investing group. Companies and banks aiming to implement technology should consider the target audience's optimism and devise strategies to foster this positive attitude through advertising campaigns, success stories, or other effective methods.

The “trust” construct ($t_{(165)}$=3.481; p<0.001) showed a more favorable perception among users who already invest. Users with investment knowledge naturally have greater confidence in investment aggregation technology. The average response for the investing group was 4.01, while for the non-investing group, it was 3.41. Companies and banks intending to implement the technology should prioritize building trust with users, ensuring their data security and instilling confidence in the technology. Traditional banks can leverage their reputation for secure transactions, while new companies must work towards earning trust in the market.

Lastly, the average response for the “intention to use the investment aggregator functionality” construct was higher among investing users (4.28) compared to non-investing users (3.44). This indicates that individuals who are already involved in investments are more likely to utilize the investment aggregation functionality. Companies and banks can capitalize on this inclination to promote the adoption of investment aggregator technology.

6. Conclusion

This study focused on predicting the intention to use investment aggregator technology within the context of Open Banking, specifically from the perspective of respondents who are already investors. A theoretical model was developed, using scales that were adapted and validated from existing literature. The findings confirmed the varying levels of importance associated with innovativeness, perceived usefulness, social influence, optimism, and trust in influencing users' adoption of investment aggregator technology within the Open Banking framework. This research makes a significant contribution by adapting scales from other domains to the specific context of Open Banking, thereby addressing a gap in the literature that previously lacked specific investigations into investment aggregators.

It is important to highlight that one of the limitations of this study is that other factors not considered in this study may have an influence on the intention to use the investment aggregator program, such as country, region, and other factor that can affect user's intention to use the investment aggregator.

The study's insights can help expand knowledge and understanding in the field of Open Banking. Moreover, it aligns with the ninth Sustainable Development Goal (SDG) of the United Nations, which focuses on "Industry, Innovation, and Infrastructure." Overall, this study provides valuable insights for organizations looking to implement investment aggregator technology within the Open Banking landscape, enabling them to better understand the factors that influence user adoption and enhance their service offerings accordingly.

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