Prospects of applying artificial intelligence to determine students' mental health status in school education

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Abstract
Development and progress in any sector are critical in today's ever changing world. People who work in the sports sector believe sports to be extremely important in their life. Football, basketball, cricket, tennis, and other sports are particularly popular among males. When dealing with diverse difficulties, organisational behaviour also refers to an organization's attitude and behaviour. To perform at their best, players must be inspired, encouraged, and trained. The first factor that influences the growth of the sports sector is organisational behaviour. Artificial intelligence is the second factor that contributes to the progress of the sports business. Marketing is the third aspect that contributes to the growth of the sports sector. Any industry's worth and value are increased through marketing. Organizational behaviour, artificial intelligence, and marketing tactics were employed as independent factors in this study. New Product Development, on the other hand, has been employed as a dependent variable. The information was gathered from 30 people and evaluated with AMOS 26v. Furthermore, the findings revealed a substantial relationship between the factors.
Keyboard: New Product Development, Artificial Intelligence, Marketing Techniques, Sports Industry, Sports Club, Industry Development.

Introduction

Every year, the number of students with mental health issues increases. Unfortunately, the schools are not equipped to deal with these students. In China, they are exploring how to use artificial intelligence and data analysis in order to predict which students might need mental health assistance before they get into a school environment. If this becomes widespread, it could help save many lives and reduce costs of student's mental illnesses.

This article discusses how AI is being used in China and what the prospects for application might be there specifically in the future. It also gives important facts about suicide rates and incidents. The article includes: The way AI is currently used in China. The data analysis and AI used by the schools. The problems that AI is trying to solve. What the future holds for AI in China, as well as its global use in other areas.

China's school system has many flaws, especially when it comes to mental health issues and suicide. Students have a very high stress level, often from family pressures and cultural expectations, leading to high suicide rates. With an international ranking #1 in annual suicide rates and #11 for annual mental health issues that require intervention or counseling, it is hard for Chinese students to receive the help they need when they need it most.In today's expanding and advancing world, development and growth in any sector are crucial. Anything that can be modernised is crucial for general progress. The introduction of new items to the market contributes to the overall development of a field. Innovation is sparked by new items. Innovation is a need in this society, and we may attain growth and progress by bringing new features of innovation and modernization in numerous industries throughout the world. The progress of the sports sector is aided by the introduction of new goods in the sphere of sports and other industries. Any industry can only develop if it progresses in all aspects of its sector by employing a variety of approaches and tactics (Beal, Norman, & Ramchurn, 2019). Many people who enjoy sports consider sports to be highly essential in their lives. People like sports of all kinds as a source of amusement. People, particularly men, are increasingly interested in sports such as football, basketball, cricket, tennis, and so on. However, today's women are also interested in sports, and many of them actively participate in them. Through their skill, sports allow athletes to connect with the rest of the world. As a result, the expansion of the sports industry and the creation of new sports items is critical for the evolution of the sports world (Chmait & Westerbeek, 2021). The three major factors that contribute to the growth of the sports sector are outlined below.

The first factor that influences the growth of the sports sector is organisational behaviour. The conduct of each individual in the organisation is referred to as

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organisational behaviour. Organizational behaviour also refers to an organization's attitude and behaviours when coping with a variety of issues. If an industry's general organisational behaviour is positive, it has a positive influence on the industry (Adib, BARAKAT, MASRI, SABOUR, & CAPAPÉ, 2021). Sports leaders should be created, and sports leadership should be turned over to them so that they may assure improved organisational behaviour in the sports business. Players must be motivated and encouraged, as well as trained, so that they can perform at their best. Only if their leaders are adept at assigning tasks to their staff will they be able to work effectively. As a result, organisation management is just as vital as dealing with organisational behaviour. Another key aspect in changing organisational behaviour is the environment. If an industry's or organization's atmosphere or environment is positive, then its employees' conduct will be positive as well (Dwivedi et al., 2021)

Artificial intelligence is the second factor that contributes to the progress of the sports business. Artificial intelligence is the capacity to use unique intellect to do any activity. Artificial intelligence aids the sports business in developing and implementing customised strategies and plans for the advancement and development of new items. Artificial intelligence's application has risen dramatically in recent years as a result of advances in science and technology. Artificial intelligence's impressive use in the sports business has greatly helped the industry. Artificial intelligence offers the sports business with a variety of approaches, including sports training, coaching, game analytics, talent identification, and so on. Artificial intelligence's skills aid in the management of the sports industry's whole process. Artificial intelligence also aids in the generation of fresh product development concepts. Artificial intelligence also improves athletes' capacity to solve sports-related challenges. Artificial intelligence helps athletes with a methodical and actionable approach for resolving sports-related issues (Galily, 2018). Artificial intelligence also aids the player in the decision-making process, allowing the player to make the best option possible at the correct time.

Marketing is the third aspect that contributes to the growth of the sports sector. Any industry's worth and value are increased through marketing. A smart marketing plan can help you get greater results. Numerous sports clubs of various sports brands have been founded in many nations across the world to improve their commercial worth. Any sports sector may progress in the world by establishing numerous sports initiatives. Any industry's value is solely determined by its marketing plan; if an industry has a strong marketing strategy, no one can stop it from progressing in the globe. One of the most essential goals of sports marketing is to inform sports fans about new developments and advancements in their favourite sport. International marketing is critical to the growth of the sports sector on a global scale. The value of the sports business rises as a result of worldwide marketing, which promotes the sports industry among international people. Marketing for a certain sports sector explains why their approaches and plans are superior than others so that people may have a full grasp of that market (Kerzel, 2021). The price of new sports items, distribution of sports products, innovation in sports products, and new arrivals of sportswear are all topics covered in sports marketing. Sports marketing is also used to publicise sporting events. Another significant component of international sports marketing is that all sports players have a large fan base, and they may establish a sports brand on their name by marketing the sports industry and sports players. As a result, sports marketing raises not just the value of the sport but also the value of the sports layer. We can develop the sports sector by better understanding the functioning mechanisms of organisational behaviour, artificial intelligence, and market strategies. These three primary characteristics are the main reasons for the growth of sports in any country throughout the world. Artificial intelligence, marketing techniques, and organisational behaviour are used to govern all new product development and manufacture in the sports business. The sports business is also significant since it promotes a healthy lifestyle and encourages physical activity (Lopes da Costa, Dias, Pereira, António, & Capelo, 2019). The sports sector and its goods have a huge impact on people all over the world because they suit the changing needs of a revolutionised world. As a result of the preceding debate, it is apparent that by implementing the three major strategies in the sports business, we may get greater results.

Literature Review

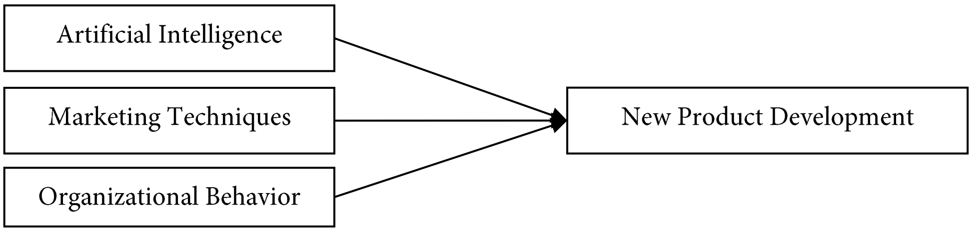
According to Ratten & Jones (2020), the marketing of new products in sports clubs has increased over time. Artificial intelligence, marketing methods, and organisational behaviour have all been examined in relation to the creation of new athletic products in this article. It has been asserted that marketing techniques are critical to the creation of new products. In addition, AI systems and organisational behaviour management techniques have a positive impact on new product development(Palanivelu & Vasanthi, 2020). Digital marketing has a significant influence on the creation of new products in sports clubs. The effects of digital marketing transformation in sport clubs are highlighted by Wang, Skeete, and Owusu (2021). In this article, it was also looked at how different marketing tactics may help in the development of new goods, as well as the relationship between organisational behaviour and new product development(Milovic & Vojvodic, 2021). Aside from that, Dwivedi et al., (2021) investigated how an Artificial Intelligence (AI) system may be used to produce new goods in sports clubs as well as a wide range of intellectual, industrial, and other economic operations(Patel, Shah, & Shah, 2020). The growth of AI technology has opened up a slew of new possibilities for commercial innovation. Marketing management approaches, artificial intelligence, and organisational behaviour all play a role in the development of new goods. With the growth of technology, the sport industry has grown quickly(Ratten & Jones, 2020). The organisational behaviour of a sports club has a significant influence on the creation of new products. According to Chmait and Westerbeek, sports products may be produced through sports sponsorships, advertising, artificial intelligence, and digital marketing. Artificial intelligence might have a big impact on the development of sports items if the right marketing methods are used(Shah, Engineer, Bhagat, Chauhan, & Shah, 2020). Furthermore, Milovic & Vojvodic (2021) investigated how organisational behaviour, marketing tactics, and AI artificial intelligence technology influenced the creation of new goods in sports teams. For this reason, data was collected from 121 different sports clubs and enterprises for this study.

Various models have been examined. Furthermore, a large number of new products in development have been evaluated by various sports clubs. And it was discovered that the development of new goods is largely influenced by marketing strategies, product quality, organisational behaviour, technical performance of the product, use of advanced AI techniques, and the firm's current success, among other factors(Shrestha, Ben-Menahem, & Von Krogh, 2019). According to Winfield and Jirotka (2018), the sport industry has grown to be a large business all over the world. For the growth of their economies, China and many other emerging nations have paid close attention to sports business. As a result, marketing management strategies have a considerable influence on the creation of new goods in sports teams. According to Stone et al., (2020), the new product will be more successful if it meets the demands and expectations of the customers. It will fail to develop successfully if the new items do not fulfil the specifications and demands of clients(Sohn & Kwon, 2020). Many other elements, such as product price, quality, and demand for new items, have a substantial influence on the creation and success of a new product. Galily (2018) found that the availability of mobile and other smart devices, as well as new AI approaches, has helped to raise awareness of the applications and benefits of new goods, and it appears to be useful in producing new products linked to sports clubs(Stone et al., 2020).

The value of any business's development is solely dependent on effective marketing strategies; it was discovered that with proper marketing strategy management, no one can halt the creation of new goods, and that AI has improved the value of product development all over the globe(Vajpayee & Ramachandran, 2019). According to Stone et al., (2020), enterprises can inform sports enthusiasts about new sports-related products using artificial intelligence and marketing management strategies, which is advantageous for the growth of the sports industry as a whole (Bhatt, 2020). Apart from that, Patel, Shah, and Shah (2020) argued that AI (Artificial Intelligence) is a broad discipline of cognitive science, neurology, and psychology with widespread applications in many aspects of life, including marketing and knowledge management. Furthermore, digitization, artificial intelligence, database management, and algorithms have important commercial implications and, as a result, the current technology environment's future(Wang, Skeete, & Owusu, 2022). After doing research, it was discovered that the most important use of advanced technology appears to be the new product business in sports clubs. As a result, Sohn & Kwon (2020) take a closer look at how artificial intelligence, organisational behaviour, and marketing strategies have affected the creation of new sports club goods. Furthermore, the sports industry has several substantial hurdles in its operations. Beal, Norman, and Ramchurn (2019) highlight the computational problems of machine learning and artificial intelligence in the sports sector. For this objective, many models have been used to examine sports business obstacles and concerns, as well as various solutions to tackle the sports domain's computational challenges. Kerzel's (2021) research focuses on several sports fields such as match prediction, creation of new sports goods, decision-making, organisational behaviour, players' demand for new products in sports organisations, and so on(Winfield & Jirotka, 2018). By discussing all of these aspects of sports, it was also discovered how AI, organisational behaviour, and marketing tactics can be used to improve product development, how AI can forecast match results, and how it can help sports teams make better tactical and strategic decisions. It was also discovered that marketing strategies, artificial intelligence, and organisational behaviour all have a vital impact in product creation. It can also have a big influence on the creation of new products in sports teams.

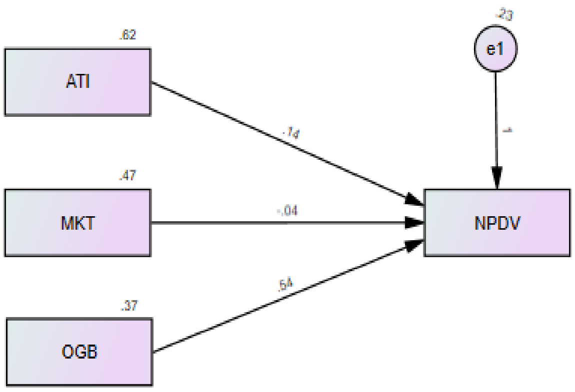
Methodology

The computational impact on the sports domain for the artificial intelligence, marketing techniques, and organizational behavior, different models have been utilized to investigate sports business impact. To better analyze the impact on new product development in sports club, this paper has used three variables as independent variables. These variables were ATI (Artificial Intelligence), Marketing Techniques (MKT), and Organizational Behavior (OGB). However, New Product Development (NPD) is used as dependent variable. The data was collected from 30 respondents, and the collected data was analyzed by using AMOS 26v.



Discussion and Analysis

The SEM Model (Structure Equation Model) for the study framework is provided in this section. This multivariate technique explores, tests, and assesses the cause-and-effect relationship between variables in a scientifically rigorous manner. This model provides the ability to calculate direct and indirect impacts on pre-assumed cause-and-effect interactions based on a set of assumptions. The loadings of variables against variables, as well as the loadings of items against variables, are shown in the results in the figure below. The error words are intended to reduce the likelihood of receiving incorrect results. The results from default model indicate that the values for Chi-square is 42.136, Degrees of freedom; 3, and Probability level = .000.



Assessment of Normality

The detailed findings of the normality test are presented in the table below for each independent and dependent variable. The result displays the minimum and maximum values, as well as the skew value and kurtosis values, for the data set under consideration. Following the results, it is determined that the measuring items for variables have a minimum value of 1.00 and a maximum value of 5.00, and the values for Skewness and Kurtosis are positive; as a result, all items are tailed to the right side of symmetry.

Variable	Min	Max	skew	c.r.	kurtosis	c.r.
OGB	1.000	3.667	.474	1.060	.452	.505
MKT	1.000	4.000	.744	1.663	.419	.469
ATI	1.000	4.000	.482	1.077	.155	.174
NPDV	1.000	4.000	.447	1.000	1.007	1.125
Multivariate					3.929	1.553

Regression Weights

The result given below illustrates the regression weight of each measurement item with respect to ICEPT and SLOPE based on the estimate values used in the calculation. The results indicate that the impact on ATI (Artificial Intelligence) and OGB (Organizational Behavior) is significant. However, the impact of Marketing techniques (MKT) on New Product Development (NPD) is insignificant as the value of p=0.085 (p>0.05).

			Estimate	S.E.	C.R.	P	Label
NPDV	<---	**ATI**	.144	.113	1.266	.006	par_1
NPDV	<---	**MKT**	-.036	.130	-.274	.084	par_2
NPDV	<---	**OGB**	.536	.147	3.650	***	par_3

Standardized Regression Weights

The values for Standardized Regression Weights are displayed in the table above. The estimates for the relationship (cause-and-effect relationship) between the measuring items and the variable are depicted in the following table.

			Estimate
NPDV	<---	**ATI**	.191
NPDV	<---	**MKT**	-.041
NPDV	<---	**OGB**	.550

Variances

Detailed results for ATI (Artificial Intelligence), MKT (Marketing Techniques), and OGB (Organizational Behavior) are presented in the table below. The estimates, confidence intervals, and significant values for each of the three studies are displayed in the table below. The statistically significant values for ATI, MKT, and OGB are 0.000, 0.000, and 0.000, respectively. Because of this, the amount of information gathered for the variables is significant.

	Estimate	S.E.	C.R.	P	Label
ATI	.623	.164	3.808	***	par_4
MKT	.473	.124	3.808	***	par_5
OGB	.371	.097	3.808	***	par_6
e1	.232	.061	3.808	***	par_7

Bootstrap

Regression Weights

After bootstrapping the data to 500 responses, the result given below illustrates the regression weight of each measurement item with respect to ICEPT and SLOPE based on the estimate values used in the calculation. The relationship between NPDV and ATI estimate value of 0.198 to 0.010, respectively, with a 100 percent significant estimated value at the SLOPE level, was found to be significant.

Parameter	SE	SE-SE	Mean	Bias	SE-Bias
NPDV <--- ATI	.198	.010	.126	-.017	.014
NPDV <--- MKT	.273	.014	-.007	.029	.019
NPDV <--- OGB	.295	.015	.506	-.031	.021

Minimization History

The minimization history shows the results of all iterations, starting at 0 and ending level is also at point 0. The results include information on negative eigenvalues, condition values, smallest eigenvalues, diameter rates, and the F-statistic value, as well as the ratio analysis of each iteration. The negative eigenvalues are 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0. Those conditions have the numbers 29.467, 17.530, 9.912, 9.479, 9.479, 9.479, and 9.479. Following the results, the f statistic values for each iteration are as follows: 49.548, 46.811, 43.229, 42.258, 42.139, 42.136, and 42.136 for given six iterations. The result reveals the history of minimization in the form of ratios of 9999.000, 0.754, 0.110, 0.088, 0.044, 0.008, and 0.000 indicating that there is a positive relationship between variables. The values of NTries are 0, 3, 1, 1, 1, 1, and 1. However, the values for Ratios are 9999.000, 0.000, 1.247, 1.187, 1.093, 1.018, and 1.000.

Iteration	Negative eigenvalues	Condition #	Smallest eigenvalue	Diameter	F	NTries	Ratio
0	0	29.467		9999.000	49.548	0	9999.000
1	0	17.530		.754	46.811	3	.000
2	0	9.912		.110	43.229	1	1.247
3	0	9.479		.088	42.258	1	1.187
4	0	9.479		.044	42.139	1	1.093
5	0	9.479		.008	42.136	1	1.018
6	0	9.479		.000	42.136	1	1.000

Model Fit Summary

CMIN

The model fit summary presented below includes ATI, MKT, OBG, and NPDV. The model explains the saturation model, as well as the independence model and the default mode. The results for NPAR are 7, 10, and 4, with a value of 3 for each model, according to the results. The CMIN of the default model is 42.136, while the saturated model's CMIN is 0.000 and the independence model's CMIN is 56.633. The result also shows the probability values, which are now 0.000 and 100% significant. According to the aforementioned model, the CMIN/DF rate for the default model is 14.045, whereas the rate for the independence model is 9.439. The CMIN models are appropriate for research and investigation in the disciplines of New Product Development, according to the findings. However, the values for DF are 3, 0, and 6.

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	7	42.136	3	.000	14.045
Saturated model	10	.000	0		
Independence model	4	56.633	6	.000	9.439

Baseline Comparisons

According to this outcome model, the NFI values for each model are 0.256, 1.000, and 0.000, respectively, while the RFI values are -0.488 and 0.000. The TLI and CFI models, which have values of -0.546 and 0.227, respectively, show a negative baseline comparison in between variables when compared to the default only, and positive baseline comparison in saturated and independence models.

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.256	-.488	.270	-.546	.227
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

The value of Parsimony Adjusted Measures may be found in the table below. This table shows how well the indexes are matched to one another in terms of correlation. The results show that the default model has a PRATIO of 0.500, the Saturated Model has a PRATIO of 0.000, and the Independence Model has a PRATIO of 1.000. When using the default model, the PNFI value is 0.128, when using the saturated model, it is 0.000, and when using the independence model, it is 0.000. The value of PCFI for the default model, on the other hand, is 0.114.

Model	PRATIO	PNFI	PCFI
Default model	.500	.128	.114
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

This result displays the NCP, LO90, and H190 values for each model, as well as a summary of model fitness for each model. An NCP of 39.136 is obtained by using the default model, however a significant ratio of 0.000 is obtained using the saturated model. The default Model is represented by the L090, which has values of 21.758 for the default model, 0.000 for the saturated model, and 30.163 for the Independence Model, respectively. The H190 hypothesis asserts that the 63.953 values in the saturation model of the values model are statistically significant, and that the dependent variable of the independence model, which is 78.566, has a positive hypothesis value.

Model	NCP	LO 90	HI 90
Default model	39.136	21.758	63.953
Saturated model	.000	.000	.000
Independence model	50.633	30.163	78.566

FMIN

The default model has a fitness summary FMIN value of 1.453, while the saturated model has a value of 0.000 and the independence model has a value of 1.953. According to the F0 model, the rate levels for each perspective are 1.350, 0.000, and 1.746, respectively. The LO 90 ratios for each model are 0.750, 0.000, and 1.040, respectively, indicating that each variable's model fitness is statistically significant and acceptable. The default model value for HI 90 is 2.205, the saturated model value is 0.000, and the independent model value is 2.709.

Model	FMIN	F0	LO 90	HI 90
Default model	1.453	1.350	.750	2.205
Saturated model	.000	.000	.000	.000
Independence model	1.953	1.746	1.040	2.709

RMSEA

RMSEA results for each model show the default mode and independence model values in the default mode and independence model, respectively. The RMSEA values for the default and independence models are 0.671 and 0.539, respectively, and the LO 90 values for the default and independence models are 0.500 and 0.416. As a consequence of the findings, the positive hypothesis value for HI 90 is 0.857 and the positive hypothesis value for model is 0.388, and the PCLOSE rate for both models is 0.000 and 0.000, indicating that both models are significant.

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.671	.500	.857	.000
Independence model	.539	.416	.672	.000

AIC

The characteristics of NPDV is evaluated using the AIC fit summary, which is linked to ATI, MKT, and OGB. 56.136 is the AIC value for each of the models. When it comes to independence models, the value is 20.0, and when it comes to saturation models, the value is 64.633. According to the findings, the BCC value is proportional to the performance of the model. There is value of 59.053 for the default model; 24.167 points are awarded for the saturated model, while 66.299 points are awarded for the independence model.

Model	AIC	BCC	BIC	CAIC
Default model	56.136	59.053	65.945	72.945
Saturated model	20.000	24.167	34.012	44.012
Independence model	64.633	66.299	70.237	74.237

ECVI

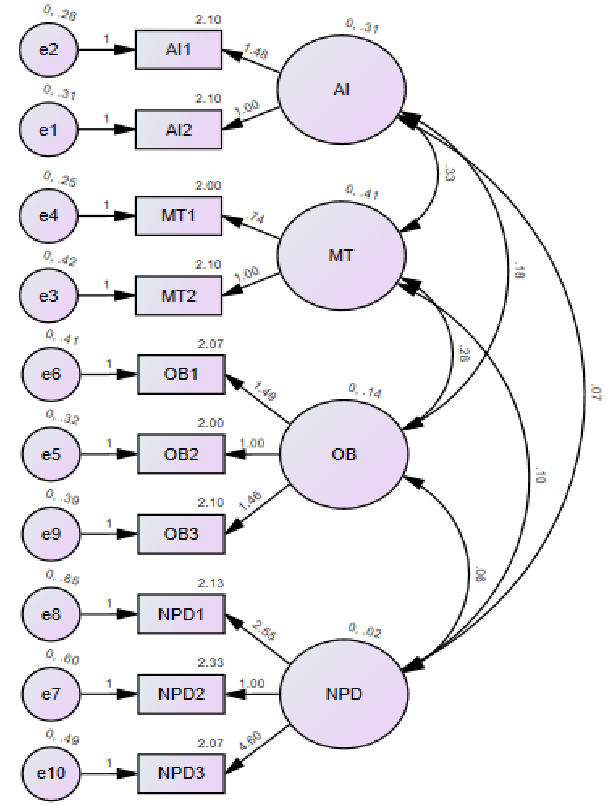
As indicated in the table below, the value for ECVI. The ECVI for the Default Model is 1.936, the Saturated Model is 0.690, and the Independence Model is 2.229 for the Independence Model. According to this model's coefficient of determination (LO 90), the saturated model's coefficient of determination (1.336), and the independence model's coefficient of determination (1.523) are all positive. According to the HI 90 Model, a value of 2.791 is acceptable, while the saturation model has 0.690 and the independence model there is a value of 3.192.

Model	ECVI	LO 90	HI 90	MECVI
Default model	1.936	1.336	2.791	2.036
Saturated model	.690	.690	.690	.833
Independence model	2.229	1.523	3.192	2.286

HOELTER

The values for the HOELTER Model are listed in the table above. The value for HOELTER.05 for the default model is 6, and the value for the Independence model is 7. Similarly, the value for HOELTER.01 for the Default Model is 8, whereas the number for the Independence Model is 9.

Model	HOELTER .05	HOELTER .01
Default model	6	8
Independence model	7	9



CFA

Using the confirmatory factor analysis test, you can make sure that the factors loading that has an impact on the variables in the model is correct, and you can detect any challenges or errors in the factors loading between the items and the model fit. Since all of the required values appear in the confirmatory factor analysis result, the values recovered are satisfactory, suggesting that the model is fit and acceptable. This is demonstrated in the figure, which shows the values recovered.

Assessment of normality

Each independent variable's normality test results are shown in the table above, along with the results of the analysis for each dependent variable. Among the values displayed in the output are the skewness and kurtosis coefficients, as well as the minimum and maximum values. According to the results, the measuring items for variables have a minimum value of 1.00 and a maximum value of 5.00, and the values for Skewness and Kurtosis are both negative and positive; therefore, fewer items are tailed to the left side and fewer are tailed to right side of the symmetry.

Variable	Min	max	skew	c.r.	Kurtosis	c.r.
NPD3	1.000	5.000	.984	2.199	1.026	1.147
OB3	1.000	4.000	.161	.359	-.854	-.955
NPD1	1.000	4.000	.315	.705	-.712	-.796
NPD2	1.000	4.000	-.257	-.574	-.742	-.830
OB1	1.000	5.000	1.479	3.308	3.152	3.524
OB2	1.000	4.000	.627	1.403	.980	1.095
MT1	1.000	4.000	.627	1.403	.980	1.095
MT2	1.000	5.000	1.140	2.550	1.784	1.995
AI1	1.000	5.000	1.082	2.418	1.048	1.171
AI2	1.000	4.000	.228	.509	-.552	-.618
Multivariate					6.349	1.122

Correlations

The correlation of estimate is defined as the interaction between covariance, variance, ICEPT mean, and SLOPE 1.000, which indicates a level of significance of 100 percent and inter-correlation of each variable, as well as the correlation of each variable with the other variables. There is a 0.917 correlation coefficient between AI and MT, a 0.869 correlation coefficient between AI and OB, and a 0.992 correlation coefficient between NPD and AI. The findings suggest that there is a strong positive relationship between the dependent and independent variables, and between independent variables as well.

			Estimate
AI	<-->	**MT**	.917
AI	<-->	**OB**	.869
NPD	<-->	**AI**	.922
MT	<-->	**OB**	1.143
NPD	<-->	**MT**	1.058
NPD	<-->	**OB**	1.019

Variances

The values of Variance in variables are displayed in the table underneath. The results show that there is a large amount of variation in AI, MT, OB, and NPD. However, OB and NPD show insignificant variation.

	Estimate	S.E.	C.R.	P	Label
AI	.309	.155	1.998	.046	par_23
MT	.408	.204	2.001	.045	par_24
OB	.143	.093	1.533	.125	par_25
NPD	.021	.045	.466	.641	par_26

Factor Score Weights

The factor score weights for each variable are shown in the following table. The predicted weight of each item in relation to the factors is represented by the variables. These weights range from one-to-one hundred percent. Taking MT→OB3 as an example, it provides the variable with the strongest loadings by supplying it with a 0.221 load against the variable.

	NPD3	OB3	NPD1	NPD2	OB1	OB2	MT1	MT2	AI1	AI2
OB	.060	.036	.025	.011	.035	.030	.175	.141	.053	.032
MT	.123	.221	.051	.022	.213	.181	.021	.017	.134	.082
AI	.064	.038	.027	.011	.037	.031	.077	.062	.260	.159
NPD	.020	.024	.008	.004	.023	.020	.039	.031	.035	.021

Conclusion

Additionally, artificial intelligence (AI) technologies and organizational behaviour management strategies have positive effects on the development of new products. Digital marketing has had a significant impact on the development of new products in sports organisations. In the sports industry, artificial intelligence, marketing techniques, and organizational behaviour are all used to control the creation and manufacturing of new products and the production of existing products. Additionally, the importance of the sports industry can be attributed to the fact that it encourages a healthy lifestyle and physical activity. Sport marketing is another method of promoting sports events and products. Another essential component of international sports marketing is the fact that all sports players have a large fan base, and that via the marketing of the sports industry and of sports players, they can establish a sports brand in their respective fields of expertise. Organizational behaviour is the first factor that contributes to the development of the sports industry. Robotics and artificial intelligence (AI) are two more factors that have played a role in the progress of the sports business. Advertising and marketing are the third aspect that contributes to the advancement of the sports business. Marketing any industry increases the worth of the industry as well as the value of the industry. Incorporating new products into the marketplace contributes to the overall development of a certain field. Innovation occurs as a result of the introduction of new products. Innovation is essential in today's society, and by introducing new features of innovation and modernizations in numerous industries around the world, we can make strides forward and make significant progress.

Recommendations

The future recommendations of the study circulate around the emerging challenges and opportunities of AI as well as their impact on the new product development in sports clubs. The study lacked the focus on huge investments requirements and the criticism of sports journalism.

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