Role of Biotech Parks in India for Achieving Bio E3 Sustainable Goals

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Biotech Parks are innovative addenda for biotechnological development in India. In the year of 2024 when BIO E3 policy is launched by GoI, all together twelve biotech parks are functioning at different parts of our motherland catering biotechnological innovations and entrepreneurship development. These Biotech Parks can play major role for 'Net Zero' carbon economy and Life (Lifestyle for Environment). Biotech Parks can facilitate Bio-foundry and Bio Manufacturing Hubs for achieving $ 300 bn by 2030, whatsoever we all are expecting and through that achievement and good number of entrepreneurs' development India may take a leap in Global Economy stand.

Keywords: Biotech Park, Sustainability, BioE3, Biotech Policy.

1. Introduction

Biotech parks are innovative addendum for supporting biotech industry in India especially in eastern part of India. Indian Biotech Industry is targeting for $ 300 bn by 2030, with a CAGR of 13.96 %. (https://dbtindia.gov.in/sites/default/files/NBDS_March%202021.pdf). Under these circumstances it is inevitable that at every zone there must be some pivotal points about which growth activities will circumfuse. Biotech parks here can play very vital roles which can help India to develop further. Genome Valley is acting from 1997. And very recent addition to this list is two bio tech parks in J & K and one in Kolkata. So all together 12 (twelve) Biotech Parks can play pivotal role for our motherland's growth not only in biotech sector but also indirectly or directly all profit making and non-profitable sectors.

Very recently (Aug'24) GoI has declared BioE3 policy (https://bmi.dbtindia.gov.in/pdf/folder.pdf). Author throughout the paper has mentioned how prime pillars of Bio E3 policy Economy, Environment and Employment can be strengthened through Biotech Parks.

Here to be mentioned that these assumed achievements can satisfy the SDGs (Sustainable Development Goals)

Present Biotech Industry growth in India: Biotech Industry in India predominantly MSME (Micro Small and Medium Enterprises). The Micro enterprises are the smallest ones, with less investment that usually does not amounts up to more than 1 Cr, with tiny number of employees (sometimes it's a solo man handling all), and usually small turnovers. The street vendors, small scale artists or maybe the individual freelancers on fiverr are counted as micro enterprises. The turnover is usually less than 5Cr. The small enterprises are the ones with slightly better conditions than micro enterprises. They usually have better turnover and investments made in them but not large enough. This might usually include the local cloth shops, small-scale food shops or gyms. Most of them can provide sustainable income. Investment amounts approximately not more than 10 Cr and turnover not more than 50 Cr. The medium enterprises generally have much better investments, turnovers, employment opportunities and market reach. For example, the medium scale manufacturing factories, 3–4-star hotels, Wholesale distribution companies etc. They are generally more diverse than the small-scale enterprises. Investment amounts not more than 50 Cr and annual turnover around 250 Cr. Here to mention maximum of biotech industries are coming under MSME section. Author here also catered the biotech industry which are not falling under MSME section.

To understand the real problems faced by the Biotech enterprises, a ground truth is needed to verify all the research done on this topic, this paper tries to encapsulate the real problems of the sector and tries to understand them in a better way how biotech parks can cater the solution for the above said problem and role of biotech park for addressing the issues.

To ensure proper research, the data was required to be collected from the entire bio tech industries surrounding biotech parks and not just one region, in multiple regions. The data was collected from the local markets of different towns of different states, all of the towns being of different development levels to understand the diversity and differences in issues faced by the members of the sector. When the data was collected the communication could be seen creating a problem for micro-enterprises but small and medium enterprises had their ways to deal with it although they had some issues too while they were trying to address the customers.

Most of the biotech micro-enterprise are happy with their offline growth and hence do not feel the requirement of reaching out to new customers, surprisingly this does not even create a barrier to growth for most of them as they are already well established that the word of mouth popularity is enough for them to attract new customers, for most of the enterprises, customer retention is the key to their growth, for them communication means to communicate with customers in the best way that they retain them for a longer time and hence ensure their growth. They also feel that if they are not able to communicate with customers in an effective way about their products then communication might become a barrier for their growth.

2. Methodology

Data Collection

1. As of now 12 (twelve) biotech parks are as mentioned below

S. No.	State/UT	Name of Biotechnology Park
1.	Uttar Pradesh	Biotech Park, Lucknow
2.	Telangana	Biotechnology Incubation Centre, Hyderabad
3.	Tamil Nadu	Tidco Centre for Life Sciences (TICEL) Biotech Park, Chennai
4.	Tamil Nadu	The Golden Jubilee Biotech Park for Women, Chennai
5.	Assam	Biotech Park Technology Incubation Centre, Guwahati
6.	Kerala	Biotechnology Incubation Centre, Cochin
7.	Karnataka	Biotechnology Park, Bangalore
8.	Jammu & Kashmir	Industrial Biotechnology Parks (IBTPs) (02)
9.	Chhattisgarh	Chhattisgarh Biotech Park
10.	Karnataka	c-CAMP
11.	West Bengal	Kolkata Biotech Park

Author has surveyed the biotech industries present surrounding the above mentioned Biotech Parks. The survey primarily conducted through Online Platform. The author has broadly divided the entire biotech industries into 4 (four) categories. (i) Bio-Pharmaceuticals (ii) Bio Agriculture (iii) Bio-waste based Industries (iv) Bio-IT and Bio-Services. (https://www.investindia.gov.in/sector/biotechnology).

Data collected from all possible companies falling under these sectors. Loads assigned according to amount of investments in these sectors.

Data Processing

Collected data are processed through EFA (Exploratory Factor Analysis). The evaluated matrices are shown below: Factor Analysis Method : SPSS was used to conduct factor analysis. Principal Component Analysis (PCA) was applied to identify the underlying factors. The rotation method used was Varimax with Kaiser Normalization to better interpret the factor loadings.

3. Data Specification

KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.606
Bartlett's Test of Sphericity	Approx. Chi-Square	178.620
	df	91
	Sig.	<.001

KMO Measure of Sampling Adequacy = 0.606

Bartlett's Test of Sphericity: Chi-Square = 178.620, df = 91, $p < 0.001$

Analysis: The KMO value of 0.606 indicates an acceptable level of sampling adequacy for factor analysis.

The Bartlett's Test of Sphericity is significant ($p < 0.001$), confirming that correlations between items are suitable for factor analysis

Communalities

	Initial	Extraction
primaryfactor	1.000	.637
support	1.000	.576
purpose	1.000	.490
contact	1.000	.584
obstacles	1.000	.476
communicationbarrier	1.000	.608
improvements	1.000	.616
knowledge	1.000	.381
reliablelock	1.000	.563
lockpreference	1.000	.658
challenges	1.000	.395
lockconsideration	1.000	.690
securityneeds	1.000	.577
newlocktechnologies	1.000	.589

Extraction Method: Principal Component Analysis.

The Communalities table displays the Initial and Extraction values for each question/item.

Analysis: High extraction values indicate a strong relationship with the extracted factors.

For instance, question 10 has an extraction value of 0.658, showing it is well explained by the extracted components, while question 8 (0.381) is less so.
Total Variance Explained

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.387	17.048	17.048	2.387	17.048	17.048
2	1.722	12.297	29.345	1.722	12.297	29.345
3	1.528	10.916	40.262	1.528	10.916	40.262
4	1.171	8.364	48.626	1.171	8.364	48.626
5	1.030	7.358	55.984	1.030	7.358	55.984
6	.982	7.017	63.001			
7	.858	6.132	69.133			
8	.790	5.641	74.774			
9	.748	5.346	80.120			
10	.676	4.829	84.948			
11	.653	4.661	89.610			
12	.574	4.101	93.711			
13	.479	3.419	97.130			
14	.402	2.870	100.000			

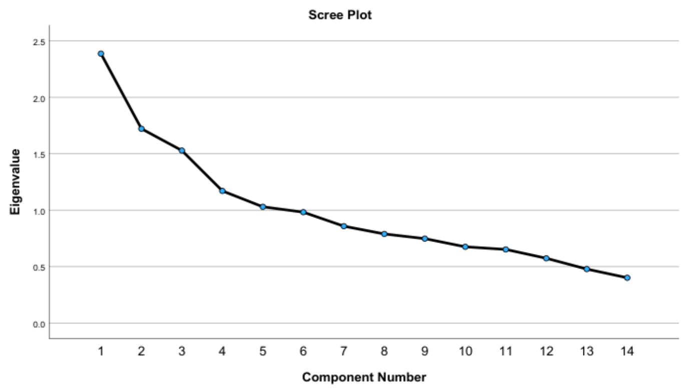
Total Variance Explained

	Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %
1	1.893	13.522	13.522
2	1.793	12.807	26.329
3	1.588	11.342	37.671
4	1.377	9.837	47.509
5	1.187	8.475	55.984
6			
7			
8			
9			
10			
11			
12			
13			
14			

Extraction Method: Principal Component Analysis.

The Initial Eigenvalues indicate the variance explained by each component. Components with eigenvalues >1 are retained.
The cumulative variance explained by the first five components is 56%, which suggests they capture a meaningful proportion of total variance.
Analysis: Five components explain over half of the variance (56%), indicating a sufficient dimensional reduction.
These five factors likely capture the primary dimensions influencing responses.

Scree Plot



The scree plot indicates the eigenvalues for each component. The "elbow" at the fifth component suggests that additional components explain minimal extra variance.
Analysis: Retaining five components is justified as additional components contribute marginally to explained variance. This aligns with the cumulative variance and supports the five-factor model
Component Matrix

Component Matrix[a]

	Component				
	1	2	3	4	5
newlocktechnologies	.658				
securityneeds	.504				
challenges					
obstacles		.616			
lockconsideration		-.531			
improvements		.505			
purpose					
support			-.645		
communicationbarrier			-.586		
reliablelock			.530		
knowledge					
lockpreference				.702	
contact					
primaryfactor					-.592

Extraction Method: Principal Component Analysis.
a. 5 components extracted.

The Component Matrix displays the loadings of each item on un-rotated factors. Higher loadings indicate a stronger correlation with each component.

Analysis: Initial loadings show how items correlate with factors before rotation. Higher loadings on certain components suggest preliminary clustering of items, supporting distinct factors.

Rotated Component Matrix

Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
reliablelock	.710				
securityneeds	.652				
knowledge	.580				
challenges					
communicationbarrier		.765			
support		.697			
newlocktechnologies		.543			
obstacles			.664		
improvements			.611		
lockconsideration			-.569		
purpose			.534		
contact				.720	
primaryfactor				.625	
lockpreference					.778

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 9 iterations.

The Rotated Component Matrix simplifies interpretation by redistributing the item loadings across components.

Analysis: The rotation clarifies the structure by loading items strongly onto single components. For example, items like question 9 have high loadings on specific factors, suggesting distinct themes within each component.

Component Transformation Matrix

Component Transformation Matrix

Component	1	2	3	4	5
1	.681	.572	.135	.412	.146
2	-.285	-.129	.872	.375	-.025
3	.594	-.783	.074	.022	.166
4	-.100	.120	.172	-.376	.897
5	.303	.169	.431	-.740	-.382

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

The Component Transformation Matrix shows correlations among rotated components, ideally close to zero.

Analysis: This confirms minimal correlation between components post-rotation, supporting an orthogonal factor model where each factor represents a unique dimension.

Component Score Covariance Matrix

Component Score Covariance Matrix

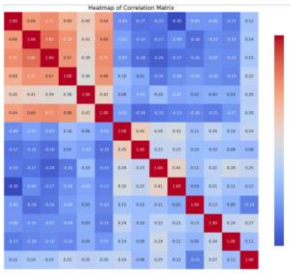
Component	1	2	3	4	5
1	1.000	.000	.000	.000	.000
2	.000	1.000	.000	.000	.000
3	.000	.000	1.000	.000	.000
4	.000	.000	.000	1.000	.000
5	.000	.000	.000	.000	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Diagonal values are 1, showing normalized variance. Off-diagonal values are zero, indicating orthogonal components.

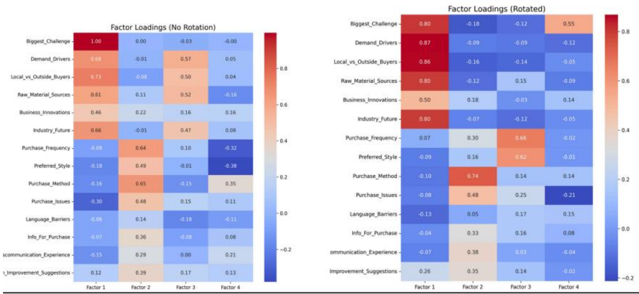
Analysis: Each factor operates independently, providing clear, non-overlapping dimensions that represent distinct themes derived from the survey data.

Data Analysis (EFA) with help of Python.



KMO Test Result: 0.820 (0.80 to 0.90 – Meritorious)
Bartlett Test: χ^2 = 580.360, p = 2.438e-72(very less then 0.05)

It is observed that result obtained even through Python analysis are signified.



4. Results and Discussions

Conclusion

In conclusion it may be said that all biotech parks mentioned above can play developmental role in Biotech Industry through giving thrust through the following sectors (i) Bio-Pharmaceuticals (ii) Bio Agriculture (iii) Bio-waste based Industries (iv) Bio-IT and Bio-Services. Sector wise thrust can be given as per zones and Biotech Parks can act as pivot for organizing the activities.

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