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Nexus between innovation ecosystem and innovation performance

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Abstract: The business climate is faced with turbulent environment. The situation is more pronounced in the manufacturing sector. The purpose of the study was therefore to investigate the influence of innovation ecosystem (IE) on innovation performance (IP) in manufacturing firms with a focus on major industrial counties in Kenya. Mixed method design was used. The target population was 2,484 employees drawn from 828 firms. Multi-stage sampling was employed to sample 345 employees drawn from 115 firms. Primary data was collected using semi-structured questionnaires, interview schedules and checklists. Data was analysed using smart partial least square. It was concluded that IE has a significant influence on IP. It was therefore recommended that the operating environment should be enhanced for improved competitiveness of the manufacturing sector. The study is useful to the various stakeholders in the manufacturing sector. Further studies should be carried out on how trust can be managed in IE.

Keywords: innovation ecosystem; innovation performance; competitiveness; knowledge entrepreneurship.

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1 Introduction

Innovation performances (IP) are the level of increase in novel products, creative processes, development of new ventures and discovery of new markets that all contribute to the sustainable growth of an enterprise. It is the degree and the rate at which enterprises innovate in terms of new products, processes, management and market (Andreeva and Kianto, 2011) in comparison with the competitors. Innovation ecosystems

(IE) on the other hand are the prevailing circumstances in an operating system at a particular time which is shaped by key players in an industry and influences firm performance. It is a local condition that is conducive to the creation of novel products through new business models. The IE is supposed to enhance IP, but Ramli et al. (2025) found that commercialisation of research is a daunting task due to lack of requisite facilities. These facilities comprises of support system within a firm or geographical spatial area. Furthermore, Dhir and Dhir (2025) found that there is need to analyse the factors that hinder IP. This paper sorts to find out the facilities that constitute IE and how they affect IP. Aziz et al. (2024) found that supply chain integration is crucial to the improvement of IP. External factors which constitute the IE are positively related to IP (Yu et al., 2023).

Innovation performances have greatly impacted on the growth of emerging economies. China has particularly outgrown developed economies and is highly regarded as one of the most attractive places to do business (Luo et al., 2011) due to its competitiveness as a result of addressing its innovation ecosystem. Innovation performance in India has also improved due to policy intervention on innovation at the national level which has resulted in tackling broader social-economic issues leading to gaining of competitive advantage (Weiss, 2011). This resulted in an impressive development of these countries' manufacturing firms to become among the most competitive globally. However, Jiang et al. (2022) found that IE stability has a direct relationship with IP. Furthermore, Robertson et al. (2023) found that IP is context dependent.

However, manufacturing sector in Africa relies heavily on exhaustible natural resources and is involved in primary and extractive activities whose outputs are semi-finished products used as raw materials in developed economies. The situation is worse in Sub-Sahara Africa which is the least industrialised part of the world (UNIDO, 2017). Value addition in the manufacturing sector in this region is therefore important in achieving competitiveness and hence economic development.

The growth of manufacturing sector in Kenya has been declining despite the several blue prints developed to revive it. Kenya's Vision 2030 envisages the country becoming the dominant supplier of manufactured products in East and Central Africa through enhanced efficiency and improved competitiveness. Manufacturing was also one of the big agenda for the past several years. However, the growth in the manufacturing sector has been dismal, lagging behind the overall economic growth rate and its contribution to exports has declined as a result of low competitiveness. The share of exports in the region from manufactured goods has also been declining.

The low competitiveness is evidenced by the country's low competitive industrial performance (CIP) index of 0.009 which is below the world's average of 0.067 while other middle-level industrial countries such as South Africa is 0.057 and India is 0.078 which are above the world average (UNIDO, 2020). The sector low competitiveness is manifested in the declining growth rate which threatens to thwart the country's ambition of becoming a globally competitive industrial nation by 2030. The World Bank Group (2018) report on Kenya's economic update shows that the growth rate in the sector has been declining from 3.6% to 2.7% and 0.2% in 2015, 2016 and 2017, respectively.

The low innovation levels in the manufacturing sector have put immense pressure on locally produced goods emanating from forces of globalisation. This has resulted in the closing down of several manufacturing firms and others relocating to different countries due to unfavourable and uncoordinated innovation ecosystems. This has denied the country the much-needed job opportunities and multiplier effect in the economy since one job created in the manufacturing sector is likely to create between 6 and 16 jobs outside the industry. The government had envisioned creating two million jobs from the manufacturing sector in 2018, but there has been a decline of jobs created from 114,400 in 2017 to 78,400 in 2018 which is a 31% decline despite an accelerated economic growth of 6.3% in 2018 from 4.9% in 2017 (World Bank Group, 2019). The study therefore sought to investigate how manufacturing firms can leverage on IE to drive IP.

1.1 The study objectives

The main objective of the study was to investigate the extent of influence of IE on IP in manufacturing firms in Kenya. The specific objectives were to find out how business services, trade support, technology spillover and government policy influence IP in manufacturing firms in Kenya. These objectives guided the study to unravel how firms can leverage on their operating context to optimise their performance.

1.2 Theoretical underpining

The interconnections is IE is a complicated web and the measurement of innovation performance can be confounding. The attempt to trace the link between the two study variables can be understood by interrogating the complexity theory. The study was anchored on the complexity theory to examine how interactions within the operating ecosystem bring about open innovation and its influence on IP in manufacturing firms.

The theory contends that micro and macro factors in complex natural and human systems are inseparable. The proponents of the theory argue that the spontaneous bottom-up process leads to the formation of path dependence which comes in handy to translate innovation in a different context (Nishiguchi, 2001). The theory reinforces the importance of leadership in learning, co-creating, creativity and adaptability. It further expounds that leadership should provide management entanglement between behaviours, adaptive and administrative structures that provides effectiveness and flexibility in a firm. Espinosa and Porter (2011) believe that the complex nature of IP requires leadership that should move from dominating innovation strategy to the facilitation of knowledge assimilation.

The theory envisions that an organisation should influence the operating context and channel the flow of learning to value networks. It advocates for emergent learning that transcends from the industrial era to the knowledge era that produces ideas that provide complex interplay of different interactions. The theory also underscores the importance of technology. It acknowledges the enabling role of technology in providing interactions that accelerates creativity (Desai, 2010).

The theory contends that a firm should have a symbiotic relationship with the society and ecosystem such as the government, business community and civil society which need to be managed carefully. It postulates that knowledge exchange between a firm, its subsystems and the external environment constitutes the ecosystem (Espinosa and Porter, 2011). The theory is appropriate because IP is characterised by dynamism developed through knowledge acquisition, sharing, transfer and utilisation. The theory is also applicable because it is difficult to model complex knowledge and to acquire it thorough a formalised approach (Granerud and Rocha, 2011). Innovation performance also requires collaborative networks that replace the single-minded myopia view on performance. The interdependence and interaction of the various components and key players brings about the concept of an ecosystem.

2 Innovation performance and innovation ecosystem

2.1 Innovation performance

Innovation performance (IP) has been defined differently according to the conceptualisation of various scholars. Many scholars however agree that it entails efforts to improve product reputation, technological aspects, market response, profitability and increase in market share. Andreeva and Kianto (2011) believe that it is the degree to which enterprises develop novelty in terms of processes, management and marketing with a comparison to competitors. Innovation performance is the degree to which firms develop new products, processes, markets and enterprises to increase their competitiveness. It results in the reduction of lead times, risk, cost and adoption of appropriate technology thus increased profitability (Secundo et al., 2017). It also enables firms to raise their market share, gain competitive advantage and enhance their sustainable development (Babalola et al., 2015). It can, therefore, be defined as the level of increase in novel products, creative processes, development of new ventures and discovery of new markets that all contribute to the sustainable growth of an enterprise.

The major contribution of IP to firms is the improvement of competitiveness which enhances their survival and propels them to soar up beyond the turbulence brought about by the ever-changing dynamics in the business environment. However, innovation is a herculean task that requires diverse mastery of several approaches and interactions with different parties. The effectiveness of innovation activities can be evaluated through IP.

There have been several attempts to measure IP by different researchers. Thomas and Tom (2009) recommended the use of multiple approaches that include output, efficiency, attraction and selected facilitation impact where each of the measurements can be selected with justification. Birchall et al. (2011) focused their study in six developed countries where they recognised that the approaches applied in measuring IP yielded little impact and recommended firms the inclusion of overall performance, effectiveness of R&D investment, change management and availability of innovation enablers. However, the measures are not associated with enterprise success.

Some efforts have been made in developing countries to measure IP. Wang and Chien (2006) conducted their study in the Taiwanese manufacturing industry and measured IP through increased new processes, the percentage increase in sales as a result of new products, the number of research development by employees and the number of patents acquired. However, there is a need to focus on different input variables rather than technical informational resources and innovation objectives. Lau and Lo (2015) conducted their study in a developing country in the Republic of Korea and measured IP in terms of innovation rates, sales growth rate, market impact and financial success. Nevertheless, the measures failed to capture the external environment. There is no evidence of an attempt to measure IP in the least developed countries.

Previous researchers have attempted to use different parameters for measuring IP. Hagedoorn (2003) utilised R&D inputs, a range of new products, number of patents and their citations as the indicators of measuring IP and found a strong statistical overlap.

Innovation studies have also shown that IP can be measured through sales performance, sales growth rates and innovation rates (Wan et al., 2003; Yam et al., 2004). Wang and Chien (2006) measured IP through increased new processes, the percentage increase in sales as a result of new products, the number of research development by employees and the number of patents acquired. The concept is useful for bench marking, but it does not illuminate on the broad aspect of innovation performance.

It would also be prudent to link the measurement scale with patents and number of new products. Innovations rates are measured as a percentage of new products commercialised with all products of a firm over a period of three years and are highly regarded because it depicts a firm's relative strength in IP while sales growth rate and performance indicate the level of market impact, advantage and financial success (Lau and Lo, 2015). It is therefore evident that there is a need to develop an integrated parameter to measure IP.

The study captured the broad spectrum of IP and includes new products and patents in the measuring scale instrument. Thomas and Tom (2009) recommended the use of multiple approaches that include output, efficiency, attraction and selected facilitation impact where each of the measurements can be selected with justification. Other researchers used the scale of sales performance, innovation rate and sales growth rate (Guan and Chen, 2010; Yam et al., 2011). The dimensions of IP measures include; firm's overall performance, the effectiveness of R&D investment, change management and availability of innovation enablers (Birchall et al., 2011). Xie et al. (2016) measured IP through new products index, modified product index and annual proportion of new product turnover. Nevertheless, the empirical review reveals a gap in the lack of an IP measurement model (Birchall et al., 2011). This study entailed a discourse, comparative analysis of the previous attempt to measure IP, processes and critical success factors within the manufacturing sub-sector to develop an appropriate model.

The approach of measuring IP captured both innovation output (IO) and innovation efficiency because IO depicts the result of an innovation effort while efficiency shows the economic value derived from innovation activities. The IO is the end product of innovation activity. The end products of IO are; new products, new processes, new enterprise and new markets. Andreeva and Kianto (2011) believe that IO is the degree to which enterprises develop novelty in terms of processes, management and marketing. Innovation output can, therefore, be defined as the increase in novel products, creative processes, and the development of new ventures and the discovery of new markets.

The IO depicts the result of an innovation effort. It can be measured as the summation of increased new products as a result of innovation, patents acquired, innovation process and unique enterprises created to cater for innovation activities. Innovation output can be enhanced by improving the innovation capacity of a firm. The innovative capacity can be improved by addressing the innovation efficiency.

Innovation efficiency has been defined as the capacity for transforming innovation inputs into outputs and thus it is the ratio between investment in innovation and the outcomes (Hollanders and Esser, 2007). Innovation efficiency can, therefore, be defined as the effectiveness of converting innovation inputs into outputs.

Innovation efficiency focuses on the commercialisation and the economic benefits of innovation activity (Wang et al., 2016). Commercialisation helps firms to develop a new approach of consolidating the local and international markets. Innovation efficiency also lead to value addition and economic utilisation of scarce resources.

There are several methods of measuring innovation efficiency. They include stochastic frontier analysis (SFA), data envelopment analysis (DEA) and two-stage innovation efficiency non-radial DEA model. This study utilised the later method because provides for optimisation of innovation components. The approach recognises innovation input as comprising of human, finances and material resources while appreciating the role commercialisation of innovation in terms of the market value and profits (Wang et al., 2016). The model, therefore, captures the optimal utilisation resources.

Innovation performance was, therefore, measured as the summation increased new products as a result of innovation, patents acquired, new innovation process and new enterprise multiplied by sales growth rate brought about by innovation. This can be illustrated mathematically as:

$$IP = \sum_{n=1}^{t=3} \{(Output)(Efficiency)\}$$

This can also be expressed as:

$$IP = \sum_{n=1}^{t=3} \{(Inp + Pa + Nip + Ne)(SGR)\}$$

where *IP* is innovation performance, *Inp* is the sum of the increased new product as a result of innovation, *Pa* is patents acquired, *Nip* is the new innovation process, *Ne* is the new enterprises as a result of innovation and *SGR* is the percentage sales growth rate brought about by innovation.

2.2 Innovation ecosystem

There are several definitions that have been advanced in an attempt to understand the innovation ecosystem (IE). Poikola et al. (2011) believe that it is the functioning inter-dependency among partners with the dynamic interaction between different actors within a given locality. Leavy (2012) urges that it is the integration of solutions from the combined efforts of multiple partners. The innovation ecosystem is, therefore, the operating environment in which firms have collaborative networks with the different players in the industry to cooperate to improve their IP.

It is a term used as a metaphor to describe the co-creation and relations that exist within a cluster or a spatial unit.

The IE has received immense interest across the globe. Firms are finding it increasingly important to manage their innovation within a complex environment that requires collaborations. The dynamics, particularly in the manufacturing sector such as the ever-changing technology and market sophistication, necessitate firms to seek collaborators to remain competitive (Engler and Kusiak, 2011). The manufacturing sector has a complex flow of information, materials and diversity of players thus firms in the sector cannot operate in isolation but rather on a comprehensive systematic collaboration (Barile et al., 2016).

The complexity, uncertainty and ambiguity in the manufacturing sector require a well-coordinated IE. The key success factors of an IE are government policy, innovation output, skills and competitiveness (Jena et al., 2016). The benefits of IE are that it allows other sector players, firms and citizens to add value to an existing product whose manufacturers cannot do it alone (Zuiderwijk et al., 2014). However, IE in developing countries is faced with numerous challenges such as the informal economy, high poverty levels, unsupportive infrastructure and low conceptual insights (Toivanen et al., 2012).

The concept of IE in Kenya is being embraced by various stakeholders but its conceptualisation is still in the initial stages yet it is faced with challenges of low networking. Innovation ecosystem involves the infrastructure, policy and social-economic diversion, but in Kenya, it is fragmented, undifferentiated and unsustainable with less coordination and collaboration (Cunningham et al., 2016).

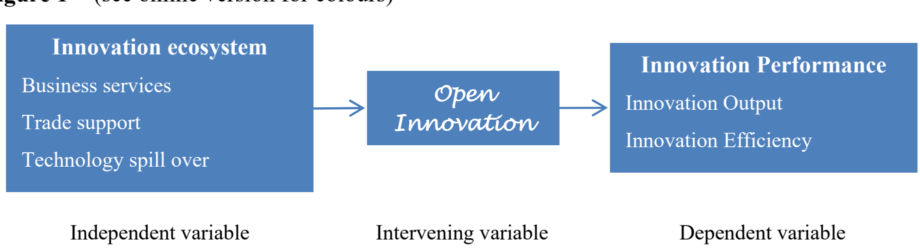
Several parameters have been used to measure IE. They include collaboration among the different stakeholders, integration and transformations (Koontz and Bodine, 2008). These can be measured by the level of networking among participants, universities, research institutions and government agencies (Zuiderwijk et al., 2014). The parameters included are accelerators, incubators, business services and trade organisation support which provides a channel for static agglomeration economies, technology spillover from research institutions, dynamic agglomeration economies and infrastructural economies. Soy (2023) also found that cooperation between enterprises and research organisations has a significant influence on IP. Moreover, Yu et al. (2023) found that external factors which constitute the IE are positively related to IP. These parameters were adopted in the study because they capture the essential ties within entities in the manufacturing innovation ecosystem such as the role of government, financial institutions, innovation and technology markets, Universities, research and innovation institutions.

2.3 Relationship between innovation ecosystem and innovation performance

The operating environment is crucial to the success of enterprises because it leads to open innovation which ultimately results in IP. Johan and Sven-Ake (2005) found that scanning the operational environment positively influences IP. This implies that IE counts when it comes to the evaluation of determinants IP, but it is not the only factor. Padula (2008) found that portfolios that are linked to several alliances have greater levels of IP, but there is a need to further examine the relationship between network structures and IP. Atilaw and Kitaw (2024) found that IP is greatly influenced by IE within a given region. Furthermore, Wang et al. (2024) found that knowledge transfer efficiency from research institutions have a direct relationship with enterprise IP. The study evaluated the existing networking structures between the various actors and their level of influence in manufacturing firms in major industrial counties in Kenya.

The integration of collaboration between different partners and networking among the various alliances bring about open innovation. This is a broad-based and collective approach that has a significant influence on IP. The relationship between IE, open innovation and IP can be depicted in a conceptual framework in Figure 1.

Figure 1 (see online version for colours)



Open innovation can lead to regional innovation. It can also foster consistent learning which helps in accelerating growth and allows knowledge-intensive enterprises to engage in innovation activities thus improving IP, but further research is required to expand the understanding and perspective in which these can happen in a different context (Secundo et al., 2017). The study addressed this gap by focusing on the broad spectrum of the sector from the small, medium and large firms while at the same time conducting a comparative analysis across the various subsectors. The complex adaptive system empowers the bottom-up organisation learning process and viable systems model enables a learning context that embraces networking which improves IP and sustainability.

3 Research methodology

The philosophical ideology that guided this study was pragmatism. Pragmatism allows the inclusion of various research methods. The study utilised mixed research method to compliment and supplement the strengths and weaknesses of both quantitative and qualitative data in capturing the phenomenon surrounding, IE open innovation and IP. Cross sectional design was used because data was collected at the same time across the various manufacturing firms in Kenya.

The sampling frame was the membership list for manufacturing firms in Kenya as contained in Kenya Association of Manufacturers' (KAM) directory of 2017/2018 which at the time of the study had a total of 828 manufacturing firms. The target population was the product of the number of firms in the counties and three respondents per firm (828 ∗ 3) which are 2,484.

A multi-stage sampling strategy was used. Purposive sampling was used to select the major industrial counties in the country. The major industrial counties which were sampled are seven and they include: Nairobi, Mombasa, Kisumu, Nakuru, Kiambu, Machakos and Uasin Ngishu because they have the largest number of manufacturing firms in the country as captured in Table 1. Stratified random sampling was then used to sample firms from the selected major counties. Purposive sampling was then used to sample the respondents. The sample size was determined by applying the Yamane's (1967) formula which states that:

$$n = \frac{N}{1 + N(e)^2},$$

where n is the sample size, N is the target population and e the level of precision which in this case is 5% which is the acceptable level of significance in social science research. Calculating the sample size using the formula gave a value of:

$$n = \frac{2{,}484}{1 + 2{,}484(0.05)} = 344.5,$$

which was rounded off to the nearest whole number of 345.

Semi-structured questionnaires, structured interview schedules and checklists were utilised to collect data. Likert scales were used to convert qualitative responses to quantitative data that was used to test relationships IE and IP.

Construct, content and criterion-related validity were used to ascertain the credibility of the research procedure. The internal consistency technique was used to show the extent to which the research procedures assessed the same characteristics. The pilot study was conducted in 12 manufacturing firms which were not part of the study.

Table 1 The number of manufacturing firms sampled per major industrial county

Serial	*Town*	*Number of firms*	*Number of firms to be sampled*	*Respondents*
1	Nairobi	493	(493/780) 115 = 73	73 ∗ 3 = 219
2	Mombasa	99	(99/780) 115 = 14	14 ∗ 3 = 42
3	Kiambu	51	(51/780) 115 = 8	8 ∗ 3 = 24
4	Nakuru	50	(50/780) 115 = 7	7 ∗ 3 = 21
5	Uasin Ngishu	27	(27/780) 115 = 4	4 ∗ 3 =12
6	Machakos	34	(34/780) 115 = 5	5 ∗ 3 = 15
7	Kisumu	26	(26/780) 115 = 4	4 ∗ 3 = 12
Total		780	115	345

Data was analysed using variance, standard deviations, structural equation model and partial least square. Results were presented in graphs, tables and path diagrams. The mathematical model to be used in the analysis of data will be $IP = \beta o + \beta IE + \varepsilon$ which will illustrate the relationship between IP and IE. Karl Pearson's coefficient of correlation and chi-square was used to determine the interrelationship between KE and IP.

Research permit was sought from the National Commission for Science, Technology and Innovation (NACOSTI) and consent to collect data from employees was obtained from the employer of the sampled firms.

4 Research findings and discussions

The completed questionnaires that were filled up and received were 295 against 345 issued representing a response rate of 86% from 101 firms out 115 firms representing 88% of the firms sampled.

4.1 Innovation performance

The dependent variable of the study was innovation performance (IP) which was derived from the product of innovation output and innovation efficiency. The innovation output was measured as the sum of new products, processes and enterprises developed as a result of innovation. Innovation efficiency was measured by the level of sales growth rate attributed to innovation.

The aggregation of new products, patents, new processes and new enterprises constituted the innovation output. The sum of the total innovation output was 1,071, mean of 10 and a range of between 1 and 19 as indicated in Table 2.

This implies that there were innovation activities that generated innovation output. This means that the outcome of innovation activities was observable and can be quantified. The standard deviation of 6.2 implies that there was widespread within the manufacturing firms. This means that there was a low level of uniformity in innovation output across manufacturing firms and thus a low degree of homogeneity in the sample.

The respondents were also asked to indicate the total sales for each of the past three years. They were also required to indicate the portion of sales attributed to innovation. The proportion of sales attributed to innovation formed the percentage sales growth rate brought about by innovations for the last 3 years as a result of a new product, patents acquired, new process and new enterprises. The sales growth rate brought about by innovations was then computed as sales emanating from innovation activities divided by total sales for a similar period multiplied by 100 to make it a percentage. This constituted the innovation efficiency.

Table 2 Innovation output distribution across the manufacturing firms

N	Valid	101
	Missing	0
Mean		10.6040
Std. deviation		6.21624
Variance		38.642
Range		19.00
Sum		1,071.00

The distribution of innovation efficiency across the manufacturing firms for the last three years was also examined. This was done by use of range and standard deviation. The mean innovation efficiency was 0.297, the range was between zero and 0.54 and the standard deviation was 0.195 as indicated in Table 3.

Table 3 Innovation efficiency distribution across the manufacturing firms

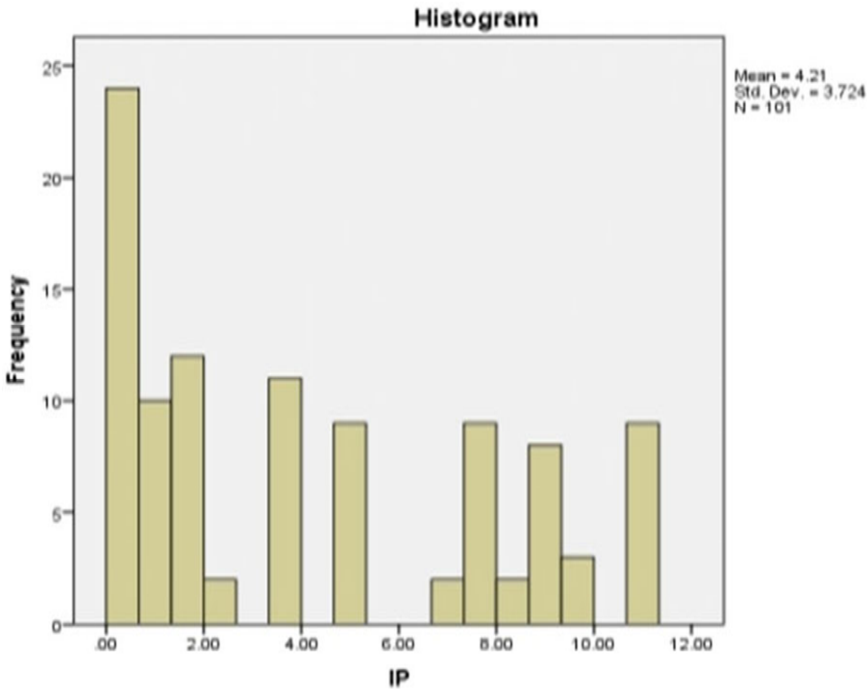
N	Valid	101
	Missing	0
Mean		.297
Std. deviation		.195
Variance		.038
Range		.54
Sum		30.01

The mean of 0.297 implies that on average, each firm had approximately 30% innovation efficiency. This means that the innovation activities in manufacturing firms contributed to about a third of sales on the average per firm. The range implies that the innovation efficiency across manufacturing firms varied from zero to 0.54. This means that the innovation output which did not have a corresponding increase in sales had no innovation efficiency while the highest sales attributed to innovation was 54%. The standard deviation of 0.19 implies that there was a small spread within the sample. This means that there was a high degree of uniformity in innovation efficiency across manufacturing firms and thus a high level of homogeneity in the sample.

The score on innovation output per firm was then multiplied by the innovation efficiency to form the composite value of IP. The majority of manufacturing firms had zero IP as indicated in Figure 2.

This implies that most of the innovation activities in manufacturing firms did not translate into IP. This means that innovation output did not necessarily result in an improvement in sales growth rate as a result of innovation. This could be attributed to huge investment whose returns were low. It can be interpreted as innovations which were not in traction with the customers' needs hence low absorption in the market.

Figure 2 The distribution of IP in the manufacturing firms (see online version for colours)



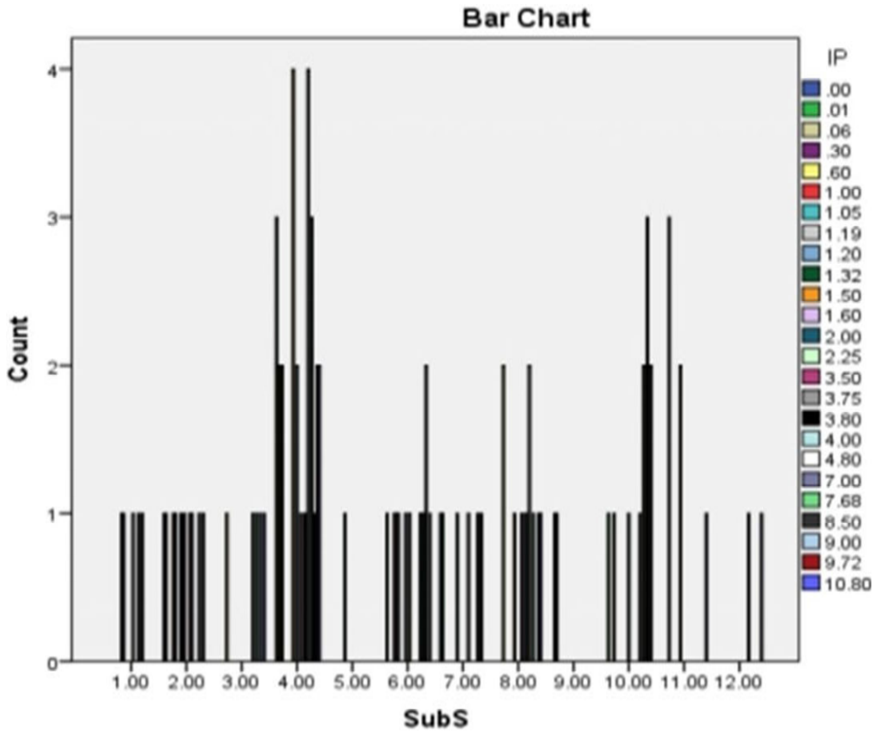
The other step was a comparison of IP in the 12 subsectors of the manufacturing sector. Cross-tabs descriptive analysis was used to examine the IP levels across the subsectors. The subsector with the highest IP was the food and beverages subsector as indicated in Figure 3.

The highest IP in the food and beverage subsectors implies that innovation intensity is important in raising the overall IP levels. This is because despite the plastics and rubber subsectors having the highest innovation output, the food and beverages subsector had the highest innovation intensity (Figure 3) emerged top in IP. Firms should therefore not only focus on raising the innovation output, but also innovation intensity for higher levels of IP. It is therefore important for firms to diversify their innovation activities across the various types of novelties to spread the risks that come with a concentration on a single type of novelty.

The analysis of the interview schedule was done by itemising each of the responses which were then tabulated and ranked to pick out the main themes. The ranking indicated that the spirit of innovation was highly encouraged by providing work autonomy, resource allocation to support new ideas, reward schemes for new idea generation, having brainstorming sessions, live streaming of events with pre and post analysis, promoting research and development in that order. It, therefore, means that work autonomy, allocation of resources and reward mechanism were the key drivers of creativity which led to innovation activities and eventually improved IP in manufacturing firms in Kenya.

This means that leadership plays a crucial role in cultivating a conducive work environment for IP to thrive.

Figure 3 The comparison of IP in the manufacturing subsectors (see online version for colours)



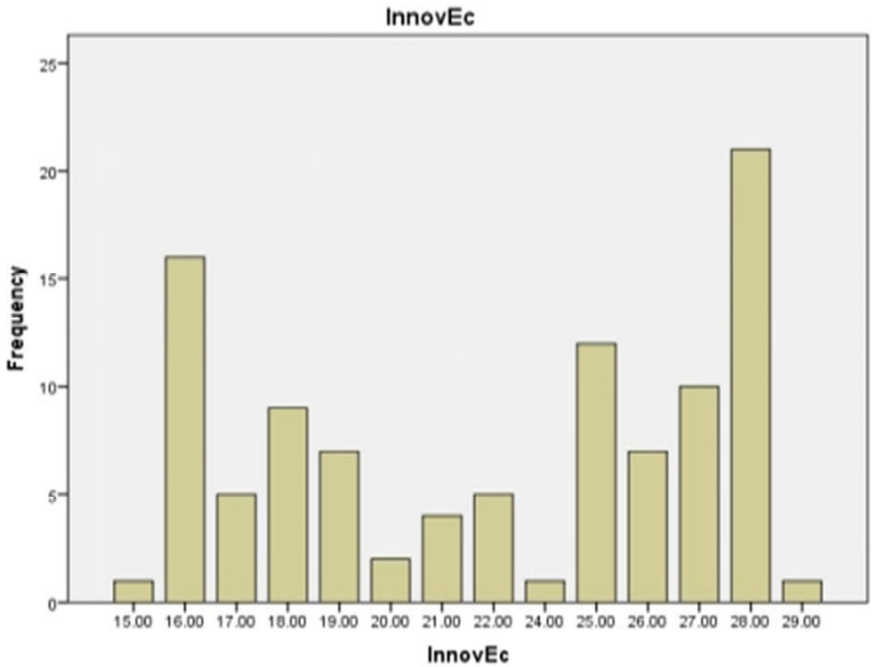
4.2 Innovation ecosystem

The dependent variable of the study was IE. The parameters of IE were derived from; a supportive environment, existing alliances, networking, collaborations and network systems. The specific parameters for measuring IE were; the presence of accelerators and incubators within the firm locality, availability of business services, trade organisation support, technology spillover in the industry from universities and other research institutions, networking within the firms in the industry and infrastructure that support business operations. The value of IE was obtained by aggregating the sum of the score of each measure. The responses were captured on a Likert scale which had six items with a scale of 1 to 5 and thus the expected maximum score was 30. The score on each of the items was then added up to form the composite value of IE in each firm.

The scores of IE were ranked in terms of their frequency of occurrence. The highest frequency in IE is a score of 28 as indicated in Figure 4.

This implies that most firms acknowledged that IE promoted innovation. It meant that the presence of accelerators and incubators within the firm locality, availability of business services, trade organisation support, technology spillover in the industry from universities and other research institutions, networking within the firms in the industry and business support services promoted innovation activities.

Figure 4 The distribution of IE score in manufacturing firms in Kenya (see online version for colours)



The mean, range and standard deviation were used to analyse the state of IE for the manufacturing sector. The mean score for leadership was 22.5545, the minimum score was 15, the maximum was 29 giving a range of 14 and the standard deviation was 4.70845 as indicated in Table 4.

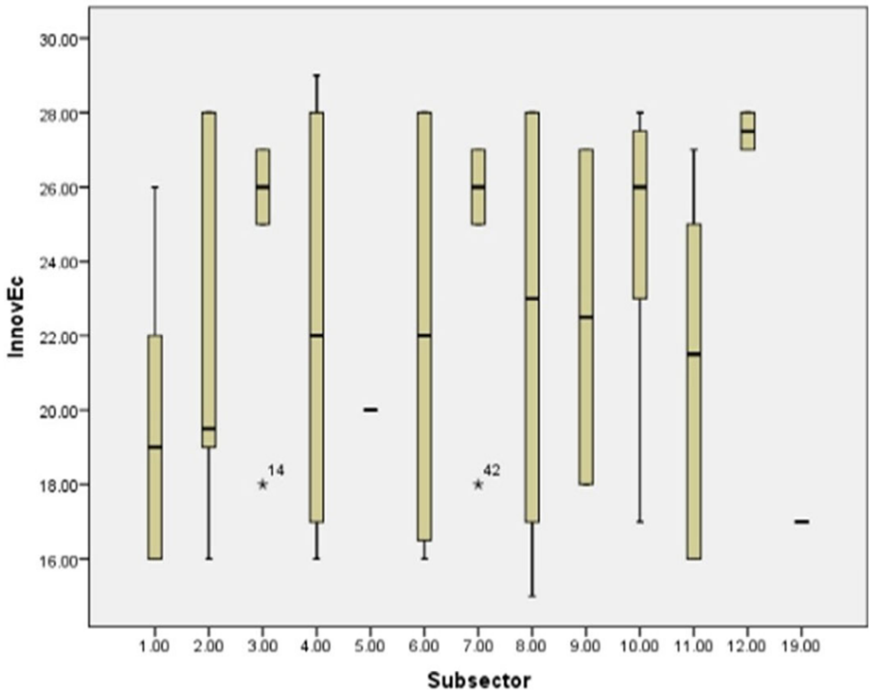
Table 4 The distribution of innovation ecosystem in manufacturing firms in Kenya

N	Valid	101
	Missing	0
Mean		22.5545
Std. deviation		4.70845
Variance		22.170
Range		14.00
Minimum		15.00
Maximum		29.00

The mean score of 22.5 implies that manufacturing firms had the right IE to enhance innovation. The standard deviation of 4.7 implies that there was a wide variance in terms of IE across the manufacturing firms. It meant that the various subsectors require different IE. This led to a further analysis of how the various subsectors performed given the prevailing IE.

The comparisons of how the different subsectors performed were carried out using explore descriptive statistics. The subsector which showed a high level of variance on the IE score was metal and allied as indicated in Figure 5.

Figure 5 Comparison of manufacturing subsectors' scores on IE in Kenya (see online version for colours)



It was observed that there was indifference as to whether IE promoted innovation in the firms within the metal and allied subsector, thus IE was enhanced in some firms within the subsector to promote innovation while it was not the case with other firms. This depicts the uniqueness of the firms in the subsector.

The respondents were asked to give the factors they felt affects the operating environment on which innovation occurs. The listed factors in descending order are; networking, statutory and regulatory requirements, infrastructure, government policy, rate of technology adoption, competition, taxation, financing, knowledge-sharing platforms, treaties and barriers of imports, training opportunities, macro-economic stability, accreditation and certification procedures. The other factors that were mentioned include; protection of patents, incubators, customer and supplier relationship, quality of the human resource, university-industry linkages, stakeholder satisfaction, trade fairs, industry leadership, dissemination of research findings, cost of doing business, trade associations and safety. It is therefore observed that there is a wide range of factors that contribute to the innovation ecosystem.

Reliability test was conducted on the measuring scale of IE to determine its stability in providing similar outcomes in repeated trials. The reliability test produced Cronbach's alpha of 0.896 for the six measures for IE. The value is above the recommended threshold of 0.7. It means that the scale used to measure IE is reliable and can replicate such outcomes in another trial. The finding is consistent with Alegre et al. (2006) who found that the Cronbach's alpha of the measures of the latent variable should be more than 0.7. It was therefore concluded that measuring scales were reliable.

4.3 The relationship between innovation ecosystem and innovation performance

The first step was to run a linear regression between the parameters of IE and IP without KE. The results indicate that all the parameters of IE had an R square of between 0.610 and 0.711 as shown in Table 5.

Table 5 Linear regression between the parameters of IE and IP without KE

	Model	*R*	*R square*	*Adjusted R square*	*Std. error of the estimate*
1	Presence of accelerators and incubators	.844	.712	.711	2.07287
2	Availability of trade organisation support	.811	.656	.657	2.26236
3	Technology spill over	.809	.654	.653	2.27216
4	Availability of business services	.786	.618	.617	2.38701
5	Dynamic networking	.782	.611	.610	2.40980
6	Infrastructural support	.818	.611	.669	2.22004

This implies that all the parameters of IE made a substantial contribution to IP. The association between IE and IP was then obtained by conducting a bivariate correlation on their aggregate values. There was a strong association between IE and IP as shown in table 6.

Table 6 Correlations between innovation ecosystem and innovation performance

		Innovation ecosystem	*Innovation performance*
IE	Pearson correlation	1	.831
	Sig. (2-tailed)		.000
	N	295	289
IP	Pearson correlation	.831**	1
	Sig. (2-tailed)	.000	
	N	289	289

The Pearson correlation value between IE and IP is 0.831 which is near one implying that a strong association between the variables exists. The value is also positive implying that IE and IP move in the same direction hence they are correlated. It means that as IE improves so does IP and vice versa among manufacturing firms.

Table 7 Analysis of variance between innovation ecosystem and innovation performance

	Sum of squares	*Df*	*Mean square*	*F*	*Sig.*
Between groups	3,403.085	17	200.181	61.597	.000
Within groups	880.706	271	3.250		
Total	4,283.791	288			

The analysis of variance between IE and IP was also conducted to test the second hypothesis. The null hypothesis stated that IE does not influence IP in Kenya manufacturing firms. The results showed a significant influence between the two variables exists as indicated in Table 7.

The P-value is zero which is less than 0.05. This led to the rejection of the null hypothesis and acceptance of the alternative hypothesis. It, therefore, means that IE has a significant influence on IP in Kenya manufacturing firms in Kenya. This implies that IE is crucial in determining the levels of IP.

Linear regression was also carried out to determine the extent to which IE influences the IP of manufacturing firms in Kenya. This was done by examining the value of R-square in the relationship between IE and IP. The results indicate an R-square value of 0.6674 as shown in table 8

Table 8 Linear regression analysis between IE and IP

Source	*SS*	*df*	*MS*
Model	2,888.10928	1	2,888.10928
Residual	1,439.29487	293	4.9122692
Total	4,327.40416	294	14.7190618

Number of obs = 295
F(1, 293) = 587.94
Prob > F = 0.0000
R-squared = 0.6674
Adj R-squared = 0.6663
Root MSE = 2.2164

IP	*Coef.*	*Std. err.*	*t*	*P > t*	*95% conf. interval*	
IE	.6414974	.0264563	24.25	0.000	.5894289	.6935659
cons	–10.17325	.6062448	–16.78	0.000	–11.3664	–8.980108

The R square value was 0.6674 which is equivalent to 66.74% implies a huge proportion of change in IP is brought about by IE. This means that about 66.74% of IP is influenced by IE. This underscores the importance of the context in which IP occurs. The operating environment should therefore be improved to raise IP in manufacturing firms in Kenya.

4.4 Normality test between IE and IP

The normality test of data for both IE and IP was done through the Levene's statistics. The p-value was zero as indicated in Table 9 which is less than 0.05.

Table 9 Test of homogeneity of variance between IE and IP

		Levene statistic	*df1*	*df2*	*Sig.*
IP	Based on mean	8.371	14	261	.000
	Based on median	4.026	14	261	.000
	Based on median and with adjusted df	4.026	14	126.825	.000
	Based on trimmed mean	7.778	14	261	.000

This implies that there was no significant difference between the responses across the firms sampled and hence the normality of data is confirmed.

The finding concurs with Frenz and Letto-Gillies (2009) who found that intra-firms own internal networks and their interactions increase the IP of an enterprise. The IE is therefore important for promoting networking and collaborations. The finding is in line with those of Ebersberger et al. (2010) who found that a broad-based and collective approach has a significant influence on IP. The finding is consistent with that of Oke (2011) who found that innovation climate has a positive influence on IP. Dirk and Hanna (2009) also found that locational factors influence innovation systems, IP. However, mistrust among the participating firms can inhibit IP. Park et al. (2014) found that high cooperation and competition have a positive influence on IP, but there is a need to investigate the nature and effects of tension, balancing and IP. The findings are also consistent with Uzkurt et al. (2013) who found that there need to include the environmental context which can be described as IE.

5 Conclusions

It was found that IE has a significant influence on IP in Kenya manufacturing firms in Kenya. Innovation ecosystem is therefore a crucial determinant of the levels of IP. The unique contribution of this study is development of new model to measure IP. However, the theoretical implication is that commercialisation of innovation is a daunting task which requires the integration of IE. It is therefore paramount that supportive environment, existing alliances, networking, collaborations and networking systems are enhanced for higher IP. Moreover, business services support such as accelerators and incubators, trade organisation support, technology transfer and infrastructure development should be encouraged for improved IP and thus high competitiveness. The implication to management is therefore to create collaboration mechanism within they key actors within the special area or mutual benefits. The policy implication is that IE should be synchronised with the national innovation system to provide a mutual and symbiotic relationship between all the stakeholders in manufacturing firms in Kenya.

5.1 Recommendations

Manufacturing firms should also tap into the immense opportunities available within their ecosystem through networking, collaboration, partnership and forming formidable strategic alliances for their improved performance. Collaboration, particularly between manufacturing and research organisations and universities, should be strengthened to promote the commercialisation of innovation emanating from research activities. Networking within the IE can create opportunities that are important for knowledge exchange, business support, lobbying and advocacy for a better operating environment such as availability of requisite infrastructure, regulatory framework, tax and tariff reductions and policy interventions on the overall competitiveness of manufacturing firms.

Synergies within the IE should also be enhanced and developed within the manufacturing sector by providing forums for peer interactions for greater value addition.

High-value addition leads to the development of new products, processes and markets which are likely to contribute to sustainable development.

Concerted efforts from stakeholders (such as government agencies like quality standard bodies, Kenya Association of Manufacturers, universities, and research institutions) should be geared towards improving the operating environment in the manufacturing sector. Transport systems and high energy costs should be addressed to reduce the cost of production. Elimination of counterfeits and safeguarding of intellectual property rights should also be prioritised to encourage innovation activities. This lead to increased IP, low cost of production, improved competitiveness of products from manufacturing firms and more exports and foreign currency thus a balanced or favourable balance of payment in international trade.

5.2 Area of further studies

It has been observed that there are issues of mistrust in collaboration as a result of competition. There is a need for further studies to find out how different actors can develop mutual trust for a win-win situation for a more vibrant manufacturing sector.

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