Role of universities and research organisations in driving innovation in high technology SMEs

Abstract:

Biotechnology and Nanotechnology are fields of high technology which have a significant impact when applied in industrial sectors. Traditionally, research and development are seen as the driver of growth in industries According to the literature, universities' roles have moved from pure knowledge dissemination organisations to critical intermediates of technological commercialization.

The aim to study is to investigate the role of education and research organisation in diffusing innovation.The study uses node level measures like degree and betweenness and network level measures like diameter, average path length, and graph density to identify the characteristics of networks developed by R programming. To gain a deeper insight into the roles of different types of organisations, visualisation is created using the software Gephi. The data is used from the European Commission project "Horizon Europe 2020" created to drive economic growth using research and innovation with the significance of tackling societal challenges

The study found a trend which seemed similar in both the types of high technologies where the organisations belonging to industry seemed to have clustered among themselves. Even though the number of industrial organisations was higher, the number of collaborations of organisations from education and research organisations was significantly higher. The result demonstrated the effectiveness of the involvement of universities and research universities in the research of high technologies. Further studies are needed to analyse the trends in the organisations in the industry.

Introduction and background:

Research aim:

Does the collaboration with universities drive innovation and development in high technology innovative SMEs?

Related literature:

Horizon Europe 2020 is a European Commission project to" drive economic growth and create jobs by coupling research and innovation (R&I), with an emphasis on excellent science, industrial leadership and tackling societal challenges." The general goal is "to contribute to the EU's overarching jobs and growth strategy by helping to build a knowledge-based society and economy and innovation across the Union; by using additional research, development, and innovation funding". It consists of 5 main missions based on 3 pillars. (European Union, 2018)

The third pillar "Innovative Europe" aims to generate knowledge and support the access and uptake of innovative solutions by SMEs (including addressing global challenges). In turn, this will ease technological development, demonstration, knowledge, and technology transfer, and strengthen the deployment and exploitation of innovative solutions. (*Funding & Tenders*, 2022)

Nanotechnology offers substantial technological advantages not only in terms of creating devices and construction procedures but also in terms of operational improvements over conventional technology. Technology cannot be improved by a single institute, firm, or even country. A cooperative framework should be developed to structure liaisons and stimulate rivalry among academic research groups, industries, and governments. Governments have traditionally supported R&D when a technology has the potential to have a noteworthy influence on the national economy. Collaboration between government-funded researchers and the private sector is now essential for nanoscale technology transfer and commercialization. (Jia, 2005)

Biotechnology seems to have an increasing impact on the environmental, agricultural, medicinal, energy, and industrial sectors, with breakthroughs in genetic engineering, diagnostic and tissue engineering, and culture engineering. (Aghmiuni et al., 2020). With more product and investment approvals occurring than ever previously observed, the European biotechnology market has grown much more in the past few years. Companies have pursued a lot of collaborations since the biotechnology business has become more regionally diverse; worldwide competitiveness has also increased in this field (Thompson,2009 cited in Aghmiuni et al., 2020).

Biotechnology is still largely confined to basic research. An approach that can be implemented is to create a mix of applied and basic research initiatives employing the company's local and international research and development resources. This could include buying or licensing technology from other companies or entering a strategic alliance to acquire technology (Aghmiuni et al., 2020). Companies can produce technological products more quickly than ever before because of the pooling of ideas, equipment, and proprietary technology that occurs in such collaborations.

The rationale of this essay is to explore the role of education, research organisations and industries (SMEs) to support the innovation ecosystems in high technology toward mission 4 of Horizon Europe 2022 of having climate-neutral and smart cities. Doing so by systemically transforming towards climate neutrality and turning the cities into innovation hubs to benefit the quality of life with increased sustainability. Due to an increase in commercialisation, the economy is changing from a linear economy to a circular economy (Ramakrishna et al., 2020). To fulfil mission 4 of increasing sustainability in cities, the essay also attempts to observe how high technology can be used in innovative SMEs to support the transformation to a more circular economy.

Methodology and results:

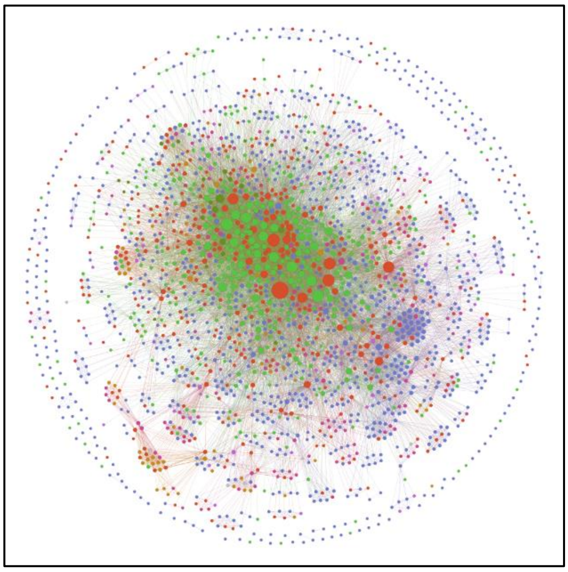
Data processing:

The network was built utilising archival data from participating organisations in the Horizon Europe 2020 initiative over seven years. The information gathered was statistical and relied on articles provided by organisations. A nominalist technique is used in data collection. The data holds project collaboration related information of organisations from different sectors like industrial, consultancies, educational organisations, research organisations and non-profit organisations. The organisations belonging to different sectors are considered the actors. The ties between them are their collaboration on different projects as well as knowledge transfer between them. The network can be classified as an affiliate network as it is a two-mode or a s-mode network having a set of events and a set of actors (Wasserman & Faust, 1994).

The degree of the node represents the number of collaborations between the organisations represented by the nodes. As it is a weighted graph, the weight of the edge is the number of projects two organisations have collaborated on.

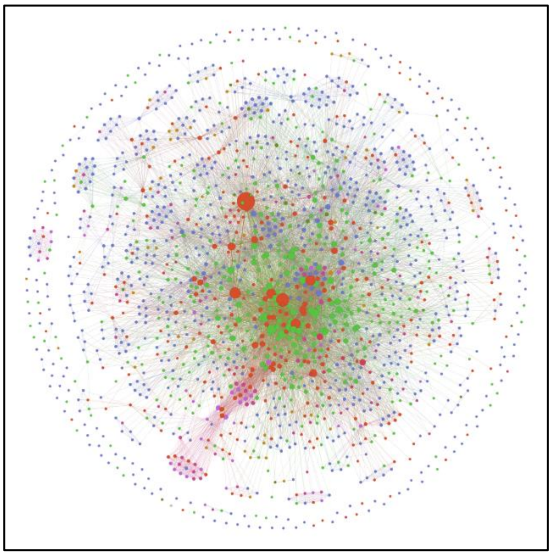
The networks in the figures shown are dense and the network between different sectors is difficult to read. To get a better insight into the connections between organisations, data is filtered out according to the sector we are interested in, by using ‘R’ programming and later is visualised using Gephi.

Figure 1a Collaborations between all sectors in Biotechnology



Average Path Length: 2.91
Diameter :6
Clustering coefficient:0.852
Connected Components: 220

Figure 1b Collaborations between all sectors in Nanotechnology



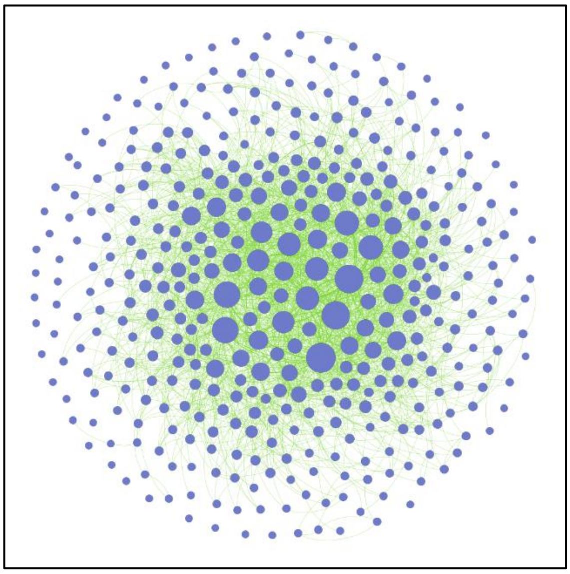
Average Path Length: 2.90
Diameter : 6
Clustering coefficient: 0.851
Connected Components: 224

Network analysis and Visualizations:

Network characterization 1: Education

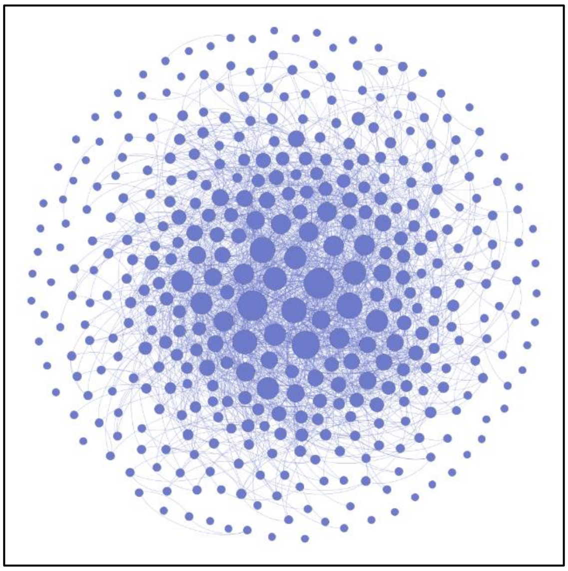
To gain a deeper understanding of the education sector in the biotechnology and nanotechnology network, we look at the network level measures of both. The clustering coefficient is close to 0.6 in both networks. The number of connected components is significantly different in the education network of nanotechnology. The average edges per node are higher in the education network of biotechnology.

Fig. 2a Collaboration in the education sector in Biotechnology



Average degree: 12.97
Graph density: 0.033
Number of connected components: 42
Average clustering coefficient: 0.642
APL: 2.643
Diameter: 6
Transitivity: 0.32

Fig. 2b Collaboration in the education sector in Nanotechnology

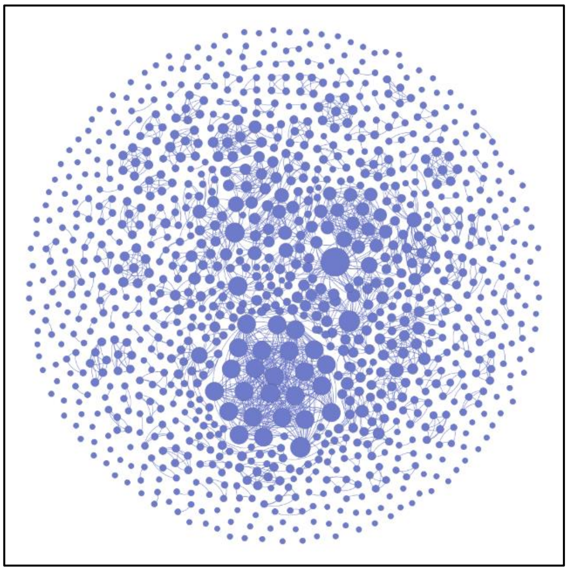


Average degree: 10.077
Graph density: 0.026
Number of connected components: 58
Average clustering coefficient:0.654
APL: 2.83
Diameter: 7
Transitivity: 0.31

Network characterization 2: Industry

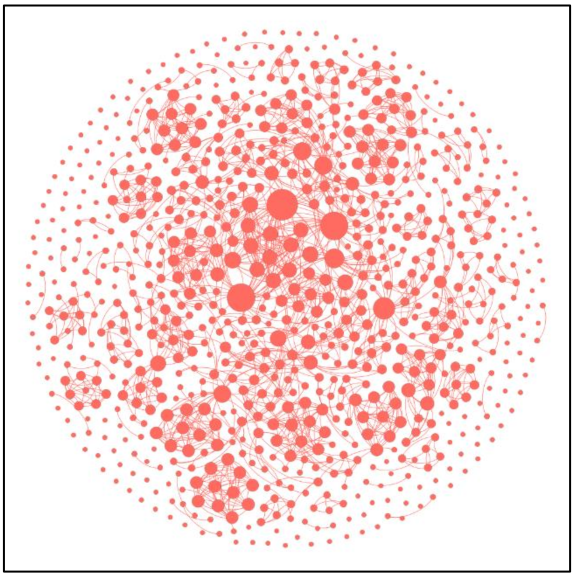
To obtain a deeper insight into the industry sector in the biotechnology and nanotechnology network, we consider the network level measures of both. The clustering coefficient is 0.9 in both the networks suggesting that they both are well-connected networks. The number of connected components is significantly higher than the connected components in the education sector suggesting more collaborations take place inside the industry sector rather than outside.

Fig. 3a Collaboration in the industry sector in Biotechnology



Average degree: 4.16
Graph density: 0.004
Number of connected components: 344
Average clustering coefficient:0.931
APL: 4.99
Diameter: 14
Transitivity : 0.76

Fig. 3b Collaboration in the industry sector in Nanotechnology



Average degree: 3.8
Graph density: 0.005
Number of connected components: 285
Average clustering coefficient: 0.946
APL: 4.3
Diameter: 10
Transitivity: 0.82

Figure 3c clusters in the industry in Biotechnology

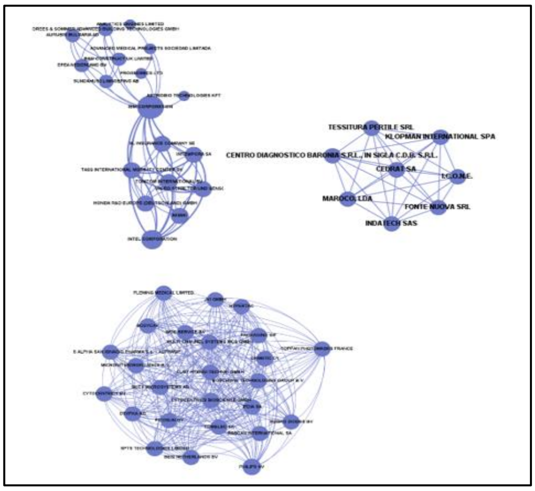
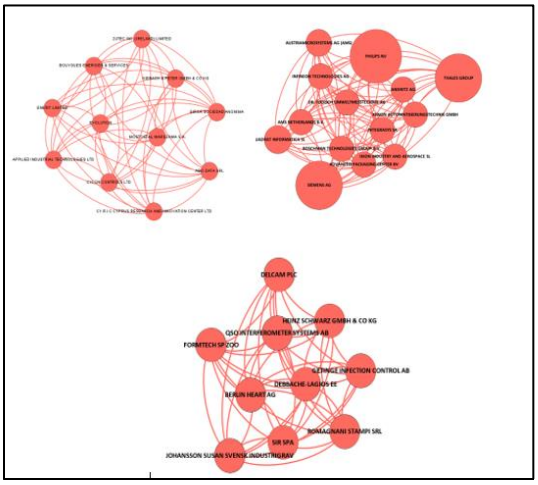


Figure 3d clusters in the industry in Nanotechnology

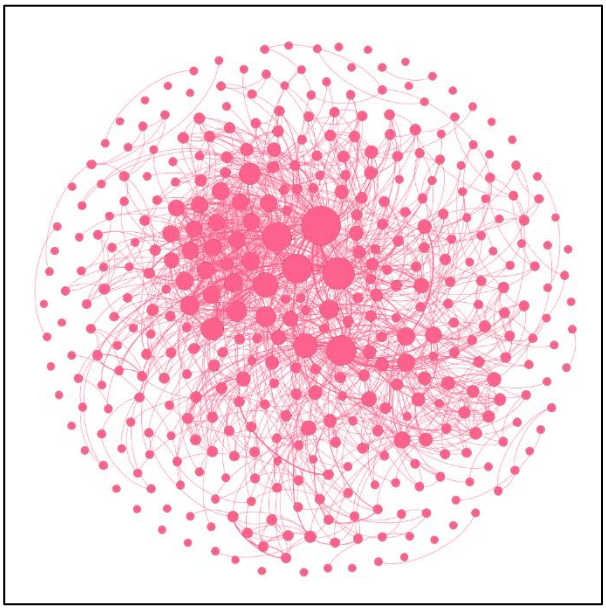


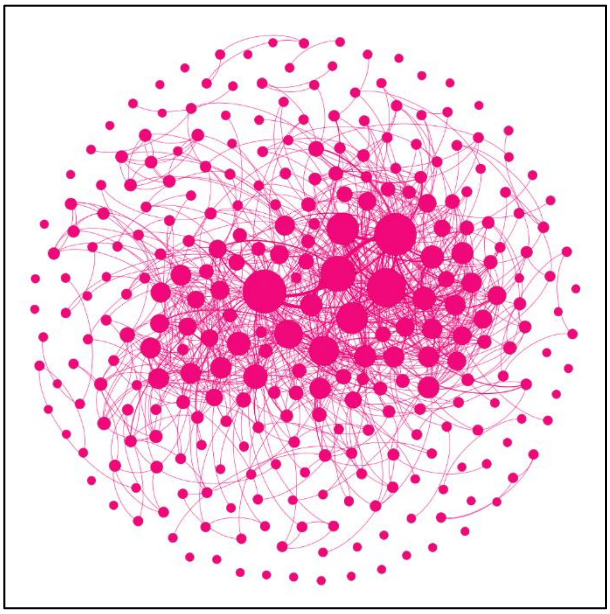
Network characterization 3: Research organisation

To gain a deeper understanding of the research organisations in the biotechnology and nanotechnology network, we look at the network level measures of both. The clustering coefficient is close to 0.7 in both networks. The number of triangles in biotechnology which are nothing, but triadic closure is double the number of triangles in nanotechnology which suggests the nodes are well connected. The average edges per node are higher in the education network of biotechnology.

Fig. 4a Collaboration in the research sector in Biotechnology

Fig. 4b Collaboration in the research sector in Nanotechnology





Average degree: 7.65
Graph density: 0.02
Number of connected components: 49
Average clustering coefficient: 0.787
APL: 3.041
Diameter: 8
Triangles (Triadic closures): 4641
Transitivity:0.42

Average degree: 6.28
Graph density: 0.022
Number of connected components: 50
Average clustering coefficient: 0.756
APL: 3.05
Diameter: 7
Triangles (Triadic closures): 2152
Transitivity:0.43

Network characterization 4: education – research organisations

For a deeper perspective, we look into the network for collaborations between education and research organisations in both biotechnology and nanotechnology. The average degree of collaboration in biotechnology is higher than the collaborations in nanotechnology. They both have clustering coefficients close to one, suggesting the presence of a high number of strong relations between nodes and their neighbours.

Fig. 5a Collaboration in education -research sector in Biotechnology

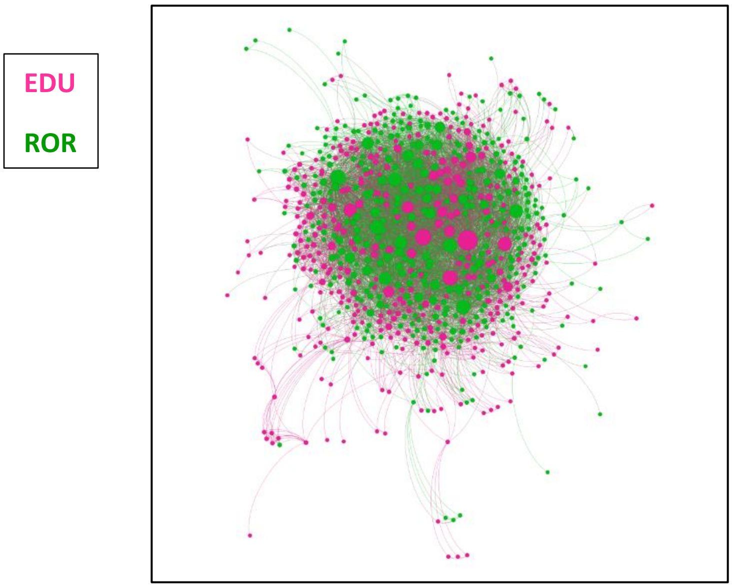
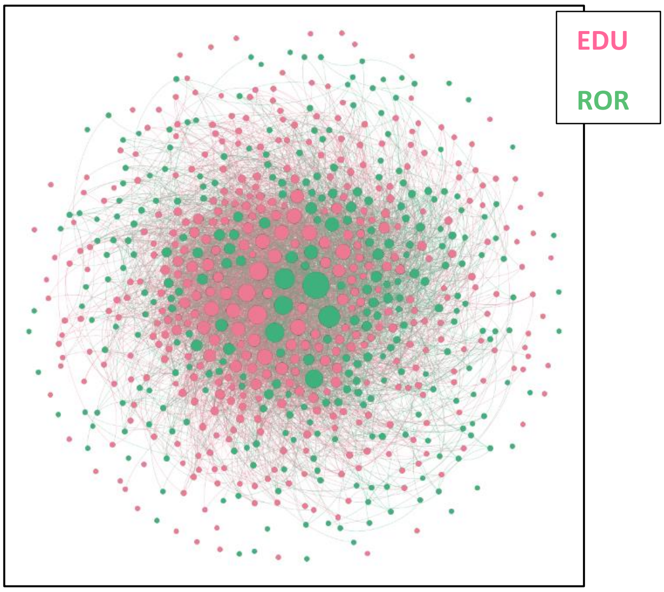


Fig.5b Collaboration in education-research sector in Nanotechnology



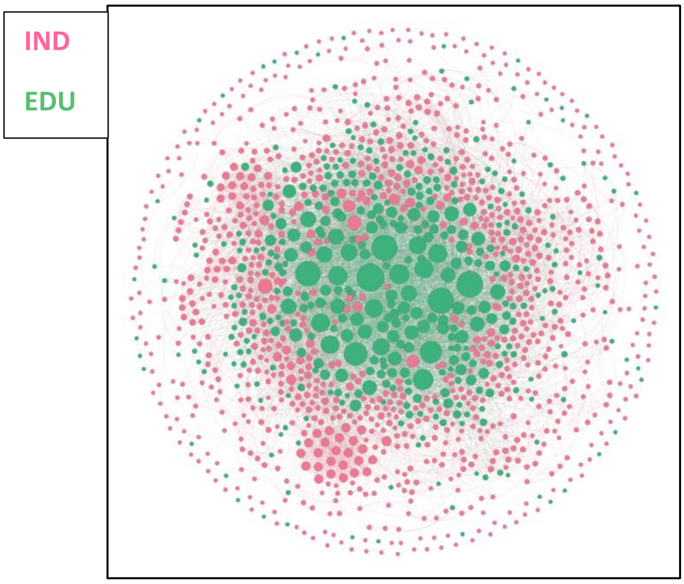
Average degree:18.7
Graph density: 0.024
Number of connected components: 55
Average clustering coefficient:0.734
APL: 2.64
Diameter: 6
Transitivity:0.34

Average degree:15.348
Graph density:0.023
Number of connected components: 71
Average clustering coefficient:0.723
APL: 2.7
Diameter: 6
Transitivity: 0.33

Network characterization 5: education – industry organisations

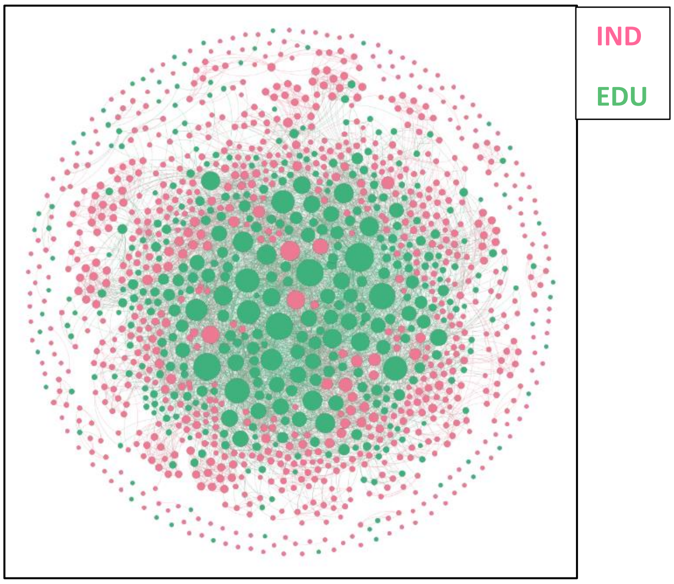
To understand the main network better, we look into the network for collaborations between education and industry organisations in both biotechnology and nanotechnology. The average degree of collaboration in biotechnology is higher than the collaborations in nanotechnology. They have the same clustering coefficients, suggesting the equal presence of a high number of strong relations between nodes and their neighbours in both fields.

Fig. 6a Collaboration in education -industry sector in Biotechnology



Average degree:11.137
Graph density: 0.008
Number of connected components: 224
Average clustering coefficient:0.85
APL: 3.16
Diameter: 7
Transitivity: 0.37

Fig.6b Collaboration in education-industry sector in Nanotechnology



Average degree: 9.664
Graph density: 0.008
Number of connected components: 209
Average clustering coefficient:0.85
APL: 3.24
Diameter: 7
Transitivity: 0.31

Network characterization 6: characteristic education – industry – research organisations

The previous networks help us understand the network for education, industry, and research organisation. The number of weakly connected components is almost similar in both fields. The average number of nodes to the edge is slightly higher in the biotechnology network. The major difference can be spotted in the number of cliques. The cliques in nanotechnology are almost 5 times the cliques in the biotechnology network. This represents that the subgroups are well connected. The inclusiveness is 0.89 in both networks meaning they are well connected.

Fig. 7a Collaboration in EDU-IND- ROR sector in Biotechnology

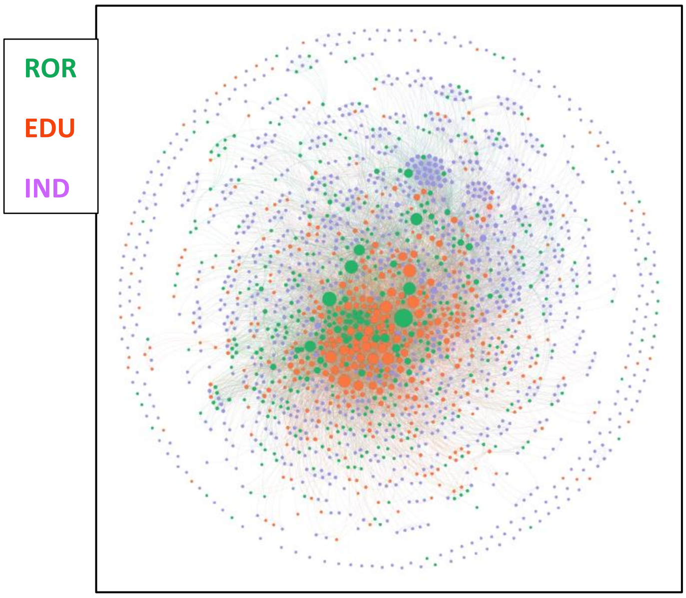
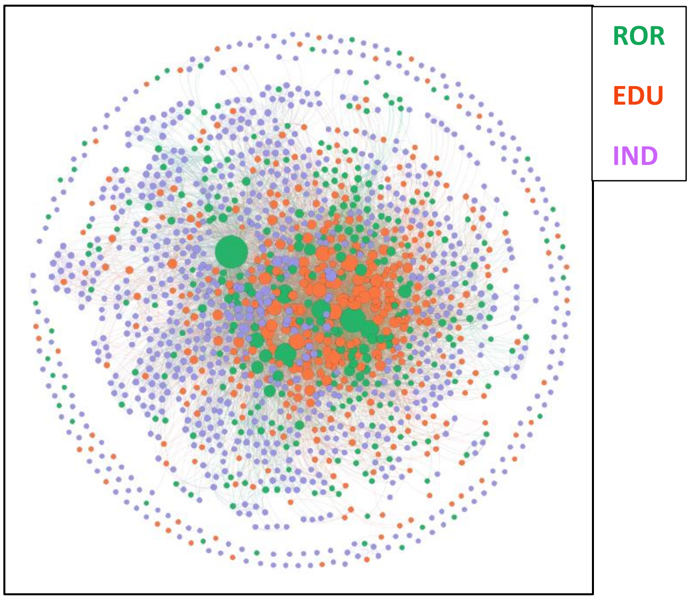


Fig.7b Collaboration in EDU -IND-ROR sector in Nanotechnology



Average degree:16.64
Graph density: 0.009
Number of connected components: 218
Average clustering coefficient: 0.842
APL: 2.88
Diameter: 6
Triangles (Triadic closures): 80358
Inclusiveness:0.89
Transitivity: 0.322
Number of Cliques: 365

Average degree:14.6
Graph density: 0.010
Number of connected components: 217
Average clustering coefficient:0.837
APL: 2.88
Diameter: 6
Triangles (Triadic closures): 50464
Inclusiveness: 0.89
Transitivity: 0.320
Number of Cliques: 1569

The betweenness centrality indicates which organisations have the highest control over knowledge dissemination.

In the biotechnology network, **CSIC - CONSEJO SUPERIOR DE INVESTIGACIONES CIENTIFICAS/HIGHER COUNCIL FOR SCIENTIFIC RESEARCH** a research organisation, has the highest betweenness of 118680.6 and degree centrality 310 overall.

Among education organisations, **WAGENINGEN UR** has the highest betweenness centrality of 55942 and it has the highest degree centrality of 199

In industry organisations, **BIOTREND - INOVACAO E ENGENHARIA EM BIOTECNOLOGIA SA** has the highest betweenness centrality of 10754 and the highest degree centrality of 73. These organisations have very high control over the dissemination of innovation.

In the nanotechnology network, **FRAUNHOFER-GESELLSCHAFT ZUR FÖRDERUNG DER ANGEWANDTEN FORSCHUNG E.V.,** a research organisation, has the highest betweenness of 164925.5 and degree centrality 310 overall.
Among education organisations, **TECHNICAL UNIVERSITY OF DENMARK - DANMARKS TEKNISKE UNIVERSITET (DTU)**has the highest betweenness centrality of 28469.92 and **UNIVERSITY COLLEGE LONDON UCL** has the highest degree centrality of 131.
In industry organisation, **THALES GROUP** has the highest betweenness centrality of **9718.1** and **PHILIPS NV** has the highest degree centrality of 72. This indicates that even though Philips NV has more collaborations, the Thales group is at the forefront in the dissemination of innovation.
The data were obtained from the Data Laboratory section in Gephi visualization tools.

Figure 8a Histograms for betweenness and degree in biotechnology

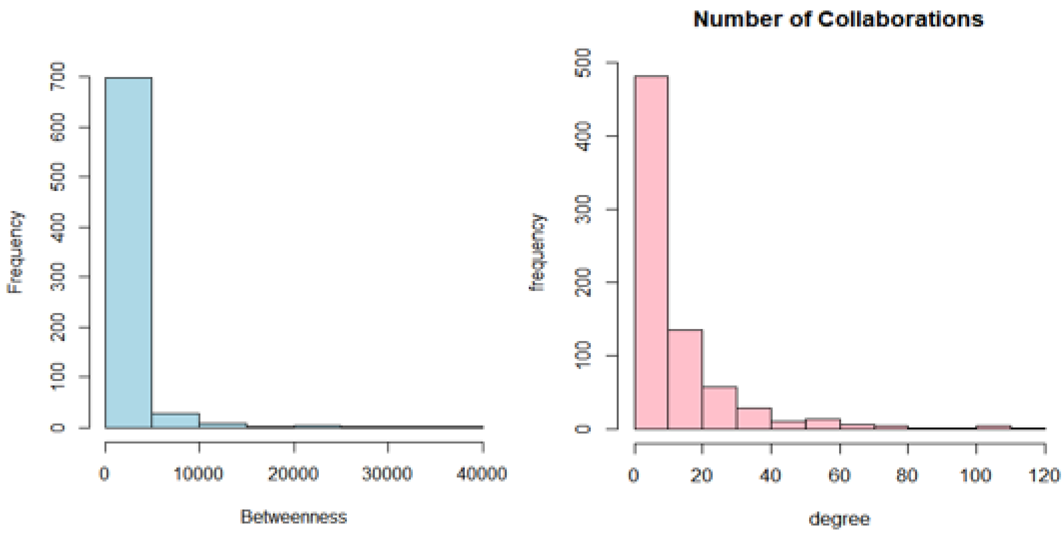
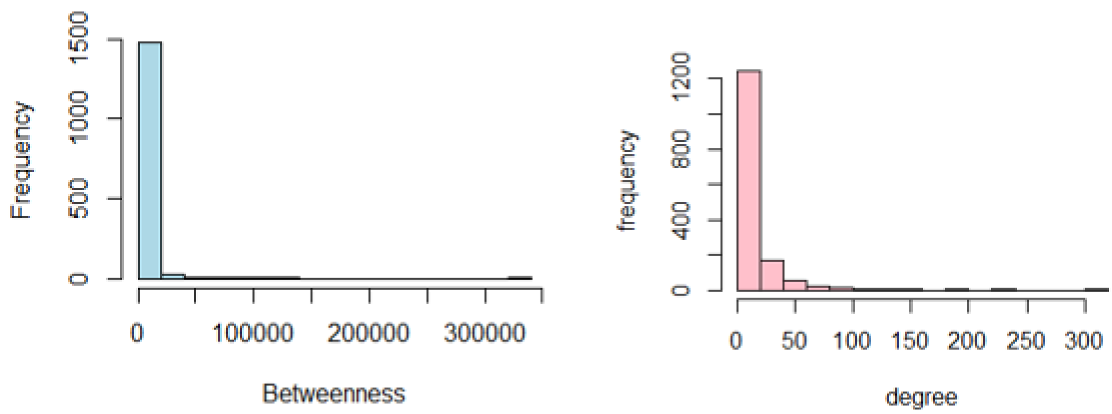
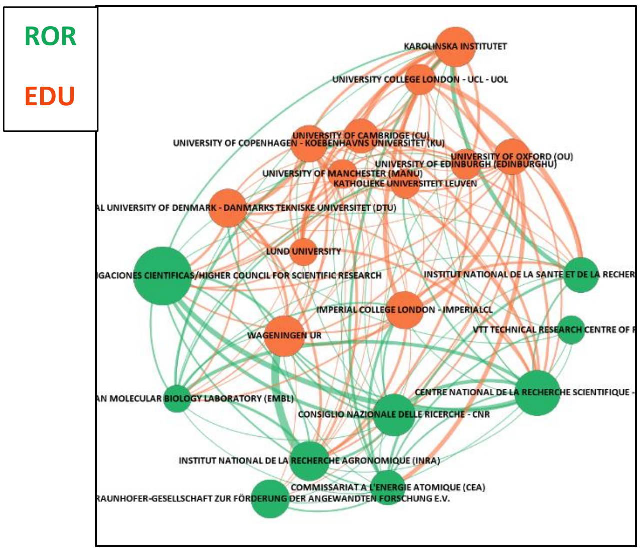


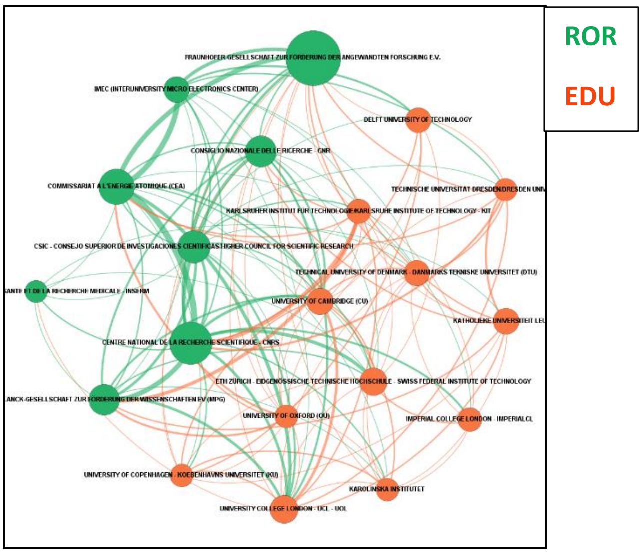
Figure 8b Histogram for betweenness and degree in nanotechnology



The figures represent histograms for degree and betweenness based on the network of collaborations between education, research organisation and industries, for biotechnology and nanotechnology respectively. It can be observed that the frequency of degree and betweenness are high in nanotechnology as compared to biotechnology.

Fig. 9a Top 20 highest degree collaborators in Biotechnology *Fig.9b Top 20 highest degree collaborators in Nanotechnology*





The networks in the figures represent the top 20 organisations that have the highest number of collaborations in biotechnology and nanotechnology respectively. As observed, the highest collaborators are research organisations and educational organisations.

Summary of the findings:

The clustering coefficients of the developed networks range from 0.6 to 0.9 which indicates that the networks are well connected with a few weak ties present between them. According to the strength of weak ties theory with social capital theory, organisations having weak ties tend to be a source of new information.

In both the technologies, it has been observed that the number of collaborations in research organisations and education is higher than the number of collaborations through industries even though the number of industries taking part in the research is higher than the number of research organisations and educational institutions.

Looking at the Gephi visualization of industrial organisations in biotechnology and nanotechnology, they can be seen clustered among themselves. The networks of the three sectors show few collaborations with educational organizations and research organizations in the clusters of industrial organisations. This represents those collaborations usually take place among industrial organisations.

In both biotechnology and nanotechnology, the involvement of organisations in education is as significant as research organisations.

Discussion:

Critical interpretation of the findings:

From the networks generated, we can observe that the same trends are followed by high technology industries.

The networks shed a light on the potential for information flow in diverse academia-industry research and development collaboration activities. Industries obtain knowledge and technologies from a variety of external sources, including universities and research institutes.

Many smaller enterprises with weaker R&D expenditures rely on academia-industry R&D collaboration. Universities have evolved into knowledge providers for technological advancement. (Chen & Lin, 2017)

To diffuse innovation and increase knowledge production by collaborating with research organisations and education in high technology fields, the industry should collaborate more often on major projects along with educational organisations.

The brokerage of a node has different roles like the coordinator role, Itinerant broker role, Gatekeeper role, Representative role, and Liaison role. In the observed multiple nodes have different brokerage roles. There are some nodes which possess multiple roles at the same time. This is beneficial as it allows control over information flow between groups but at the same time gains new knowledge.

Knowledge and technological innovation are critical components for the development of the rising biotechnology industry, which is a knowledge-intensive high-tech sector. The findings demonstrate the significance of information sources from universities/RIs in the growth of the high technology sector. Biotechnology is still largely confined to basic research. Existing colleges can easily provide more innovation than other traditional technology industries, as long as the corporation can afford the high expenses and risks of widespread product development which can be provided by multinational firms. (Chen & Lin, 2017)

The innovation ecosystem is poised for academia-industry collaboration; universities not only disseminate knowledge but also act as important middlemen in the process of leveraging science and technology created at universities. There can be an increase in participation between institutions and companies if the knowledge transmission is incentivized. (Chen & Lin, 2017)

The rising globalization has made it essential for R & D organisations across the globe to start collaborations for the development of nanotechnology. Nanotechnology has become increasingly important in every technological field. As nanotechnology is an emerging high technology industry, the number of collaborations that have been observed are less.

The quality of R&D cooperation is heavily influenced by technology transfer, technological characteristics, and different environmental aspects during R&D partnerships; for example, incubators and geographic location can greatly impact firms' desire to collaborate. This can be seen in the case of industries, in which clusters are most likely to be regionally specific.

Limitations and future work:

Industries have a greater number of connected components as compared to education and research organisation. It has also been observed that the connected components increase when there are collaborations with industries. They also tend to cluster more which means collaborations within the industrial organisation are higher. We can conclude that industrial organisations are not being inclusive from these observations. This is limiting the development of each sector as research and development is traditionally seen as the driver of growth in industries.

Future research can investigate the phenomenon where the industries are more collaborative amongst themselves and eventually form clusters. It should also look into the exact cause of the relationship of innovations in high technology in terms of industry characteristics and the types of organisations involved.

With the role of universities changing in research and development, future work can elaborate on the impact of the changing role of educational organisations on research organisations.
The study does not consider the government's role in collaborations in research and innovation in biotechnology and nanotechnology. Future studies can further into the government's role and the policy implications in high technology innovation.

Reference :

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Appendix;

Biotechnologygml.R

```
rm(list=ls())
library(igraph)
library(tidyverse)
library(readr)
library(sna)
library(influenceR)
library(RColorBrewer)
g =read_graph("Biotech_UTF8.gml", format = "gml")

summary(g)
vcount(g)
ecount(g)
V(g)
E(g)[sample(1:ecount(g), 10)]

coords = layout.kamada.kawai(g)
plot(g, layout=coords, vertex.label=NA, vertex.size=10,vertex.color=colrs)

title(main = "Collaborations in different sectors in Biotechnology",cex.main=1)
legend(x=-1.5,y=-1.1, c("EDU","IND","ROR","GOV","CON","OTH","RH","PNP"), pch=21,
    col="#777777", pt.bg=colrs, pt.cex=2, cex=.8, bty="n", ncol=1)

V(g)$OrgType
##colour nodes
#display.brewer.all()
#colrs<-brewer.pal(10, "Spectral")
#my_coul<- colrs[as.numeric(as.factor(g$OrgType))]

V(g)$OrgType <- c("EDU","IND","ROR","GOV","CON","OTH","RH","PNP")
colrs <- c("lightblue", "tomato","darksalmon","orange","darkgreen","pink","maroon","gold1")
V(g)$color <- colrs[V(g)$OrgType]

##subgraphs
#education subgraph for biotech
education=V(g)$OrgType=="EDU"
education
sum(education)
h1 = induced.subgraph(g, V(g)[education])
plot(h1, vertex.label=NA,vertex.size=5,vertex.color="lightblue")
transitivity_g1 <- transitivity(h1, type = "globalundirected")
#write_graph(h1, "BiotechEDU.gml", format = "gml")

#industry subgraph
industry=V(g)$OrgType=="IND"
industry
```

```
sum(industry)

h2 = induced.subgraph(g, V(g)[industry])
plot(h2, vertex.label=NA,vertex.size=5)
write_graph(h2, "BiotechIND.gml", format = "gml")
transitivity_g2 <- transitivity(h2, type = "globalundirected")
```

#research subgraph

```
research_org=V(g)$OrgType=="ROR"
research_org
sum(research_org)
h3 = induced.subgraph(g, V(g)[research_org])
plot(h3, vertex.label=NA,vertex.size=5)
write_graph(h3, "BiotechROR2.gml", format = "gml")
transitivity_g3 <- transitivity(h3, type = "globalundirected")
```

#EDU IND

```
h5 = induced.subgraph(g, V(g)[industry | education ])
plot(h5, vertex.label=NA,vertex.size=5,vertex.color=c("tomato","lightblue"))
write_graph(h5, "BiotechEI.gml", format = "gml")
transitivity_g5 <- transitivity(h5, type = "globalundirected")
```

#EDU RES

```
h6 = induced.subgraph(g, V(g)[education | research_org ])
summary(h6)
plot(h6, vertex.label=NA,vertex.size=5,vertex.color=c("lightblue","darksalmon"))
write_graph(h6, "BiotechER.gml", format = "gml")
transitivity_g6 <- transitivity(h6, type = "globalundirected")
```

#IND RES

```
h7 = induced.subgraph(g, V(g)[industry | research_org ])
plot(h7, vertex.label=NA,vertex.size=5,vertex.color=c("tomato","darksalmon"))
write_graph(h7, "BiotechIR.gml", format = "gml")
```

#EDU IND ROR subgraph

```
h4 = induced.subgraph(g, V(g)[industry | education | research_org])
plot(h4, vertex.label=NA,vertex.size=5,vertex.color=c("tomato","lightblue","darksalmon"))
#write_graph(h4, "BiotechERI.gml", format = "gml")
summary(h4)

h4.new <- delete_vertices(h4, V(h4)$degree_w==0)
par(mfrow=c(1, 1), mar=c(0,0,0,0))
plot(h4.new, vertex.size=igraph::degree(h4.new)*0.5, vertex.label=NA,
layout=layout_with_kk,vertex.color=c("tomato","lightblue","darksalmon"))
title(main = "Collaborations between Industry, Educationa and Research Organisations in
Biotechnology",cex.main=1)
legend(x=-1.5,y=-1.1, c("IND","EDU","ROR"), pch=21,
```

```
      col="#777777", pt.bg=c("tomato","lightblue","darksalmon"), pt.cex=2, cex=.8, bty="n", ncol=1)
#pdf('gmlrbiotech1.pdf', width = 75, height = 75)
dev.off()

#Centrality measures for weighted graphs node level measures
V(h4)$degree_w <- strength(h4, mode = "all", loops = F)
V(h4)$degree_w

V(h4)$closeness_w <- igraph::closeness(h4.new)
V(h4)$closeness_w

V(h4)$betweenness_w <- betweenness(h4)
V(h4)$betweenness_w

hist(igraph::degree(h4.new), col= "pink",
    xlab = "degree",
    ylab = "frequency",
    main = "Number of Collaborations")
dev.off()

hist(betweenness(h4.new), col= "light blue",
    xlab = "Betweenness",
    ylab = "Frequency",
    main = "")

#brokerage
G <- get.adjacency(h4, sparse = F)                          #Get the adjacency matrix

br <- sna::brokerage(G, V(h4.new)$betweenness_w)                         #Calculate brokerage measures
summary(br)

brraw_nli_csv <- write.csv(br$raw.nli,"br_raw1biotech.csv")
centr_degree(h4.new, mode = "total", loops = F)                  #Degree centralisation
centr_clo(h4.new, mode = "total")                              #Closeness centralisation
centr_betw(h4.new, directed = F)                               #Betweenness centralisation

d_g <- diameter(h4.new, directed = FALSE, unconnected = FALSE)         #diameter
apl_g  <- mean_distance(h4, directed = FALSE, unconnected = FALSE)    #APL
ed_g <- edge_density(h4)                                                    #Calculate density
cp_g <- articulation_points(h4.new)                                          #Cutpoints
cliques_g <- cliques(h4.new, min = 3)                                        #List of cliques
numcliques_g <- count_max_cliques(h4, min = 3)                                #Number of cliques
transitivity_g <- transitivity(h4.new, type = "globalundirected")              #Calculate transitivity

numisolates_g <- sum(igraph::degree(h4)==0)                                 #Number of isolates
isolates_g <- V(h4)[igraph::degree(h4)==0]                                  #List of isolates
inclusiveness_g <- (vcount(h4)-numisolates_g)/vcount(h4)
```

```
V(h4.new)$constraint <- constraint(h4.new)

V(h4.new)$effective_net <- influenceR::ens(h4.new)
V(h4.new)
summary(h4.new)

const <- constraint(h4)
invConstraint <-1.125 - const
names = V(h4)$Label
#export data in csv
d <-data.frame(node.name=names, constraint=const,Inverse_constraint= invConstraint)
write.csv(d,"constraint.csv")
```

Nanotechnologygml.R

```
rm(list=ls())
library(igraph)
library(tidyverse)
library(readr)
library(sna)
library(influenceR)
library(RColorBrewer)
g =read_graph("Nanotech_UTF8.gml", format = "gml")
summary(g)
vcount(g)
ecount(g)
V(g)
E(g)[sample(1:ecount(g), 10)]

coords = layout.kamada.kawai(g)
plot(g, layout=coords, vertex.label=NA, vertex.size=10)

V(g)$OrgType

#allocating vectors
industry=V(g)$OrgType=="IND"
industry
sum(industry)

education=V(g)$OrgType=="EDU"
education
sum(education)

research_org=V(g)$OrgType=="ROR"
research_org
sum(research_org)
```

```
V(g)$OrgType <- c("EDU","IND","ROR","GOV","CON","OTH","RH","PNP")
colrs <- c("lightblue", "tomato","darksalmon","orange","darkgreen","pink","maroon","gold1")
V(g)$color <- colrs[V(g)$OrgType]

coords = layout.kamada.kawai(g)
plot(g, layout=coords,vertex.color=colrs ,vertex.label=NA, vertex.size=5)
legend(x= 1.5,y= 1.1, c("EDU","IND","ROR","GOV","CON","OTH","RH","PNP"), pch=21,
    col="#777777", pt.bg=colrs, pt.cex=2, cex=.8, bty="n", ncol=1)

##############
#education subgraph
education=V(g)$OrgType=="EDU"
education
sum(education)
h1 = induced.subgraph(g, V(g)[education])
plot(h1, vertex.label=NA,vertex.size=5)
transitivity_g1 <- transitivity(h1, type = "globalundirected")
#write_graph(h1, "NanotechEDU.gml", format = "gml")

#industry subgraph
industry=V(g)$OrgType=="IND"
industry
sum(industry)
h2 = induced.subgraph(g, V(g)[industry])
plot(h2, vertex.label=NA,vertex.size=5)
transitivity_g2<- transitivity(h2, type = "globalundirected")
#write_graph(h2, "NanotechIND.gml", format = "gml")

#research organisation subgraph
research_org=V(g)$OrgType=="ROR"
research_org
sum(research_org)
h3 = induced.subgraph(g, V(g)[research_org])
plot(h3, vertex.label=NA,vertex.size=5)
transitivity_g3 <- transitivity(h3, type = "globalundirected")
#write_graph(h3, "NanotechROR2.gml", format = "gml")


#EDU IND RES Subgraph
h4 = induced.subgraph(g, V(g)[industry | education | research_org])
plot(h4, vertex.label=NA,vertex.size=5)
write_graph(h4, "NanotechERI1.gml", format = "gml")
summary(h4)

legend(x= 1.5,y= 1.1, c("EDU","IND","ROR","GOV","CON","OTH","RH","PNP"), pch=21,
    col="#777777", pt.bg=colrs, pt.cex=2, cex=.8, bty="n", ncol=1)
write_graph(h, "nanotechF1.gml", format = "gml")
```

```
#EDU IND
h5 = induced.subgraph(g, V(g)[industry | education ])
plot(h5, vertex.label=NA,vertex.size=5,vertex.color=c("tomato","lightblue"))
write_graph(h5, "NanotechEI.gml", format = "gml")
transitivity_g5 <- transitivity(h5, type = "globalundirected")

#EDU RES
h6 = induced.subgraph(g, V(g)[education | research_org ])
summary(h6)
plot(h6, vertex.label=NA,vertex.size=5,vertex.color=c("lightblue","darksalmon"))
write_graph(h6, "NanotechER.gml", format = "gml")
transitivity_g6 <- transitivity(h6, type = "globalundirected")


#IND RES
h7 = induced.subgraph(g, V(g)[industry | research_org ])
plot(h7, vertex.label=NA,vertex.size=5,vertex.color=c("tomato","darksalmon"))
write_graph(h7, "NanotechIR.gml", format = "gml")


V(h4)$degree_w <- strength(h4, mode = "all", loops = F)
V(h4)$degree_w

V(h4)$closeness_w <- igraph::closeness(h4)
V(h4)$closeness_w

V(h4)$betweenness_w <- betweenness(h4)
V(h4)$betweenness_w

hist(igraph::degree(h4), col= "pink",
    xlab = "degree",
    ylab = "frequency",
    main = "")

hist(betweenness(h4), col= "light blue",
    xlab = "Betweenness",
    ylab = "Frequency",
    main = "")


G <- get.adjacency(h4, sparse = F)                          #Get the adjacency matrix

br <- sna::brokerage(G, V(h4)$betweenness_w)                          #Calculate brokerage measures
summary(br)

brraw_nli_csv <- write.csv(br$raw.nli,"br_raw1nanotech.csv")
centr_degree(h4, mode = "total", loops = F)                    #Degree centralisation
```

```
centr_clo(h4, mode = "total")                            #Closeness centralisation
centr_betw(h4, directed = F)                             #Betweenness centralisation


d_g <- diameter(h4, directed = FALSE, unconnected = FALSE)         #diameter
apl_g  <- mean_distance(h4, directed = FALSE, unconnected = FALSE)  #APL
ed_g <- edge_density(h4)                                  #Calculate density
cp_g <- articulation_points(h4)                           #Cutpoints
cliques_g <- cliques(h4, min = 3)                         #List of cliques
numcliques_g <- count_max_cliques(h4, min = 3)                   #Number of cliques
transitivity_g <- transitivity(h4, type = "globalundirected")      #Calculate transitivity

numisolates_g <- sum(igraph::degree(h4)==0)                        #Number of isolates
isolates_g <- V(h4)[igraph::degree(h4)==0]                        #List of isolates
inclusiveness_g <- (vcount(h4)-numisolates_g)/vcount(h4)

effective_net <- influenceR::ens(h4)

const <- constraint(h4)
invConstraint <-1.125 - const
names = V(h4)$Label
d <-data.frame(node.name=names, constraint=const,Inverse_constraint=
invConstraint,effectiveNetworksize=effective_net)
write.csv(d,"constraint1.csv")
```